Longitudinal Trends in Produce Purchasing Behavior: A Descriptive Study of Transaction Level Data from Loyalty Card Households

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Title Page

Longitudinal Trends in Produce Purchasing Behavior: A Descriptive Study of Transaction Level Data from Loyalty Card Households

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Abstract

Background: Household food purchases (HFP) are in the pathway between the community food environment and the foods available in households for consumption. As such, HFP data have emerged as alternatives to monitor population dietary trends over-time. In this paper, we investigate the use of loyalty card datasets as unexplored sources of continuously collected HFP data to describe temporal trends in household produce purchases.

Methods: We partnered with a grocery store chain to obtain a loyalty card database with grocery transactions by household from January 2016-October 2018. We included households in an urban county with complete observations for head of household age group, household income group, and family size. Data were summarized as weighted averages (95% CI) of percent produce purchased out of all foods purchased by household per month. We modeled seasonal and linear trends in the proportion of produce purchases by age group and income while accounting for repeated observations per household using generalized estimating equations.

Results: There are 290,098 households in the database (88% of all county households). At baseline, the smallest and largest percent produce purchases are observed among the youngest and lowest income (12.2%, CI 11.1; 13.3) and the oldest and highest income households (19.3, CI 18.9; 19.6); respectively. The seasonal variations are consistent in all age and income groups with an April-June peak gradually descending until December. However, the average linear change in percent produce purchased per household per year varies by age and income being the steepest among the youngest households at each income level (from 1.42%, CI 0.98;1.8 to 0.69%, CI 0.42;0.95) while the oldest households experience almost no annual change.

Conclusions: We explored the potential of a collaboration with a food retailer to use continuously collected loyalty card data for public health nutrition purposes. Our findings suggest a trend towards a healthier pattern in long-term food purchases and household food availability among the youngest households that may lessen the population chronic disease burden if sustained. Understanding the foods available for consumption within households allows public health advocates to develop and evaluate policies and programs promoting foods and nutrients along the life course.

Key Words: Food purchases, Produce Purchases, Loyalty card, Grocery Stores, Diet, Diet monitoring, Purchasing behavior.

Trial registration: Not applicable.

Background

Diet-related non-communicable diseases (DRNCD) are the leading cause of morbidity and mortality globally and in the United States. Globally, 22% of all deaths and 15% of disability-adjusted life-years (DALYs) were attributed to dietary factors (1). In the US, where DRNCD disproportionally affect older adults, racial/ethnic minorities and lower income groups, dietary factors accounted for the largest number of deaths and were the third leading cause of DALYs (2). Of concern, dietary risk factors have remained relatively unchanged in the past 10 years (3). Combined nutrition public health policy and programs addressing all components of the food system will contribute to the improvement of dietary intake eventually lessening the population burden of DRNCD (1, 2).

Monitoring population diet quality to identify food and nutrient inadequacies is necessary to develop and evaluate public health nutrition policies and programs. To date, self-reported dietary intake assessments, such as 24-hour dietary recalls or food frequency questionnaires, are the most frequently used tools for nutrition monitoring (4). These tools are resource intensive, prone to measurement errors and social desirability bias, and some do not capture seasonal variation of food intake (5) if assessing a few days at a time (e.g.; 24-hour diet recalls, food records); making them impractical to monitor long-term dietary intake at the population level. To circumvent the limitations of self-report, the search for biomarkers of dietary intake has intensified, particularly using metabolomics (6). Despite considerable advancement in the field, few biomarkers of specific nutrients and food groups are available and even fewer capture average long term dietary intake (7). Together with the challenges in the collection and storage

of biological samples, biomarkers of dietary intake are not yet suitable for population monitoring (8).

Food purchase data have gained popularity as an alternative method to monitor population dietary intake trends and to evaluate nutrition policies and programs (9, 10). Food purchase data by households do not directly measure individual dietary intake but rather represents the foods available to consume by household members. People make food choices in the context of the food stream, the flow of foods from the national food supply through food processing (e.g.; manufacturers) and the community food environment (e.g.; markets, grocery stores, schools), to individual food intakes (11). Food purchasing behavior is then considered a mediator between the community food environment, the food available to members of a household and individuals' dietary intake (12, 13). The mediator role of food purchasing behavior is supported by evidence of its relative concordance with individual nutrient intakes (12, 14, 15) and of providing reasonable estimates of overall diet quality when compared with self-report methods (12). Thus, household food purchases data appears to be suitable for population monitoring and evaluation. Thus far, data on food purchases have been obtained from commercially available household food purchasing panels and have examined the quality of food purchases of nutritional assistance programs (e.g.; WIC), and the nutrient compositions of purchased foods at the brand-level,(10) associations between sociodemographic factors and household food and beverage purchases, the effect of marketing (e.g.; coupons) and public health interventions (e.g.; food taxes). A recent report, however, has identified the need to develop partnerships between nutrition researchers and independent and chain food retailers willing to share loyalty card data to support healthy eating and to advance policy and practice (16).

In this paper, we report the results of loyalty card data analyses based on a partnership between a regional supermarket chain in Western New York that accounts for 65% of total dollar food expenditure in the county (private communication with the food retailer) and an academic health center as a demonstration of these collaborations' potential to advance public health nutrition. We chose to focus on household purchases of fresh fruits and vegetables because they are major sources of dietary fibers, antioxidants, flavonoids and polyphenols and primary components of the Healthy U.S.-, Vegetarian-, and Mediterranean-Styles Patterns recommended by the US dietary guidelines for the prevention of chronic conditions across the life course (17). Fruit and vegetable intake is inversely associated with cardiovascular disease morbidity and mortality, and all-cause mortality (18-21). Some studies have reported a lower incidence of pancreatic and gastric cancers, age-related macular degeneration, and type 2 diabetes (20-22) with increased fruit and vegetable consumption, although others have found weak or inconsistent associations with all cancers (18, 23) and diabetes (19). Despite this evidence, population intake of fruits and vegetables, as reported in national nutrition surveys (24, 25), is consistently below the recommendations (17, 26). It follows that these food groups are ideal targets of public health nutrition programs and policies for the prevention of DRNCD. The objective of this paper is to describe household fresh fruits and vegetables (hereafter produce) purchases as the interface between the community food environment and individual eating behaviors and to examine temporal and seasonal trends by demographic characteristics.

