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Association between hourly wages and dietary intake after the first phase of implementation of the Minneapolis minimum wage ordinance

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Abstract

Objective: In 2018, Minneapolis began phased implementation of an ordinance to increase the local minimum wage to $15/h. We sought to determine whether the first phase of implementation was associated with changes in frequency of consumption of fruits and vegetables (F&V), whole-grain-rich foods, and foods high in added sugars among low-wage workers.
Design: Natural experiment.
Setting: The Wages Study is a prospective cohort study of 974 low-wage workers followed throughout the phased implementation of the ordinance (2018–2022). We used difference-in-difference analysis to compare outcomes among workers in Minneapolis, Minnesota, to those in a comparison city (Raleigh, North Carolina). We assessed wages using participants' pay stubs and dietary intake using the National Cancer Institute Dietary Screener Questionnaire.
Participants: Analyses use the first two waves of Wages data (2018 (baseline), 2019) and includes 267 and 336 low-wage workers in Minneapolis and Raleigh, respectively.
Results: After the first phase of implementation, wages increased in both cities, but the increase was $0·84 greater in Minneapolis ($P = 0·02$). However, the first phase of the policy's implementation was not associated with changes in daily frequency of consumption of F&V (IRR = 1·03, 95 % CI: 0·86, 1·24, $P = 0·73$), whole-grain-rich foods (IRR = 1·23, 95 % CI: 0·89, 1·70, $P = 0·20$), or foods high in added sugars (IRR = 1·13, 95 % CI: 0·86, 1·47, $P = 0·38$) among workers in Minneapolis compared to Raleigh.
Conclusions: The first phase of implementation of the Minneapolis minimum wage policy was associated with increased wages, but not with changes in dietary intake. Future research should examine whether full implementation is associated dietary changes.

Keywords
Minimum wage
Natural experiment
Social policy
Dietary intake

Disparities in dietary intake are a major focus of public health research, practice, and policy in the USA. On average, low-income Americans have lower intakes of fruits and vegetables (F&V) and lower quality diets than higher-income Americans[1,2]. Higher cost of healthier foods may contribute to these disparities[3–5]. Therefore, policies that increase hourly wage for lower-income Americans could increase household income[6] and thus, the ability to purchase healthier, often more costly foods such as F&V.

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In June 2017, Minneapolis, Minnesota passed an ordinance that will incrementally increase the minimum wage above the state level to \$15 an hour, from \$9·50 per hour for all businesses with greater than 100 employees, and from \$7·75 per hour in smaller businesses[12]. The incremental annual wage increase must be fully implemented by 1 July 2022 for large businesses and 2 years later for small businesses (Fig. 1)[12].

Because minimum wage increases could increase income for lower-wage workers, they could improve diet quality as affording healthier food becomes more possible. However, it is unclear if minimum wage ordinances actually translate to higher household income (because other changes in household income related and unrelated to the minimum wage may occur). Further, even if income does increase, it is not clear that additional income would be used for healthier food purchases. It is also unclear whether an increase in household income would cause participants to experience a reduction in their federal food assistance or reduce their hours worked. Figure 2 presents a conceptual model that displays various hypothesised relationships between a minimum wage ordinance and improvements in dietary intake.

Three prior cross-sectional studies have examined associations between minimum wage increases and F&V consumption but had mixed results[9–11]. Horn *et al.* found no association between minimum wage increases and the daily number of F&V consumed in lesser-skilled female workers and found an inverse association among males[9]. Similarly, Andreyeva & Ukert found that a one-dollar wage increase was associated with a 0·17% reduction in F&V consumption[10]. In contrast, a 2020 study by Clark *et al.* estimated an increase of approximately 0·08 daily F&V servings when the minimum wage increased by one dollar[11]. However, these cross-sectional studies used proxy measures such as education and household income to approximate the likelihood of being affected by minimum wage increases, rather than measuring this directly. Thus, a longitudinal study that follows groups exposed, and unexposed, to a legislated minimum wage increase and directly measures hourly wage is needed.

The aim of this study is to examine whether the first phase of a minimum wage increase in Minneapolis is associated with changes in frequency of consumption of F&V, whole-grain-rich foods (in which a food's first ingredient is a whole grain) and foods high in added sugars (> 5 grams of sugar per serving) among low-wage workers. We hypothesised that the minimum wage ordinance would be associated with increased wages and household income and would be associated with improvements in dietary intake.

Methods

Study population

The Wages Study is a prospective cohort study. Recruitment methods and inclusion criteria are described in detail elsewhere[13]. In January 2018, the Wages Study began following a cohort of 974 low-wage workers (those earning ≤ \$11·50 an hour at baseline) in Minneapolis (*n* 495) and low-wage workers in a comparison city with no minimum wage increase (Raleigh, North Carolina, *n* 479). The study aims to follow this cohort throughout 4·5-years of implementation of the Minneapolis minimum wage ordinance (1 January 2018–1 July 2022). Recruitment and baseline data collection occurred from January to October 2018. Of note, the baseline data collection period (hereon referred to as Wave 1) was extended from the original completion date of July 2018 to October 2018 due to challenges in recruitment. Details of this are discussed elsewhere[13]. Wave 2 data collection occurred during the summer and fall of 2019. Data will be collected again in the summers of 2020 (Wave 3), 2021 (Wave 4) and 2022 (Wave 5).

This study described in this manuscript uses the first two waves of longitudinal data from the currently ongoing Wages Study (*n* 655, as 319 participants of the originally recruited 974 participants were lost to follow-up at Wave 2). After exclusions, data from 603 Wages participants at Waves 1 and 2 were available for the study's first set of analyses (Fig. 3), and 540 Wages participants were available for the second set of analyses (Fig. 4). The study was approved by the institutional review boards of the University of Minnesota and the University of North Carolina at Chapel Hill, and participants gave written informed consent to participate.

Hourly wage assessment

Wages participants attend one data collection appointment each year in which wages are verified and a computer-based survey is administered. Participants are asked to bring a recent pay stub or other document from their primary employer to verify their hourly wage at the annual data collection appointment. At Wave 1, 75·67 % of participants verified their hourly wage (737/974). At Wave 2, 81·37 % of the 655 participants who returned for a follow-up appointment verified their hourly wage (533/655). All other participants self-reported their hourly wage.

Dietary assessment

To assess dietary intake, the computer-administered survey included 22 questions from the validated 26-item National Cancer Institute's (NCI) Dietary Screener Questionnaire (DSQ)[14,15]. The primary investigators for the Wages research team excluded four DSQ items from the computer survey (milk, cheese, red meat and processed meat) because the research team wanted to keep only the most relevant questions in the computer survey to minimise participant survey fatigue.