METHODS

153 We follow the guidelines of Strengthening the Reporting of Observational Studies in
154 Epidemiology extension for nutritional epidemiology (STROBE-nut) (27) (Supplemental Table
155 1)

156 This is a secondary data analysis of a grocery store loyalty card database with household food
157 transactions to describe seasonal and temporal trends in fresh produce purchases from January
158 2016 to October 2018 (33 months). The data were obtained as part of a long term collaboration
159 between the authors and a regional grocery store chain in a Western NY county. The dataset
160 includes all purchases of food and non-food items of loyalty cardholders by household.
161 Purchases made by each household member with a loyalty card are merged into a unique
162 household identifier and each household visit to a store is identified by a unique transaction
163 number and date. Household information includes zip code, household income (nine categories:
164 0-14,9K; 15-19.9K, 20-29,9K; 30-39,9K; 40-49.9K, 50-74,9K; 75-99,9K; 100-124.9K; ≥ 125K),
165 age of head of household (six categories: 18-24.9, 25-34.9, 35- 44.9, 45-54.9, 55-74.9, 75-89),
166 household size (1 to ≥ 6), and whether or not the household is a family (yes/no). No data on
167 gender, education, nor race/ethnicity were available. Purchase information includes the store
168 where the purchase was made, a short description of the item, brand name, department (e.g.;
169 dairy), category (e.g.; yogurt), and class (e.g.; Greek yogurt). All data are de-identified except
170 for the household 5-digit zip codes, which are updated from the National Change of Address data
171 from the United States Postal Service. Likewise, the company updates all demographic data
172 from households annually using commercial databases. We included households in zip codes for
173 one mostly urban county (17 stores) and excluded all non-food related departments (e.g.;
174 pharmacy) and households with a head of household ≥ 90 years old (1.6% of households) under
175 the assumption that their involvement in food shopping is minimal (28) and to comply with

research review board standards of using de-identified data. Additionally, we manually checked all food departments to eliminate non-food products (e.g.; candy making mold and supplies and pet foods found in bulk food department, coupons); and foods and drinks not considered for households every day consumption (produce party trays ≥ 1 pound, cheese and cold cut party trays of ≥ 2 pounds, beer kegs).

Variables:

Produce was identified as all fresh raw produce categories in the loyalty card database selected from the department 'produce' (excluding frozen, dried, canned, juice): summer fruit, berries, grapes, store organic farm, seasonal/specialty, apples and pears, salad vegetables, citrus, tropical fruit, bananas, melons, potatoes and onions, cooking vegetables, and salad leaf. To model seasonal and annual trends we estimated the weighted average of the percent produce purchases (fresh produce purchased/all foods purchased) per household across all households per month (weight = the number of foods purchased per household) for 33 months. In this way, we controlled for the effect of family size in the amount of produce purchased (larger families, more purchases). In these analyses, each unique food item purchased in a single transaction is considered to be one unit, regardless of true quantity purchased; thus, percent produce purchased represents the frequency rather than the quantity of foods purchased. Categories of age groups from the original dataset were collapsed (18-24, 25-34, 35-54, 55-74, and 75-89 years old) because exploratory analyses showed overlapping percentage produce purchases over time in the 35-44 and 45-54 age groups. A similar finding among income groups allowed for additional data reduction from nine groups to six (0-14,9K; 15-29,9K; 30-49,9K; 50-74,9K; 75-99,9K; >100K).

Statistical Analyses

198 We describe the characteristics of loyalty card households by age of head of household,
199 household income, family (yes/no), and household size. To assess how representative the loyalty
200 card households were of the general population of the county, we compared the proportion of
201 households in each household income and age of head of household groups with county data
202 from 2017 American Community Survey (ACS) (29). Since the ACS does not include data on
203 age of head of households, we compared our data to the county population age groups. For
204 comparison with the available ACS household income groups, we collapsed groups 15-29.9K
205 and 30-49.9K into a 15-49.9K income group.

206

207 We modeled temporal trends in the proportion of percent fresh produce purchases over time
208 while accounting for repeated observations per household using generalized estimating equations
209 (30, 31). The basic statistical model used to describe purchasing trends is

210 Equation (1)
$$logit\{P(Y_{ij} = y_{ij})\} = \beta_0 + \beta_S s(t_{ij}) + \beta_L t_{ij} + \beta_X X_i + \beta_{XL}(X_i \times t_{ij})$$

211
$$\beta_S s(t_{ij}) = \beta_{S_1} \sin\left(\frac{2\pi t_{ij}}{12}\right) + \beta_{S_2} \cos\left(\frac{2\pi t_{ij}}{12}\right)$$

212 where, Y_{ij} is a binomial random variable representing the number of fresh produce items
213 purchased by the *i*th household during the *j*th month based on a total of n_{ij} food items purchased
214 during the *j*th month. The terms in the model include time (t_{ij}) recorded as an integer from 1 to
215 33, X_i are demographic variables (age or income groups), and $X_i \times t_{ij}$ are covariate-by-time
216 interactions (age group x time; income group x time; age group x income group x time).
217 Importantly, seasonal trends of percent produce purchased $s(t_{ij})$ are modeled as the sum of
218 sinusoidal and cosinusoidal terms as written in the second line of Equation (1). The unknown

regression coefficients are $\beta_0, \beta_{S_1}, \beta_{S_2}, \beta_L, \beta_X, \beta_{XL}$ and estimated by the statistical procedure. Thus, the percent fresh produce purchasing trends are modeled as the sum of seasonal variations (β_S) and linear trends (β_L) over time, with the linear trends different by age and income groups. We draw statistical inference using the robust empirical sandwich covariance under a working independence correlation model. We use linear contrasts of coefficients in models via Equation (1) that include the three-way time-by-age-by-income interaction to estimate the age-by-income slopes over the 33-month period. After rescaling the coefficients, the slopes are interpreted as the average linear change in percent produce purchased per household per year over 33 months after controlling for seasonal variation. We depicted the seasonal variations graphically by overlaying the fitted curve atop the data; in these figures (1 and 2), the data are summarized as weighted averages of percent produce purchased by household across all households per month and a 95% confidence interval, where weight is equal to the number of foods purchased per household. We included a horizontal line in each graph representing the grand mean of percent produce purchased by household as a reference. The analysis of repeated binomial proportions has a rich history in the statistics literature and is an appropriate tool for modeling the percent produce purchased in our sample. Because the proportion is the ratio of number of produce items purchased divided by the total number of food items purchased and re-computed on a monthly basis per household, the statistic controls automatically for monthly fluctuations in number of food items purchased per household. Furthermore, the precision of the proportion of produce items purchased increases as the number of total food items purchased increases. Thus, households that purchase more food items are weighted more heavily in the analysis. We analyzed data with complete observations. Models were fit in SAS statistical software (SAS Version 9.4; SAS Institute, Cary, NC). The University

of Rochester Human Subjects Review Board approved all study procedures and granted a waiver of consent.

RESULTS

Descriptive Statistics

There are 290,098 households who are loyalty cardholders in the county, of which 4% and 9% had missing data on age of head of household and household income, respectively, and 15% had missing data on family status (yes/no) and family size. Consequently, sample size totals in Tables 1-3 differ. Most of the head of households are in the 35-54 and 55-74 age groups (72%) while less than 3% are in the youngest age group (18-24). The largest income group among loyalty card households (28%) is 50-74.9k, while 6% are in the lowest income bracket (0-14.9K) (table 1). Half of the households identified themselves as a family, 81% of them have 1-4 members (table 2). Loyalty card households constitute 88% of all county households in 2017. The loyalty card database has a smaller proportion of households in the lower income groups (≤$49.900) than county households, 35.5% vs 45.6%, respectively, and older head of households (≥ aged 55) than the county population, 47% vs. 37%, respectively (table 3).

Table 1. Characteristics of Loyalty Card Households by Age and Income groups. January 2016-October 2018

	Annual Household Income						
Age Head of Household (years)	**0-14.9 K** % (n)	**15 – 29.9K** % (n)	**30-49.9K** % (n)	**50 – 74,9K** % (n)	**75-99.9K** % (n)	**≥ 100K** % (n)	**All** Row % (n)
18-24	6.5 (997)	4.1 (1054)	3.2 (1573)	2.2 (1559)	1.9 (804)	2.4 (1280)	2.8 (7267)
25-34	25.5 (3909)	19.6 (5021)	14.5 (7252)	12.0 (8709)	10.9 (4625)	13.5 (7190)	14.2 (36706)
35-54	33.3 (5105)	33.5 (8605)	34.8 (17346)	37.6 (27166)	34.6(14641)	33.7 (18007)	35.1 (90870)
55-74	23.7 (3638)	28.5 (7326)	33.4 (16667)	34.6 (26331)	43.5 (18385)	43.1 (23015)	36.8 (95362)
75-89	11.1 (1704)	14.3 (3675)	14.2 (7069)	11.8 (8518)	9.1 (3856)	7.4 (3950)	11.1 (28772)
All Column %	5.9 (15353)	9.9 (25681)	19.3 (49907)	27.9 (72283)	16.3 (42311)	20.6(53442)	100 (258977)

Table 2 goes here

Table 3. Comparison of Loyalty Card and County Household Characteristics.

Annual HH[1] Income ($)*	**LC[2]** **% (n HH)**	**ACS[3] (2017)[29]** **% (n HH)**
0-14.9 K	6.1 (16233)	12.3 (37056)
15 – 49.9 K	29.4 (77691)	33.3 (100056)
50 – 74.9 K	27.7 (73276)	17.7 (53308)
75 – 99.9	16.2 (42785)	12.4 (37354)
≥ 100K	20.5 (54074)	24.2 (72722)
Total HH	100 (264059)	100 (300496)
Age-Group (years)	**% (n HH)**	**% (n People)[4]**
18-24	3.7 (10246)	13.4 (79001)
25-34	14.7 (41048)	17.6 (103767)
35-54	34.9 (97378)	31.8 (187328)
55-74	36.0 (100248)	28.3 (166797)
75 -89	11.0 (30215)	8.9 (52183)
Total	100 (279135)	100 (589076)

[1]HH: Household. [2]LC: Loyalty Card. [3]ACS: American Community Survey. [4]ACS does not provide data on age of head of household. *No statistically significant difference based on a Chi-square test p-value < 0.0001 for household income group comparison between LC and ACS.

Seasonal Trends (figures 1 and 2).

Models for seasonal variation fit the data well for all months except for December and January, in which the model over- and under-fits the data, respectively. The seasonal trends are consistent in all age-and income-groups. A steady increase in percent produce purchased is observed from January each year reaching its peak in April through July and gradually descending until

December. The differences between these seasonal peaks and valleys are between 2% and 3% produce purchased in all age and income groups. In the youngest age group (18-24 years old) the peak percent produce purchased by households is below the overall mean (17%) until the spring of 2018 (figure 1). In the other age groups, the peak percent produce purchased by households are above the mean for all households (17%) in the spring, particularly in the 75-89-year-old group. In the three lowest income groups, percent produce purchased are below the mean for all households regardless of season (figure 2). Households whose income is ≥ 100k have a percent produce purchased always above the mean regardless of the season.