For the current analysis, we used the DSQ frequency data to estimate participants' daily frequency of intake of three different food groups to be used as the study's dependent variables: F&V, whole-grain-rich foods (in which the first ingredient is a whole grain) and foods high in added sugars (> 5 grams of sugar per serving). These food groups

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Date	Large businesses (>100 employees)	Small Businesses (≤100 employee)
2017	$9·50	$7·75
1 January 2018 (Wages Study baseline (Wave 1) data collection begins)	$10·00	No increase
1 July 2018	$11·25	$10·25
1 July 2019 (Wages Study Wave 2 data collection begins)	$12·25	$11·00
1 July 2020 (Wages Study Wave 3 data collection begins)	$13·25	$11·75
1 July 2021 (Wages Study Wave 4 data collection begins)	$14·25	$12·50
1 July 2022 (Wages Study Wave 5 data collection begins)	$15·00*	$13·50
1 July 2023	$15·00*	$14·50
1 July 2024	$15·00*	$15·00* (Equal to Large Businesses)

*Increases to account for inflation, every subsequent on 1 January

Fig. 1 Scheduled implementation of hourly wage increases in the city of Minneapolis, and the corresponding Wages Study data collection time points

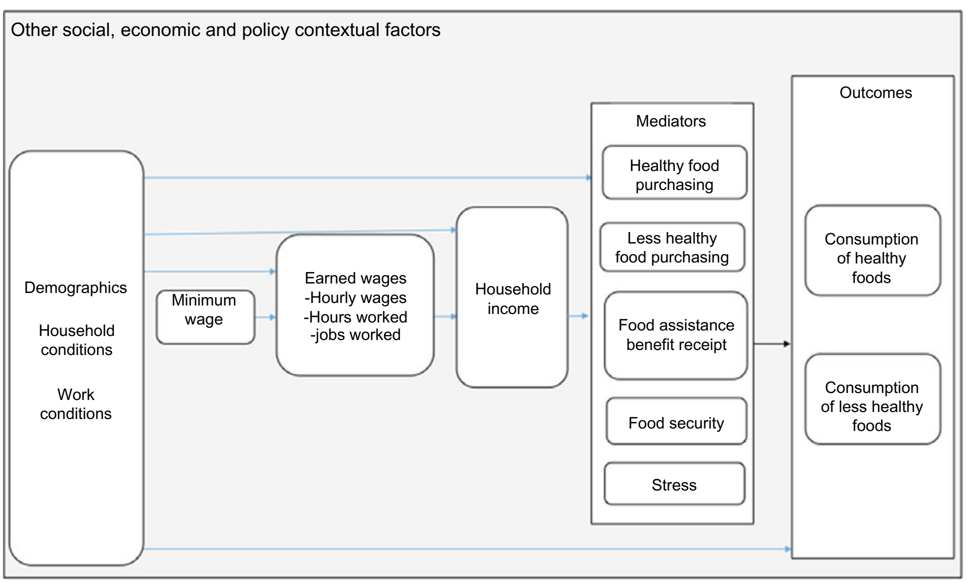

Fig. 2 (colour online) Conceptual model for the present study using data from Wave 1 (2018) and Wave 2 (2019) of the Wages Study

were created because all three are associated with weight gain (a lower risk for F&V[16] and whole-grain-rich foods[17] and a higher risk for foods high in added sugars[18,19]) and chronic disease risk (a reduced risk for F&V[20] and whole-grain-rich foods[21] and an increased risk for foods high in added sugars[22]) in previously conducted scientific literature. The five-gram cut-off was chosen for foods high in added sugars because the daily value of added sugars is 50 grams per day based on a 2000 kilocalorie per day diet[23], and the Food and Drug Administration considers a food to be a 'good' source of a nutrient if it contains 10–19 % of the daily value[24]. Thus, we designated a food as being high in added sugar if it contained more than 10 % daily value for sugar (greater than 5 grams). Supplemental Table 1 displays the foods from the DSQ that contribute to each food group.

To create the food group-dependent variables, the research team first classified all foods from the DSQ as to whether they belonged, or not, in each of the three food groups. Foods could belong to more than one food group. We then converted participants' responses to the DSQ into daily frequencies for each food (e.g. if a participant responded that he/she consumed popcorn '2–3 times last month,' we divided 2·5 by 30 and assigned that participant a value of 0·083 for their popcorn consumption variable). Finally, we created three new variables for each participant

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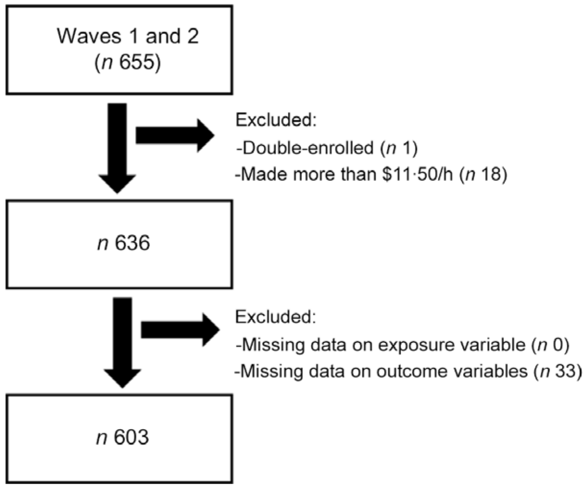

Fig. 3 Flow chart for Wages participant exclusion in the present study's policy analyses

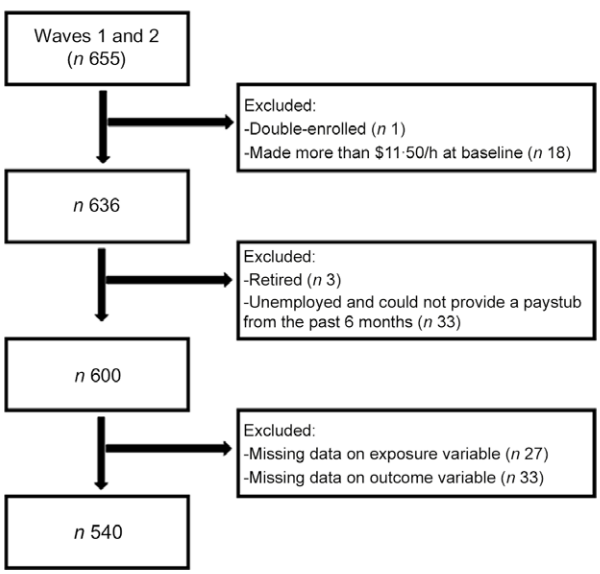

Fig. 4 Flow chart for Wages participant exclusion in the present study's hourly wage analyses

in the data set. The first variable was the sum of the daily frequencies for all F&V foods, the second variable was the sum of the daily frequencies for all whole-grain-rich foods and the third was the sum of the daily frequencies for all foods high in added sugars.