Percent Produce Purchased at Baseline (Supplemental Table 4)

The baseline percent produce purchased is the expected percent produce purchased by households as of January 1, 2016 (Supplemental Table 4). The youngest and oldest age groups purchased the smallest and largest percent of produce (13.5%, 95% CI 13.1-13.9; and 16.8%, 95% CI 16.6-16.9, respectively) (main effect of age group), although the trend is not consistently upward by age group. Conversely, the percent produce purchased is larger as household income increases, 13.9% (95% CI 13.6-14.1) in the lowest and 17.1% (95% CI: 17.1-17.2) is the highest household income (main effect of income group). When examining the joint contribution of age and income groups to the percent produce purchased (interaction of age and income groups), among households in age groups between 35 and 89, the higher the household income the larger the percent produce purchased. In the youngest age groups, the contribution of income to percent produce purchased does not have a consistent trend, particularly among the 18-24 year-old households in which the proportion of produce purchased by income group is the most varied. Within each household income group, although the oldest households always purchased proportionally more produce than the youngest, the effect of age on percent produce purchased

293 does not have a monotonic trend upward. In households at each income level, those in the 25-34
294 year old age group purchased a larger percentage of their groceries as produce than the
295 immediately younger (18-24) and immediately older (35-54) households. The largest difference
296 between the highest and lowest income groups in percent produce purchased is observed among
297 the 55-74 and 75-89 year old households (4.1% and 5.2%, respectively).

298 Linear Trends (Figure 3 and Supplemental Table 4)

299 Over the 33 months of data, there is an upward average linear change in percent produce
300 purchased per year of varied degrees. The youngest households increased their annual produce
301 purchased by 0.89% (95% CI 0.74-1.04) with a steady flattening of the trend in the subsequent
302 age groups down to the oldest households in which no change over time was observed (0.03%;
303 95% CI -0.02,0.08) (table 4 suppl, main effect by age). Although the income groups experienced
304 an annual increase in percent produce purchased, the rate of change was relatively similar across
305 income groups, with an annual increase in produce purchased of 0.41% (95% CI 0.31-0.51) in
306 the lowest income group to 0.29% (95% CI 0.31-0.51) in the highest one (table 4, main effect by
307 income). The joint contribution of age and income groups to annual average linear trend in
308 percent produce purchased is steepest among the 18-24 year old households at each income level
309 with more than or close to 1% a year up to the 50K-74K income group while the rate of annual
310 increase slows down at higher income groups although still higher than all other age-income
311 combinations. All other age-income combinations have average annual increase not exceeding
312 0.5%. Of note, the oldest households (75-89 years-old) have almost no change in the average
313 annual percent produce purchased at all income levels

314

DISCUSSION

We collaborated with a regional grocery store chain to explore the use of household food purchasing data from a loyalty card dataset to examine long-term population trends in food purchases. In this study, we described seasonal and linear trends in household fresh produce purchasing as a proportion of total food purchases by age of head of households and household income. We found clear seasonal trends over the 33 months of data in all age and income groups. Superimposed to seasonal variations, we observed upward annual linear trends in percent produce purchased over time in most households. The influence of household income and age of head of household was more pronounced in the overall magnitude of produce purchasing (baseline percent produce purchase as of January 2016) while change overtime seemed to be more a function of age rather than income. Older households and households with the largest income purchased a larger proportion of produce at baseline than younger and lower income households in almost all combinations but the effect of income was particularly pronounced in the two oldest household groups. The annual rate of change, however, was especially fast in the youngest households (18-25 years-old) at all levels of household income. Out of all food purchases, these young households are increasing the share of fresh produce purchased by around 1% per year while the oldest households (75-89 years-old) had an almost flat annual rate of change in produce purchasing overtime regardless of household income.

The observed seasonal trends are as expected, a peak in the harvest months with valleys in between (32). The seasonal peaks observed are parallel to the increase in variety and volume of fruits and vegetables grown by farmers in the region who sell produce to the local groceries stores (33). To our knowledge, no previous study described the joint effects of age of head of

338 household and household income on linear trends in produce purchases in relation to all
339 household food purchases over almost three years of continuously collected data. Studies
340 present averaged data over time and show substantial methodological heterogeneity. Produce
341 purchases have been operationalized as dollars spent as a percentage of total household food
342 expenditures (34-37), per capita expenditures (34, 36), percent of purchased energy from
343 produce,(38) and per capita purchased servings per 1000 purchased kilocalories (39). Data on
344 purchases were collected from participants' receipts of purchases in all food outlets (grocery
345 stores, convenient stores, restaurants, markets, etc.) for 2-4weeks (35), self-scanned purchases in
346 all food outlets for one year (37, 38) and participants' diary of all food expenses for 2 weeks
347 (34). Despite these differences, their findings are consistent with ours in that household income
348 consistently seems to drive produce purchasing. The wealthier the household the larger the share
349 of produce purchased (34, 35, 40). Income was not related to produce purchases in only one
350 study (39) although the narrow range of household incomes in the sample may explain this
351 finding. In studies that adjusted for race, marital status (35) and educational attainment (34, 35),
352 the effect of income did not hold probably due to the high correlation among some of these
353 variables. Also consistent with previous evidence is the finding that the youngest households
354 (18-24 years old) purchase less produce than older ones but still the share of produce purchases
355 increases with household income (37). The 18-24 year old household's purchasing behavior may
356 reflect the transitional characteristics of this age group. People in this age group are more likely
357 to be living alone for the first time at college or working lower paying jobs or both and juggling
358 a young family; thus, favoring convenience (purchasing prepared or easy to make foods) over
359 fresh produce (37, 41). Another characteristic of younger shoppers is that they are value driven
360 and tend to prioritize organic foods and pay attention to their origin and to whether food is grown

361 sustainably, characteristics that are mostly found at natural food sources, farmers markets, and
362 limited assortment stores (42, 43). The later may explain why younger households with high
363 incomes in our grocery store sample have a smaller percent produce purchased than older
364 households with the same income. Lower income households tend to favor calorically dense
365 foods to obtain more energy for dollar spent (44). Regional data on barriers to buying healthy
366 food support our interpretation. A little over 50% of area residents with income under $25 K
367 report cost as the most important barrier compared to 20% with an income over $75,000. A
368 higher proportion of area residents aged 18-24 years old, relative to those aged 64 years and
369 older, reported cost (50% vs. 18%) and limited time to shop and prepare meals (30% vs. 5%) as
370 barriers to purchasing healthier foods (33).
371

372 The current study brings to light the effect of household age and income on long-term
373 longitudinal trends in produce purchasing behavior. We found that the rate of change over time
374 seems more a function of age rather than income. The fastest rate of growth among the youngest
375 households (18-25 year-olds) across income levels seems to indicate households' decisions to
376 purchase produce among this age group are influenced by factors other than income (e.g.;
377 adaptations over time, more education over the 33 months period). We do not have data to
378 evaluate whether this upward trend is the cross-sectional effect of age or a cohort effect. If the
379 latter, the findings among 18-24 year-old households highlights a healthy trend of increased fresh
380 produce purchases in the future. At an average rate of 1% increase per year in the proportion of
381 fresh produce purchased out of all other food products, in 10 years the share would increase by
382 10% of all food purchases. Assuming that household produce purchases represent produce
383 availability in homes to consume, the upward trend in household produce purchases suggests a

trend towards a healthier pattern in long term food consumption at the population level that may contribute to a lesser chronic disease burden as the 18-24 year-old head of household cohort ages. In all other age and income groups, the upward change is similar and relatively slow especially in the 75-89 year-old household. The oldest households do not change their purchasing behavior over time and income does not factor in, perhaps reflecting a generalized resistance to change among older adults (45).

Contrary to the previous literature (34-38), our food purchase data were obtained from a single grocery store chain in the county, thus missing purchases from other food outlets. It is difficult to predict the effect these missing food sources has on our estimates, although we do not expect it to be substantial given the store's large contribution to total dollar food expenditure in the county and the broad representation of the county's total households (88%) by loyalty card household members. We expect, however, that the peaks in the harvest months observed might be underestimated because produce bought at farmers markets or through community supported agriculture shares are not included. Also contrary to large consumer panel studies with a representative sample of the entire population (34, 37, 38, 41), our data are representative of our county's population albeit with a smaller representation of lower income households. We are unable to compare the food purchasing behaviors of the lower income households in our dataset to the behaviors of lower income households in the county without loyalty cards. A meaningful methodological advantage of the grocery store dataset is the absence of reporting errors. Datasets obtaining purchase information from food receipts or scanners provided by study participants are prone to random omissions or social desirability bias. In addition, the grocery store dataset has

all household food purchases continuously collected for 33 months; thus, capturing usual long term shopping behaviors.

CONCLUSIONS

Our study demonstrates the feasibility of a collaboration between researchers and a food retailer to use loyalty card data for public health nutrition purposes. Since household food purchases are in the intermediate pathway between the community food environment and household food availability for consumption, household food purchases from grocery store databases have the potential to be a more unbiased and representative estimate of long-term population dietary patterns and be more sensitive to programs and policies than periodic surveys of self-reported dietary intake. In larger markets, collaboration with all major food outlets would be necessary to assess population purchasing trends. Household purchasing data from grocery store databases offer many possibilities for public health nutrition research. For example, purchasing trends of all other food groups may be examined to estimate the overall quality of foods available for consumption within households, proportion of food dollars allocated to each food group, differences by additional demographic characteristics, the effect of price fluctuations in foods purchases, etc. Through the application of data science methods, grocery store foods, including ready-to-eat and unprepared, can be linked with USDA nutrient composition databases for a variety of uses related to better understanding the linkage between foods available for consumption and the health status of a population. Understanding the food available within households for consumption allows public health advocates to emphasize and promote the purchasing of foods containing critical nutrients for specific stages along the life course such as promoting the purchase of foods rich in lutein and zeaxanthin for the secondary prevention of

429 age-related macular degeneration or rich in folate among women of reproductive age for the
430 primary prevention of birth defects.

431

432 **LIST OF ABBREVIATIONS**

433 DRNCD: Diet-related non-communicable diseases; US: United States of America; DALYs:
434 Disability-Adjusted Life-Years; ACS: American Community Survey.

435

436 **SUPPLEMENTAL INFORMATION**

437 **Additional file 1.** Table 1. STROBE-nut: An extension of the STROBE statement for nutritional
438 epidemiology

439 **Additional file 2. Supplemental Table 4**. Baseline[1] and Rate of Change[2] in Percent Produce
440 Purchased by Age and Income Groups.

441

442 **ETHICS APPROVAL AND CONSENT TO PARTICIPATE**

443 The University of Rochester Research Subjects Review Board approved all study procedures and
444 granted a waiver of consent.

445 **CONSENT FOR PUBLICATION**

446 Not applicable

447

448 **AVAILABILITY OF DATA AND MATERIALS**

The data analyzed in the current study are not publicly available because these data are proprietary. Data are however available from the authors upon reasonable request and with permission of the grocery store leadership.

COMPETING INTERESTS

Mr. S. Prevost holds a managerial position in the grocery store company. All other authors declare no competing interests.

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AUTHOR'S CONTRIBUTIONS

IDF: conceptualization, methodology, data interpretation, writing original draft. BAJ: statistical analyses methods, interpretation of results, writing, reviewing and editing manuscript. NW conceptualization, food data management, interpretation of results, writing, reviewing and editing manuscript. AK: food data management, interpretation of results, reviewing and editing manuscript. JJ: methodology, data management and analysis, interpretation of results, reviewing manuscript. SP: providing the data, interpretation of results, reviewing. JL: conceptualization, reviewing manuscript. RSR: conceptualization, methodology, data interpretation, reviewing and editing manuscript. Finally, all authors approved the manuscript.

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The views expressed in this manuscript are the authors'only and are not necessarily shared by the regional grocery store that has provided the data.