Covariate assessment

We collected data on demographic, economic and health-related factors, including age (continuous), sex (male, female and non-binary), race (White alone, Black or African American alone, Asian alone, Native Hawaiian or Pacific Islander alone, Native American or Alaskan native alone, more than one race, or other race), ethnicity (Hispanic/Latino and non-Hispanic/Latino), marital status (married or single), birthplace (born in the USA, born abroad to American parents or born abroad), whether or not a participant was a food service worker (as food service employees are often provided meals on the job[25], which may impact their dietary intake), educational attainment (less than high school, some high school, high school diploma, associate/technical degree, some college, or Bachelor's degree or higher), number of adults living in the household (one, two, three, four, or five or more), number of children living in the household (one, two, three, four, or five or more), pregnancy status (pregnant and not pregnant), smoking status (current smoker, quit less than 12 months ago, quit more than 12 months ago or never smoker), health insurance status (insured all year (any type of health insurance), uninsured for at least part of the year or uninsured all year), BMI (continuous), the timing (in weeks) of the participant's data collection appointment relative to the minimum wage increase, number of jobs worked (one job worked or more than one job worked) and the amount received in Supplemental Food and Nutrition Assistance Program (SNAP) benefits (I do not receive any SNAP benefits, $1–$25, $26–$50, $51–$75, $76–$100, $101–$150, $151–$250, $251–$500, $501–$750, more than $750).

Statistical analysis

The research team performed two sets of difference-in-difference (DID) analyses to address the present study's aims. The first DID analysis examined whether living in a city with a mandated minimum wage increase was associated with changes in daily frequency of F&V consumption (model one), whole-grain-rich foods (model two) and foods high in added sugars (model three). This analysis categorised participants by city of residence (0 = Raleigh and 1 = Minneapolis) when assessing the exposure in the DID models. We term these the 'policy' analyses. The second analysis examined whether changes in individual hourly wage were associated with changes in daily frequency of F&V consumption (model four), whole-grain-rich foods (model five) and foods high in added sugars (model six). This analysis used Wages participants' hourly wage as the exposure variable in the DID models. We term these the 'hourly wage' analyses.

The research team chose to conduct two sets of DID analyses for several reasons. First, the policy analysis examines the association between the change in policy and the change in outcome, acknowledging that some Wages participants in Minneapolis may not experience a wage increase from Wave 1 to Wave 2 (due to the possibility that some businesses may not be compliant in implementing the minimum wage ordinance, or due to the possibility that wage changes may not be linear and positive over time among low-wage workers, particularly if job changes, job losses or a reduction in hours worked occur). This is important as it estimates the impact of the ordinance under 'real-world' conditions of adherence. Additionally,

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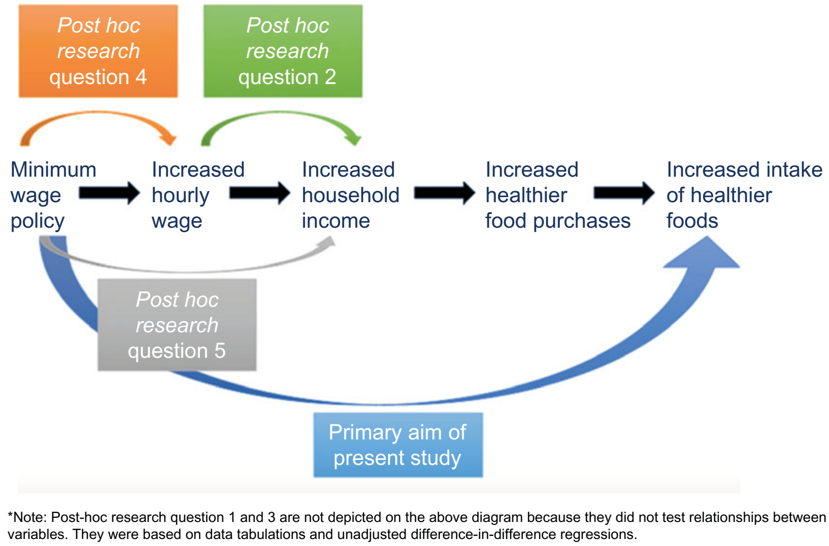

Fig. 5 (colour online) Hypothesised causal pathway for the relationship between a minimum wage policy and changes in dietary intake

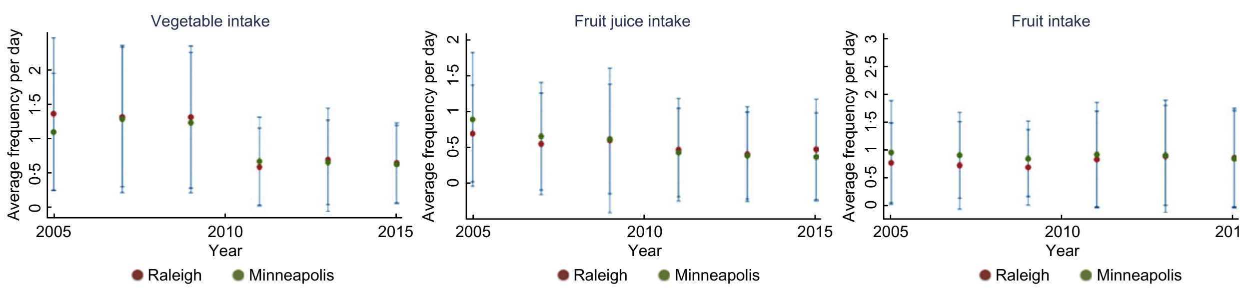

Fig. 6 (colour online) Dietary intake by metropolitan statistical area 2005–2015 BRFSS SMART data – incomes < \$35 000 per year

participants in Raleigh may also experience wage increases (due to job promotions, raises, etc.). Lastly, it accounts for any impact of simply living in an area with a mandated wage increase on dietary outcomes (e.g. changing attitudes, beliefs and norms)[26]. However, the research team also wanted to run models in which participants' individual hourly wage served as the primary predictor variable. This is important to test, as increasing hourly wage is the key mechanism by which a minimum wage ordinance may increase household income and therefore improve dietary intake (Fig. 5). Prior to conducting these DID analyses, the research team examined the parallel trends assumption[27] using BRFSS SMART data[28] (Fig. 6) and found that current trends in dietary intake between the two cities did not differ meaningfully when comparing data from residents with incomes less than \$35 000 per year from 2005 to 2015. All analyses were conducted in Stata/IC (version 16.0, 2019, StataCorp LLC).

Analysis 1 – Policy analysis

In the first DID analytic approach, the Wave 1 Wages data were designated as the pre-policy period, while Wave 2 served as the post-policy period. The treatment group consisted of the Minneapolis participants and the control group the Raleigh participants. A product term for these two variables provided the DID estimate (city * time period). For all models, analyses adjusted for the covariates listed above, except for amount received in SNAP benefits, as we thought this variable could be a potential mediator in the relationship between a minimum wage increase and dietary intake.

The DID models were estimated using negative binomial regression, as the outcomes were over-dispersed count data. Likelihood ratio tests that the dispersion parameter was equal to zero revealed that negative binomial models were a better fit than Poisson models[29–31]. Data were analysed with longitudinal regression analysis (generalised estimating equations (GEE) with clustering by the individual), using the Huber – White sandwich estimator of variance and an autoregressive correlation matrix in order to account for repeated measures within individuals[32]. Sensitivity analyses were performed, and results did not change when alternative correlation matrices were specified.

Analysis 2 – Hourly wage analysis

The second analytic approach was identical to the first analytic approach, except continuous DID models were specified and Wages participants' hourly wages, rather than city

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of residence, were used to calculate the DID indicator (hourly wage * time period). The researchers adjusted for the same covariates as done in the first set of analyses, except city was added as an additional covariate.

Sensitivity analyses

Given the study's high attrition rate and thus the possibility of selection bias and biased parameter estimates[33], we examined differential attrition by baseline measures of age, sex, race, ethnicity, educational attainment and SNAP usage among those who returned for a Wave 2 appointment (n 655) *v.* those who did not (n 319) using t tests and chi-square tests (Tables 3 and 4). We also conducted sensitivity analyses for both the 'policy' analyses and the 'hourly wage' analyses using inverse probability-of-censoring weights. Inverse probability-of-censoring weight inversely weights regression analyses by the probability of participation (determined based on a logistic regression model for probability of participation given past history covariates and outcomes)[34–37]. This inflates the impact of underrepresented subjects, so we can observe associations that would have been observed if all subjects had stayed in the Wages Study at Wave 2 (assuming the models are correctly specified)[40–43].

To perform inverse probability-of-censoring weight, we first fit a logistic regression model to estimate the probability of not returning at Wave 2 based on baseline characteristics of age, sex, race, ethnicity, educational attainment, birthplace, marital status, number of children living in the household, SNAP usage, hourly wage, job type and whether the participant lived in Minneapolis or Raleigh. We then used weights derived from this model to re-estimate the six DID regression models and the associations that would have been observed if all subjects from Wave 1 had remained in the study at Wave 2. The six weighted DID models used 1/P as weights. All covariates used in the weighted DID models were identical to the covariates in the original unweighted DID models.

Post hoc *analyses*

In the event that results were not as hypothesised and a minimum wage policy change was not associated with changes in dietary intake between the cities, the research team decided to conduct *post hoc* analyses to understand why. We hypothesised that if results were null, perhaps the first phase of change in minimum wage policy did not translate to higher hourly wages or higher household income between the two cities. We therefore decided to examine the following *post hoc* research questions: RQ1) on average, did the hourly wage significantly change between the cities from Wave 1 to Wave 2?; RQ2) were changes in hourly wage associated with changes in household income?; RQ3) on average, did household income categories significantly change between the cities from Wave 1 to Wave 2?; RQ4) was the policy associated with changes in hourly wage between the cities from Wave 1 to Wave 2?; and RQ5) was the policy associated with changes in household income categories between the cities from Wave 1 to Wave 2? Because only 1 year had passed between Waves 1 and 2, we did not inflation-adjust hourly wages in the *post hoc* analyses. Figure 5 displays how we thought the change in policy would lead to change in wages and outcomes, and what relationship each set of *post hoc* analyses tested.

To address *post hoc* RQ1 (did the hourly wage significantly change between the cities from Wave 1 to Wave 2?), the research team performed data tabulations to examine the average wages and change in wages among Raleigh and Minneapolis participants at Waves 1 and 2. Additionally, we estimated unadjusted DID regressions using longitudinal regression analysis (GEE with clustering by the individual), and using Huber–White sandwich estimator of variance and an autoregressive correlation matrix to adjust for the within-subject correlation.

Given that household income was an ordinal variable in our data set, the research team addressed RQ2 (were changes in hourly wage associated with changes in household income?) by estimating a multinomial logistic regression model. A multinomial logistic regression model was estimated rather than an ordinal logistic regression model because the proportional odds assumption was tested and violated. Standard errors were clustered at the level of the individual.

Again, because household income was an ordinal variable, the research team addressed RQ3 (did household income categories significantly change between the cities from Wave 1 to Wave 2?) by estimating a DID ordinal logistic regression model with standard errors clustered at the level of the individual. The same DID product term was used as described in RQ1. The proportional odds assumption was tested and held.

The same DID model from RQ1 was used for RQ4 (was the policy associated with changes in hourly wage between the cities from Wave 1 to Wave 2?). However, the following covariates were added: race, sex, age, education level, job classification and the number of job trainings completed during the past 12 months. These covariates were selected because they are associated with both hourly wages and living in a particular area in existing economic literature[38,39].

To address RQ5 (was the policy associated with changes in household income categories between the cities from Wave 1 to Wave 2?), the research team estimated a multinomial logistic DID regression model because the proportional odds assumption was again violated. Standard errors were clustered at the level of the individual. The following covariates were included in the models: race, sex, age, number of adults living in the household, marital status, education level, job classification and the number of job trainings completing during the last 12 months[38,39].

Results

At Wave 2, 655 out of 974 Wages participants (67·25%) returned for a follow-up appointment (attrition rate of

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Table 1 Baseline characteristics of the Wages participants in Minneapolis, Minnesota, and Raleigh, North Carolina that will be used in analyses

	Analysis 1: policy analysis (*n* 603)*				Analysis 2: wage analysis (*n* 540)†			
	Minneapolis		Raleigh		Minneapolis		Raleigh	
	n	%	*n*	%	*n*	%	*n*	%
Total sample	267	44·3	336	55·7	219	40·6	321	59·4
Average hours worked per week								
Mean	25·77		32·52		25·89		32·71	
SD	10·41		9·72		10·38		9·59	
Average hourly wage ($)								
Mean	10·32		9·36		10·34		9·37	
SD	1·17		1·76		1·22		1·76	
Age								
18–29	49	18·4	108	32·1	42	19·2	103	32·1
30–39	44	16·5	95	28·3	40	18·3	91	28·4
40–49	47	17·6	58	17·3	42	19·2	56	17·5
50–59	88	33·0	58	17·3	63	28·8	54	16·8
60+	39	14·6	17	5·1	32	14·6	17	5·3
Missing	0	0·0	0	0·0	0	0·0	0	0·0
Sex								
Male	123	46·1	105	31·3	99	45·2	99	30·8
Female	138	51·7	230	68·5	116	53·0	221	68·9
Non-binary	3	1·1	1	0·3	1	0·5	1	0·3
Missing	3	1·1	0	0·0	3	1·4	0	0·0
Race								
White alone	58	21·7	40	11·9	51	23·3	37	11·5
Black or African American alone	159	59·6	274	81·6	130	59·4	264	82·2
Asian alone	2	0·8	2	0·6	2	0·9	2	0·6
Native Hawaiian or Pacific Islander alone	1	0·4	0	0·0	0	0·0	0	0·0
Native American or Alaskan Native alone	15	5·6	2	0·6	10	4·6	2	0·6
More than one race	18	6·7	8	2·4	15	6·9	8	2·5
Other	10	3·8	10	3·0	7	3·2	8	2·5
Missing	4	1·5	0	0·0	4	1·8	0	0·0
Ethnicity								
Hispanic/Latino	11	4·1	19	5·7	10	4·6	18	5·6
Non-Hispanic/Latino	249	93·3	316	94·1	203	92·7	302	94·1
Missing	7	2·6	1	0·3	6	2·7	1	0·3
Education								
Less than high school	9	3·4	4	1·2	6	2·7	3	0·9
Some high school	49	18·4	34	10·1	37	16·9	34	10·6
High school diploma	75	28·1	144	42·9	60	27·4	138	43·0
Associate/technical degree	37	13·9	30	8·9	33	15·1	29	9·0
Some college	68	25·5	91	27·1	56	25·6	86	26·8
Bachelor's degree or higher	28	10·5	32	9·5	27	12·3	30	9·4
Missing	1	0·4	1	0·3	0	0·0	1	0·3
SNAP‡ usage								
Receiving SNAP	164	61·4	142	42·3	129	58·9	138	43·0