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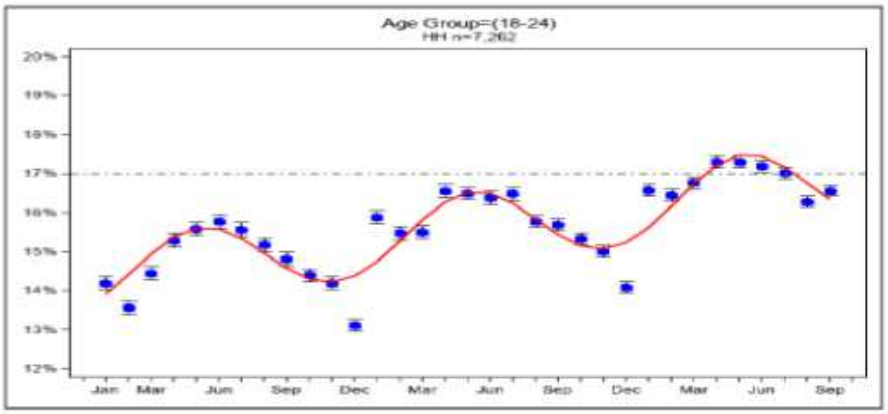
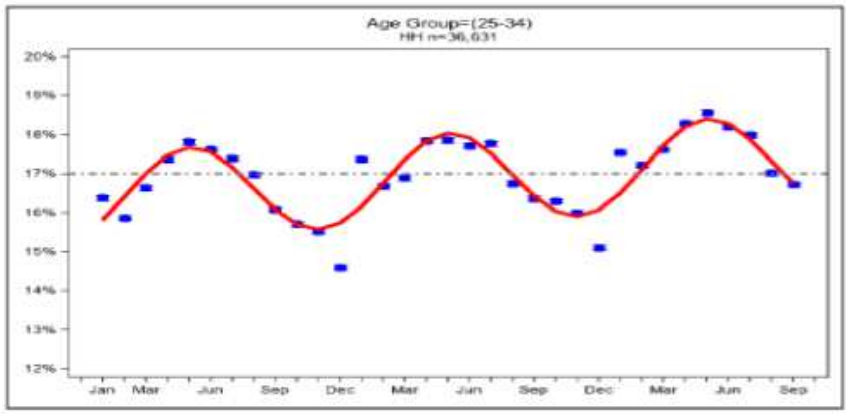
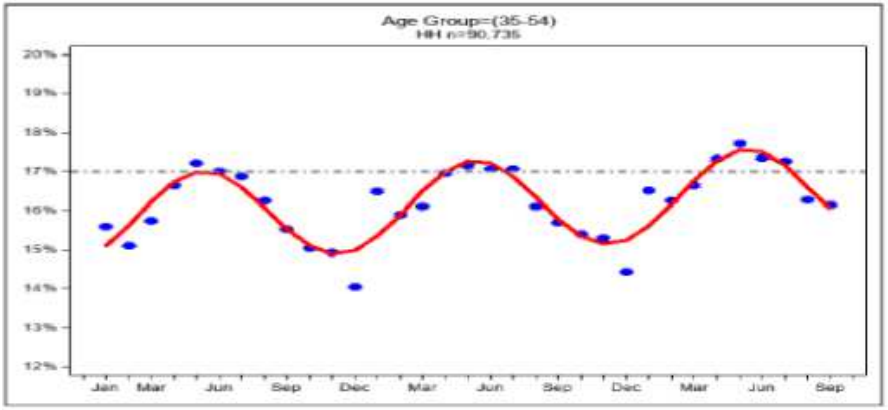
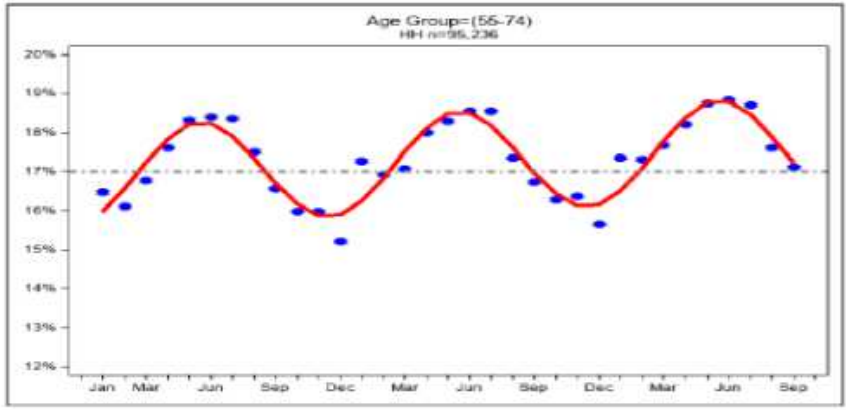
604

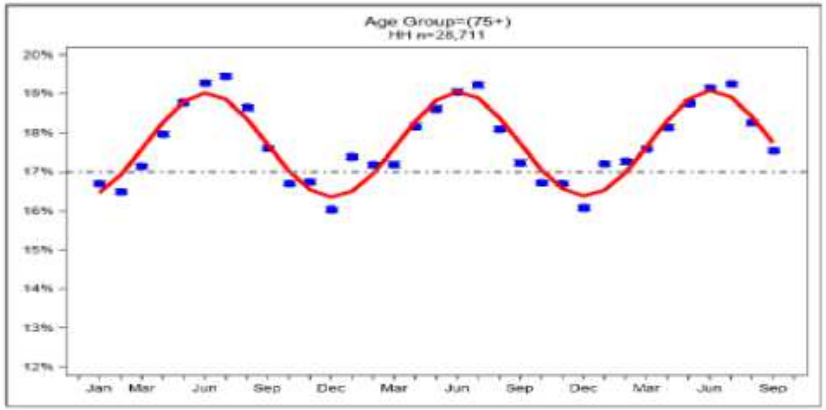
Figure 1. Seasonal Trends in Percent Household Produce Purchased by Age Group (January 2016-October 2018).