SNAP, Supplemental Nutrition Assistance Program.
*Excludes participants who double-enrolled in the study (*n* 1), made more than $11·50 per hour at baseline (*n* 18) and who were missing more than one response on the Dietary Screener Questionnaire at either Wave 1 or Wave 2 (*n* 33).
†Excludes participants who double-enrolled in the study (*n* 1), made more than $11·50 per hour at baseline (*n* 18), who were missing more than one response on the Dietary Screener Questionnaire at either Wave 1 or Wave 2 (*n* 33), missing hourly wage information (*n* 27), were unemployed and could not provide a pay stub or self-report hourly wage from their most recent job in the past 6 months (*n* 33), or were retired (*n* 3).
‡SNAP.

32·75%). For the study's 'policy' analyses, we used Wages data from Waves 1 and 2 (*n* 655) but excluded participants who double-enrolled in the Wages Study (*n* 1), made more than $11·50 per hour at baseline and therefore did not meet the study's inclusion criteria for enrolment (*n* 18) and were missing more than one response on the DSQ at either Waves 1 or 2 (*n* 33). After exclusions, data from 603 Wages participants were available for the study's 'policy' analyses (Fig. 3). For the 'hourly wage' analyses, we excluded the same participants as the 'policy' analyses but also excluded participants who had retired at Wave 2 (*n* 3) and therefore had no hourly wage, participants who were unemployed and could not provide a pay stub or self-report hourly wage from their most recent job in the past 6 months (*n* 33), and participants who were missing hourly wage information (*n* 27). After exclusions, data from 540 Wages participants were available for analyses (Fig. 4).

Baseline demographic information for participants included in both sets of this study's analyses is presented in Table 1. The majority of Wages participants were Black or African American, non-Hispanic, and had received at least a high school diploma or higher. The average wage

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Table 2 Comparison of job classification, weekly hours worked and number of jobs worked among Wages participants at Waves 1 and 2 in Minneapolis, Minnesota and Raleigh, North Carolina, for the present study's policy analysis (*n* 603)

	Policy analysis Wave 1 (*n* 603)						Policy analysis Wave 2 (*n* 603)					
	Minneapolis		Raleigh		Total		Minneapolis		Raleigh		Total	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Total sample	267	44·3	336	55·7	603	100·0	267	44·3	336	55·7	603	100·0
Number of participants working more than 1 job	34	12·7	41	12·2	75	12·4	19	7·1	24	7·1	43	7·1
Average weekly hours worked												
Mean	25·77		32·52		29·54		28·83		35·64		32·90	
SD	10·41		9·72		10·57		13·29		10·23		12·02	
Breakdown of weekly hours worked												
0–9	10	3·8	7	2·1	17	2·8	14	5·2	8	2·4	22	3·7
10–19	48	18·0	23	6·9	71	11·8	23	8·6	9	2·7	32	5·3
20–29	95	35·6	69	20·5	164	27·2	81	30·3	42	12·5	123	20·4
30–39	68	25·5	106	31·6	174	28·9	38	14·2	95	28·3	133	22·1
40–49	39	14·6	123	36·6	162	26·9	56	21·0	156	46·4	212	35·2
50–59	1	0·4	0	0·0	1	0·2	3	1·1	8	2·4	11	1·8
60+	1	0·4	3	0·9	4	0·7	5	1·9	9	2·7	14	2·3
Missing	5	1·9	5	1·5	10	1·7	47	17·6	9	2·7	56	9·3
Job classification*												
Food preparation and serving related	42	15·7	71	21·1	113	18·7	32	12·0	91	27·1	123	20·4
Office and administrative support occupations	21	7·9	79	23·5	100	16·6	20	7·5	63	18·8	83	13·8
Building and grounds cleaning/maintenance	37	13·9	20	6·0	57	9·5	23	8·6	26	7·7	49	8·1
Healthcare support occupations	17	6·4	27	8·0	44	7·3	25	9·4	25	7·4	50	8·3
Sales and related occupations	22	8·2	30	8·9	52	8·6	18	6·7	23	6·9	41	6·8
Transportation and material moving	38	14·2	31	9·2	69	11·4	9	3·4	18	5·4	27	4·5
Other	86	32·2	72	21·4	158	26·2	72	27·0	88	26·2	160	26·5
Missing	4	1·5	6	1·8	10	1·7	68	25·5	2	0·6	70	11·6

*Classified according to the Bureau of Labor Statistics' guide to Standard Occupational Codes for job descriptions and the North American Industry Classification System for employer sector.

at Wave 1 was $10·32 per hour in Minneapolis and $9·36 per hour in Raleigh. The average number of weekly hours worked at Wave 1 was 25·77 h per week in Minneapolis and 32·52 h per week in Raleigh.

Tables 2 and 3 display descriptive statistics about economic indicators for participants included in both sets of analyses. On average across the sites, the most common job type among participants was 'Food Preparation and Serving,' and the distribution of the different job types remained relatively constant between Waves 1 and 2. For both sites, the average number of hours worked each week increased from Wave 1 to Wave 2. Lastly, for both sites, the per cent of participants who worked more than one job decreased from Wave 1 to Wave 2.

Analysis 1 – Policy results

Table 4 displays average daily frequencies of consumption for each food group by city for each wave. On average, consumption decreased for all three food groups in both cities. Table 5 displays results from the multivariable DID longitudinal regression analyses. There were no significant differences between the cities for daily frequency of consumption of F&V (IRR = 1·03, 95 % CI: 0·86, 1·24, $P = 0·73$), whole-grain-rich foods (IRR = 1·23, 95 % CI: 0·89, 1·70, $P = 0·20$) or foods high in added sugars (IRR = 1·13, 95 % CI: 0·86, 1·47, $P = 0·38$) (Table 5).

Analysis 2 – Hourly wage results

Table 4 displays average daily frequencies of consumption for each food group by city for each wave. Again, on average, consumption decreased for all three food groups in both cities. Results from the continuous multivariate DID longitudinal regression analyses indicated that there were no significant differences between the cities for daily frequency of consumption of F&V (IRR = 0·98, 95 % CI: 0·94, 1·02, $P = 0·32$), whole-grain-rich foods (IRR = 0·97, 95 % CI: 0·91, 1·05, $P = 0·48$) or foods high in added sugars (IRR = 1·01, 95 % CI: 0·97, 1·06, $P = 0·57$) (Table 5).

Sensitivity analyses results

Prior to performing our sensitivity analyses, the research team first used *t* tests and chi-square tests to examine differences in baseline measures of age, sex, race, ethnicity, educational attainment and SNAP usage among those who returned for a Wave 2 appointment (*n* 655) *v.* those who did not (*n* 319). There were no significant differences in age, race, ethnicity, educational attainment or SNAP usage, but baseline measures of sex were significantly different between the groups (see online supplementary material, Supplemental Table 2). A higher percentage of females returned for a Wave 2 appointment. Supplemental Table 3 presents results from the sensitivity analyses using inverse probability-of-censoring weight. Results did not change

Table 3 Comparison of job classification, weekly hours worked and number of jobs worked among Wages participants at Waves 1 and 2 in Minneapolis, Minnesota and Raleigh, North Carolina, for the present study's hourly wage analysis (*n* 540)

	Hourly wage analysis Wave 1 (*n* 540)						Hourly wage analysis Wave 2 (*n* 540)					
	Minneapolis		Raleigh		Total		Minneapolis		Raleigh		Total	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Total sample	219	40·6	321	59·4	540	100·0	219	40·6	321	59·4	540	100·0
Number of participants working more than 1 job	30	13·7	39	12·2	69	12·8	18	8·2	24	7·5	42	7·8
Average weekly hours worked												
Mean	25·89		32·71		29·93		28·92		35·62		32·93	
SD	10·38		9·59		10·46		13·30		10·32		12·06	
Breakdown of weekly hours worked												
0–9	9	4·1	6	1·9	15	2·8	13	5·9	8	2·5	21	3·9
10–19	36	16·4	21	6·5	57	10·6	23	10·5	9	2·8	32	5·9
20–29	84	38·4	65	20·3	149	27·6	78	35·6	40	12·5	118	21·9
30–39	57	26·0	103	32·1	160	29·6	37	16·9	94	29·3	131	24·3
40–49	30	13·7	119	37·1	149	27·6	54	24·7	149	46·4	203	37·6
50–59	1	0·5	0	0·0	1	0·2	3	1·4	8	2·5	11	2·0
60+	1	0·5	3	0·9	4	0·7	5	2·3	9	2·8	14	2·6
Missing	1	0·5	4	1·3	5	0·9	6	2·7	4	1·3	10	1·9
Job classification*												
Food preparation and serving related	35	16·0	69	21·5	104	19·3	30	13·7	89	27·7	119	22·0
Office and administrative support occupations	20	9·1	77	24·0	97	18·0	20	9·1	60	18·7	80	14·8
Building and grounds cleaning/maintenance	24	11·0	19	5·9	43	8·0	19	8·7	24	7·5	43	8·0
Healthcare support occupations	15	6·9	25	7·8	40	7·4	25	11·4	24	7·5	49	9·1
Sales and related occupations	20	9·1	29	9·0	49	9·1	18	8·2	23	7·2	41	7·6
Transportation and material moving	34	15·5	31	9·7	65	12·0	9	4·1	17	5·3	26	4·8
Other	69	31·5	68	21·2	137	25·4	69	31·5	84	26·2	153	28·3
Missing	2	0·9	3	0·9	5	0·9	29	13·2	0	0·0	29	5·4

*Classified according to the Bureau of Labor Statistics' guide to Standard Occupational Codes for job descriptions and the North American Industry Classification System for employer sector.

Table 4 Average daily frequencies of consumption of the three food groups between Minneapolis and Raleigh at Waves 1 and 2

	Minneapolis			Raleigh		
	Wave 1	Wave 2	Difference	Wave 1	Wave 2	Difference
Policy analysis (*n* 603)						
Average daily frequency of consumption of fruits and vegetables	3·28*	3·10	–0·18	3·30	3·18	–0·12
Average daily frequency of consumption of whole-grain-rich foods	1·01	0·98	–0·03	0·90	0·74	–0·16
Average daily frequency of consumption of foods high in added sugars	3·11	2·68	–0·43	3·27	2·93	–0·34
Hourly wage analysis (*n* 540)						
Average daily frequency of consumption of fruits and vegetables	3·38	3·22	–0·16	3·34	3·18	–0·16
Average daily frequency of consumption of whole-grain-rich foods	1·01	1·00	–0·01	0·91	0·73	–0·18
Average daily frequency of consumption of foods high in added sugars	3·27	2·71	–0·56	3·32	2·99	–0·33

*An interpretation of this number would be: on average, Wages participants in Minneapolis consumed fruits and vegetables 3·28 times per day at Wave 1.

and remained null for all models when inverse probability weights were incorporated into the DID regression models.

Post hoc *analysis results*

First, we examined whether the policy's intended target, hourly wage, changed on average between the cities from Wave 1 to Wave 2. Based on data tabulations, the average hourly wage in Minneapolis was \$10·32 at Wave 1 and \$12·73 at Wave 2, equating to an average increase of \$2·41. In Raleigh, the average hourly wage at Wave 1 was \$9·36 and \$10·93 at Wave 2, resulting in an average increase of \$1·57. Thus, on average, the hourly wage increased in both Minneapolis and Raleigh, but it increased by 84 cents more in Minneapolis ($P=0·02$, based on t test, data not shown). Similarly, results from the DID linear regression (RQ1 – did the hourly wage significantly change between the cities from Wave 1 to Wave 2?) indicated that on average, the hourly wage significantly increased from Wave 1 to Wave 2, and it increased significantly more in Minneapolis than in Raleigh ($\beta=0·82$, 95 % CI: 0·13, 1·51, $P=0·02$, Table 6).