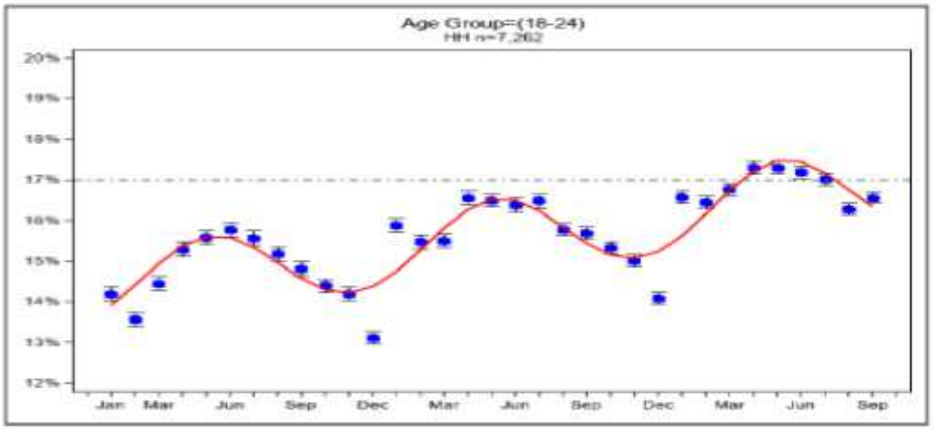


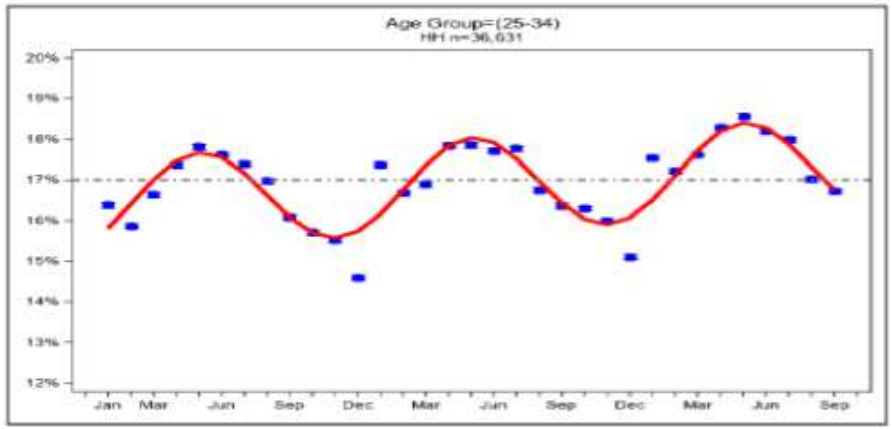


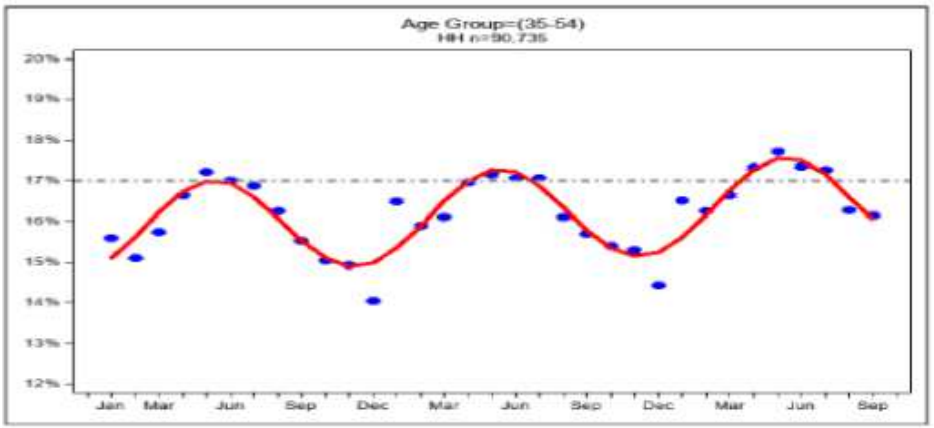


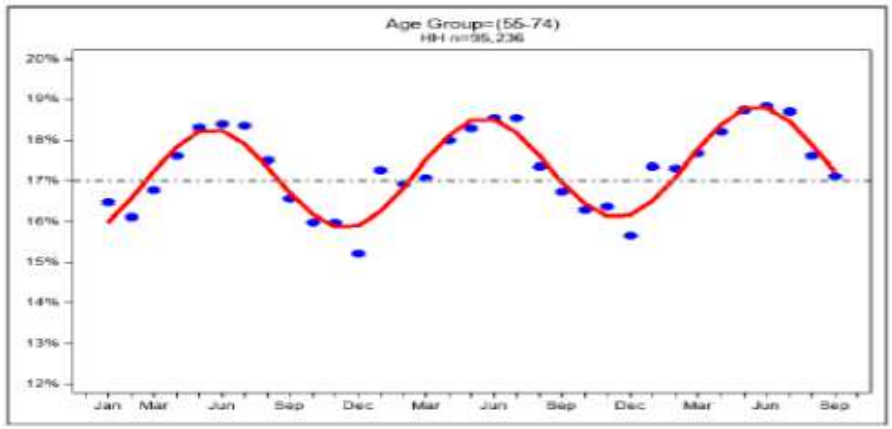
Observed Predicted Value Overall Avg

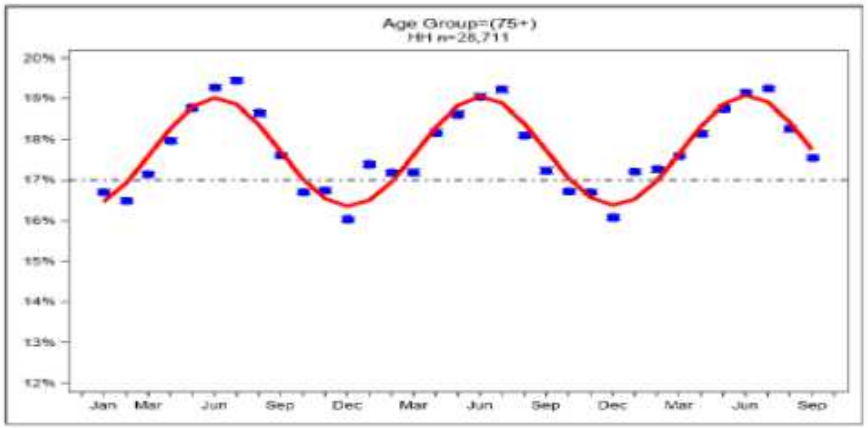
Figure 2. Seasonal Trends in Percent Household Produce Purchased by Income Group (January 2016-October 2018).