Changes in hourly wage were associated with changes in household income for higher categories of income ($P<0·001$ for income categories 4, 5, 6 and 7 compared to income category 1, Table 6, RQ2 – were changes in

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Table 5 Difference-in-difference models of the longitudinal relationship between an area-level wage increase and frequency of consumption of various food groups among Wages participants in Minneapolis, Minnesota, and Raleigh, North Carolina, from Wave 1 (baseline, 2018) to Wave 2 (2019)

	Daily frequency of consumption of food groups								
	Fruits and vegetables			Whole-grain-rich foods			Foods high in added sugars		
Model	IRR*	95 % CI	*P*-value	IRR	95 % CI	*P*-value	IRR	95 % CI	*P*-value
Policy analysis (*n* 603):									
Crude model	0·98	0·86, 1·12	0·80	1·18	0·95, 1·47	0·13	0·96	0·81, 1·14	0·67
Adjusted model†	1·03‡	0·86, 1·24	0·73	1·23	0·89, 1·70	0·20	1·13	0·86, 1·47	0·38
Hourly wage analysis (*n* 540):									
Crude model	0·98	0·95, 1·01	0·13	0·97	0·93, 1·02	0·26	1·00	0·96, 1·04	0·96
Adjusted model§	0·98	0·94, 1·02	0·32	0·97	0·91, 1·05	0·48	1·01	0·97, 1·06	0·57

*The exponentiated difference-in-difference (DID) parameters (incidence rate ratios) using negative binomial regression and generalised estimating equations. The DID parameter is city*time point in the policy analysis and hourly wage*time point in the hourly wage analyses. City and time point are included as indicator variables in the DID parameter for the policy analysis.
†Models were adjusted for age, sex, race, ethnicity, marital status, whether participant was born in the USA, whether participant is a food service worker, education level, household size, pregnancy status, smoking status, health insurance status, BMI, the timing (in weeks) of the participant's data collection appointment relative to the minimum wage increase and number of jobs worked.
‡An interpretation for this coefficient would be: had there been no minimum wage policy, the difference in the rate of daily frequency of fruit and vegetable consumption between the cities was 1·03 times higher than would have been expected, holding other predictor variables in the model constant.
§Models were adjusted for city, age, sex, race, ethnicity, marital status, whether participant was born in the USA, whether participant is a food service worker, education level, household size, pregnancy status, smoking status, health insurance status, BMI, the timing (in weeks) of the participant's data collection appointment relative to the minimum wage increase and number of jobs worked.

hourly wage associated with changes in household income?). Household income increased overall from Wave 1 to Wave 2; on average, participants had a 47% higher odds of moving into one higher household income category from Wave 1 to Wave 2 ($P < 0{\cdot}001$, Table 6, RQ3 – did household income categories significantly change between the cities from Wave 1 to Wave 2?). However, there was no significant difference in changes in household income between the cities ($P = 0{\cdot}23$, Table 6, RQ3).

Results from the multivariate DID linear regression *post hoc* analysis (RQ4 – was the policy associated with changes in hourly wage between the cities from Wave 1 to Wave 2?) indicated that a change in wage policy was significantly associated with a change in hourly wage ($P = 0{\cdot}03$, Table 6). However, a change in wage policy was not significantly associated with changes in any of the household income categories (Table 6, RQ5 – was the policy associated with changes in household income categories between the cities from Wave 1 to Wave 2?).

Discussion

This study found that, among low-wage workers in an area with policy-mandated minimum wage increase, the first phase of policy implementation was not associated with changes in daily frequency of consumption of F&V, whole-grain-rich foods, or foods high in added sugars compared with low-wage workers in a control setting. *Post hoc* analyses indicated that, on average, hourly wage increased after 1 year in both cities, but the increase was greater in Minneapolis than in Raleigh. However, this differential increase in hourly wage did not translate to differential increases in household income between the cities. Similarly, *post hoc* analyses using multivariable DID regression found that living in a city with a minimum wage increase was associated with increases in hourly wage, but not increases in household income categories. Given that increased household income may be the key mechanism by which a higher mandated minimum wage could improve dietary intake[40], the lack of change in household income between the cities may explain why there were no significant changes in dietary intake after the first year of implementation.

There are several potential reasons household income did not increase more in Minneapolis than Raleigh. First, perhaps the partially implemented policy did affect household income, but our categorical income measure was not sensitive enough to detect it. Second, it is possible that the minimum wage policy did not affect household income because of unintended consequences of the policy, such as reduced hours for workers. However, we did not find that this was the case, as average hours worked increased from ~30 h per week at Wave 1 to ~33 h per week at Wave 2. Third, perhaps the policy did not affect household income differentially between the cities because it is impacted by so many other non-policy-related components, including other household members' income and childcare situations.

Interestingly, consumption of all three food groups decreased from Waves 1 to 2 (based on raw tabulations of the data). The decrease in consumption may be attributable to a number of factors. First, these decreases may have been due to regression to the mean. Additionally, it is possible that the DSQ contains measurement error, and a more comprehensive measure of dietary intake, such as 24-h recalls, may have better captured changes in mean intake over time. However, validation studies have shown close agreement when comparing mean values from nutrients

Table 6 Results from the *post hoc* analyses regression models assessing whether the Minneapolis minimum wage policy was associated with changes in hourly wage and household income categories between Minneapolis, Minnesota, and Raleigh, North Carolina, from Wave 1 (2018) to Wave 2 (2019)

Model	RRR*	95 % CI	*P*-value	Time coefficient, OR† or RRR	95 % CI	*P*-value	DID coefficient,‡ OR or RRR	95 % CI	*P*-value
RQ1 – did the hourly wage significantly change between the cities?§	–	–	–	1·58	1·22, 1·93	< 0·001	0·82	0·13, 1·51	0·02
RQ2 – were changes in hourly wage associated with changes in household income?‖									
$5001–$10 000	1·00	0·93, 1·07	0·94	–	–	–	–	–	–
$10 001–$20 000	0·99	0·92, 1·06	0·73	–	–	–	–	–	–
$20 001–$30 000	1·18	1·10, 1·28	< 0·001	–	–	–	–	–	–
$30 001–$40 000	1·19	1·08, 1·30	< 0·001	–	–	–	–	–	–
$40 001–$50 000	1·26	1·15, 1·39	< 0·001	–	–	–	–	–	–
More than $50 000	1·24	1·12, 1·38	< 0·001	–	–	–	–	–	–
RQ3 – did household income categories significantly change between the cities?¶	–	–	–	1·47	1·24, 1·76	< 0·001	0·84	0·63, 1·11	0·23
RQ4 – was the policy associated with changes in hourly wage between the cities?**	–	–	–	1·55	1·20, 1·90	< 0·001	0·79	0·07, 1·52	0·03
RQ5 – was the policy associated with changes in household income categories between the cities?††									
$5001–$10 000	–	–	–	1·05	0·68, 1·65	0·82	0·84	0·44, 1·60	0·59
$10 001–$20 000	–	–	–	1·17	0·78, 1·75	0·44	0·95	0·52, 1·73	0·86
$20 001–$30 000	–	–	–	2·13	1·43, 3·17	< 0·001	0·70	0·33, 1·50	0·36
$30 001–$40 000	–	–	–	1·55	0·90, 2·65	0·11	1·79	0·65, 4·97	0·26
$40 001–$50 000	–	–	–	1·91	0·78, 4·63	0·15	0·99	0·24, 4·16	0·99
More than $50 000	–	–	–	2·22	0·98, 5·02	0·06	0·79	0·10, 6·35	0·83

*Relative Risk Ratio.
†OR.
‡The DID parameter is city*time point. City and time point are included as indicator variables in the DID parameter.
§RQ1 asked: on average, did the hourly wage significantly change between the cities from Wave 1 to Wave 2? To address RQ1, we estimated a difference-in-difference longitudinal linear regression model using generalised estimating equations with clustering by the individual, using the Huber–White sandwich estimator of variance and an autoregressive correlation matrix. Presented are the time and DID coefficients.
‖RQ2 asked: Were changes in hourly wage associated with changes in household income? To address RQ2, we estimated a multinomial logistic regression model because the proportional odds assumption was violated. Standard errors were clustered at the level of the individual. The reference category is $0–$5000. Presented are the relative risk ratios.
¶RQ3 asked: on average, did household income categories significantly change between the cities from Wave 1 to Wave 2? To address RQ3, we estimated an ordinal logistic difference-in-difference regression model, with standard errors clustered at the level of the individual. The proportional odds assumption was tested and held. Presented are the OR for the time and DID estimate.
**RQ4 asked: Was the policy associated with changes in hourly wage between the cities from Wave 1 to Wave 2? To address RQ4, we estimated a multivariate difference-in-difference longitudinal linear regression model using generalised estimating equations with clustering by the individual, using the Huber–White sandwich estimator of variance and an autoregressive correlation matrix. The model was adjusted for race, sex, age, education level, job classification and the number of job trainings completed in the past 12 months. Presented are the time and the DID coefficients.
††RQ5 asked: Was the policy associated with changes in household income categories between the cities from Wave 1 to Wave 2? To address RQ5, we estimated a multinomial logistic difference-in-difference regression model because the proportional odds assumption was violated. Standard errors were clustered at the level of the individual. The following covariates were included in the model: race, sex, age, number of adults living in the household, marital status, education level, job classification and the number of job trainings completed in the last 12 months. The reference category is $0–$5000. Presented are the relative risk ratios for the time and DID estimate.

and food groups between the DSQ and 24-h recall data (gold standard) for both males and females[15]. The research team therefore chose to administer the DSQ rather than 24-h recalls and instead invest our resources into obtaining precise hourly wage data (using open-ended response questions for our hourly wage variable and asking for paystub verification) because this was the variable that the policy was directly targeting.

An additional explanation as to why consumption decreased is that perhaps SNAP benefits decreased among some participants at Wave 2. SNAP benefits inversely track with household income; given that wages and household income increased in both cities at Wave 2, some loss of benefits was expected. However, the amount of SNAP benefits participants received did not significantly change between Waves 1 and 2 overall or when stratified by city (based on an ordinal logistic regression model, see online supplementary material, Supplemental Table 4). Despite this, even small changes in SNAP benefits could impact food purchasing and dietary intake for low-income populations. Future research should examine how minimum wage ordinances impact usage of and eligibility for government food assistance programmes.

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Our results are similar to studies from the health and economics literature demonstrating that minimum wage policies are associated with increasing hourly wage[40–43]. However, unlike these studies, we did not find that the policy was associated with changes in household income. This is most likely because our study uses data from only baseline and the first year of the Minneapolis policy's implementation. Thus, it is possible that hourly wages have not yet have increased enough to translate to changes in household income between the cities. Our results are also similar to Horn *et al.*[9] in that there was no association between minimum wage increases and F&V consumption for women; however, we found no association, rather than an inverse association, for F&V consumption in men. Our results were also dissimilar from Ukert *et al.*[10] and Clark *et al.*[11] in that Ukert *et al.* found an inverse association between minimum wage increases and F&V consumption, whereas Clark *et al.* found a positive association. Again, our results are most likely dissimilar from these studies because the differential wage increases in the first phase of phased minimum wage policy (which in this case equated to less than a $1·00 more than the comparison area) may not have been large enough to produce changes in dietary intake.

This study has several limitations. First, the NCI DSQ dietary screener assumes a standard portion size for all participants. Although portion sizes could vary among participants, validation studies have shown close agreement when comparing mean values from nutrients and food groups between the DSQ and 24-h recall data for both males and females[15]. Thus, the DSQ is a valid tool for assessing dietary intake for the Wages Study. Additionally, the research team did not schedule a participant's Wave 2 appointment based on the timing of their Wave 1 appointment (as this may have harmed the study's retention rate). Study participants could therefore complete their Waves 1 and 2 appointments at different times of the year. Thus, seasonality may have impacted their responses to various DSQ items between waves (e.g. perhaps fruit was in season at their Wave 1 appointment in July, but not at their Wave 2 appointment in October). The study's dietary intake data may therefore have been 'muddied' by these potential seasonality effects. However, the majority of data collection occurred during the summer at both sites in both waves, so the season effect is likely to be minimal. An additional limitation is that the Wages Study had considerable attrition from Wave 1 to Wave 2. However, this attrition rate is similar to attrition rates in other non-clinical cohort studies containing low-income study populations with high rates of racial/ethnic minorities[44].

This study also has several strengths. First, the research team collected data on individual wages using an objective measure for the majority of our sample. We could therefore calculate the precise 'wage dose' received for each participant in the study. This is a significant improvement over previous minimum wage studies that have used proxy measures such as educational attainment and household income to estimate the likelihood of being affected by minimum wage increases[9–11]. Additionally, no prospective longitudinal studies have evaluated the impact of a minimum wage increase on dietary outcomes among adults. Unlike previously conducted cross-sectional studies, our longitudinal data from a natural experiment design allows us to track the same participants throughout the phased implementation of the Minneapolis ordinance, which allows us to determine individual changes in health and economic indicators over time.

Conclusions

Through this study, we found that after the first phase of implementation, a policy-mandated minimum wage increase was not associated with changes in daily frequency of consumption of F&V, whole-grain-rich foods or foods high in added sugars among low-wage workers in Minneapolis compared to low-wage workers in Raleigh. However, the policy was associated with increases in hourly wage between the cities after 1 year of implementation. We did not detect changes in overall household income categories following the first phase of implementation, which may explain the lack of significant changes in dietary intake in our sample. However, as the minimum wage increase has not been fully implemented, it is possible that the planned increases could have greater effects. Therefore, it will be important to re-examine the questions addressed in this study once the full implementation has occurred. Ultimately, the question is whether minimum wage ordinances are likely to improve diet quality for low-wage workers, or whether other policy changes are needed. Additionally, improving dietary intake is not the main goal of minimum wage ordinances. Future research should evaluate the ordinance based on other health and economic outcomes.

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had no role in the design, analysis or writing of this article. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. *Conflict of interest:* Seth Berkowitz reports receiving personal fees from the Aspen Institute, outside of the submitted work. *Authorship:* CC obtained funding for the study and designed the study. CC and MDM led the implementation of the study. LC and SB analysed the quantitative data. LC wrote the first draft with contributions from SB. All authors reviewed and commented on the subsequent drafts of the manuscript. *Ethics of human subject participation:* This study was conducted according to the guidelines laid down in the Declaration of Helsinki and all procedures involving research study participants were approved by the University of Minnesota Institutional Review Board and the University of North Carolina at Chapel Hill Institutional Review Board. Written informed consent was obtained from all subjects.

Supplementary material

For supplementary material accompanying this paper visit https://doi.org/10.1017/S1368980021000707

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