Observed Predicted Value Overall Avg

Figure 3. Annual Rate of Change in Household Produce Purchased by Income and Age Groups

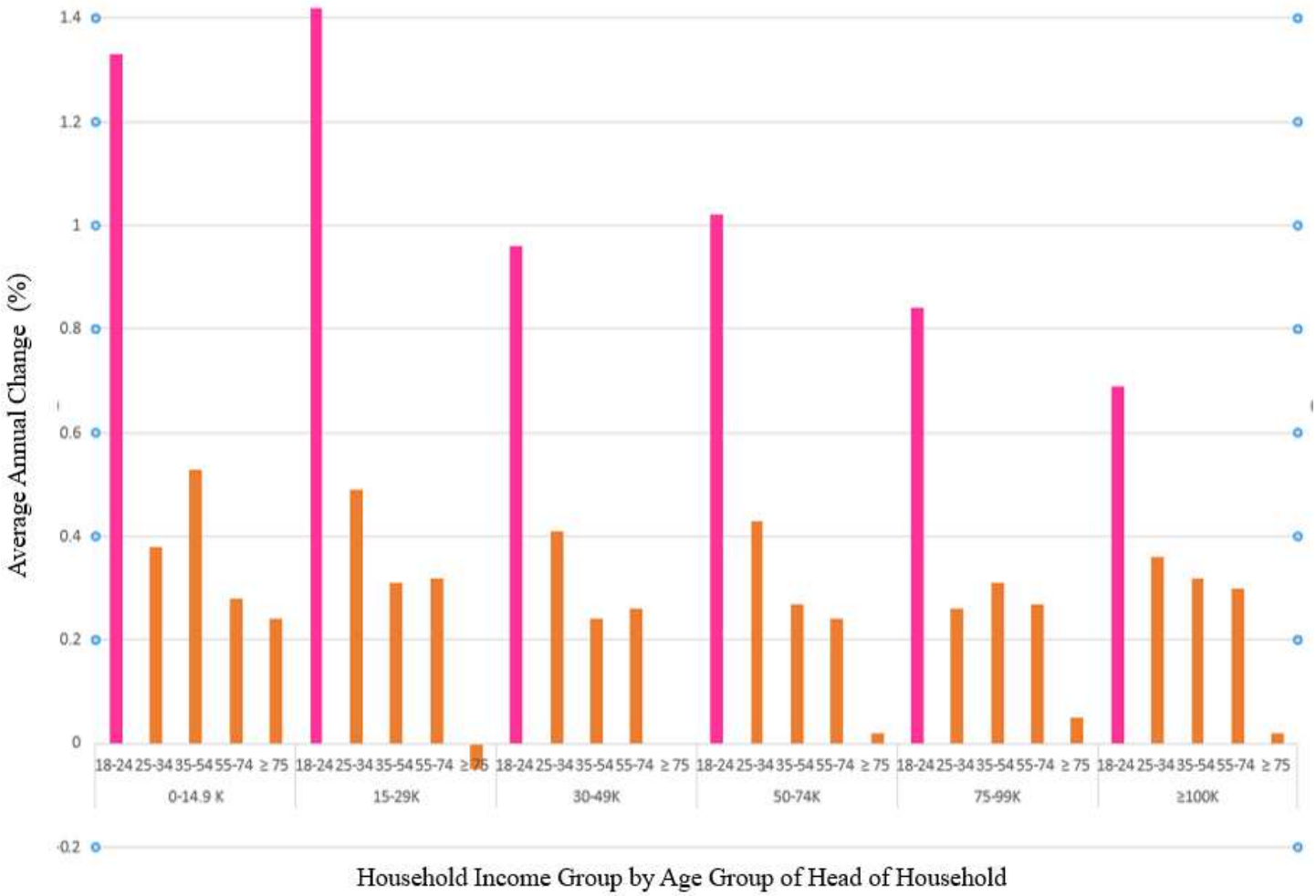

Average Annual Change (%)
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
18-24 25-34 35-54 55-74 ≥ 75
0-14.9 K
15-29K
30-49K
50-74K
75-99K
≥100K
Household Income Group by Age Group of Head of Household

Table 2. Characteristics of Loyalty Card Households by Age and Family Characteristics.

	Family			Household Size						
Head of HH[1] Age (years)	**No** % (n)	**Yes** % (n)	**All** % (n)	**1** % (n)	**2** % (n)	**3** % (n)	**4** % (n)	**5** % (n)	**> 6** % (n)	**All** % (n)
18-24	1.8 (2258)	2.3 (2787)	2.1 (5045)	3.1 (1400)	1.2 (691)	1.4 (814)	2.0 (751)	2.4 (566)	3.8 (823)	2 (5045)
25-34	13.7 (16937)	12.4 (14990)	13.1 (31927)	22.4 (10041)	10.9 (6300)	10.3 (6045)	10.0 (3817)	11.5 (2722)	13.9 (3002)	13 (31927)
35-54	28.3 (34919)	42.5 (51584)	35.4 (86503)	36.8 (16467)	32.2 (18653)	35.5 (20759)	36.1 (13745)	37.6 (8897)	36.9 (7982)	35 (86503)
55-74	39. 7 (48919)	36.1 (43851)	37.9 (92770)	29.5 (13236)	38.6 (22369)	39.4 (23006)	41.5 (15785)	41.1 (9726)	40.0 (8648)	38 (92770)
75-90	16.4 (20154)	6.7 (8116)	11.6 (28270)	8.2 (3658)	17.2 (9943)	13.4 (7814)	10.3 (3927)	7.5 (1773)	5.3 (1155)	12 (28270)
All	50.4 (123187)	49.6 (121328)	100% (244515)	18.3 (44802)	23.7 (57956)	23.9 (58438)	15.6 (38025)	9.7 (23684)	8.8 (21610)	100% (244515)

[1]HH: households.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix1.Fernandezetal.STROBEnutchecklisttable.docx
- Appendix2.SupplementalTable4.docx