The relationship between sugar-sweetened beverages consumption and weight gain: Empirical evidence from Central Asia

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Motivation

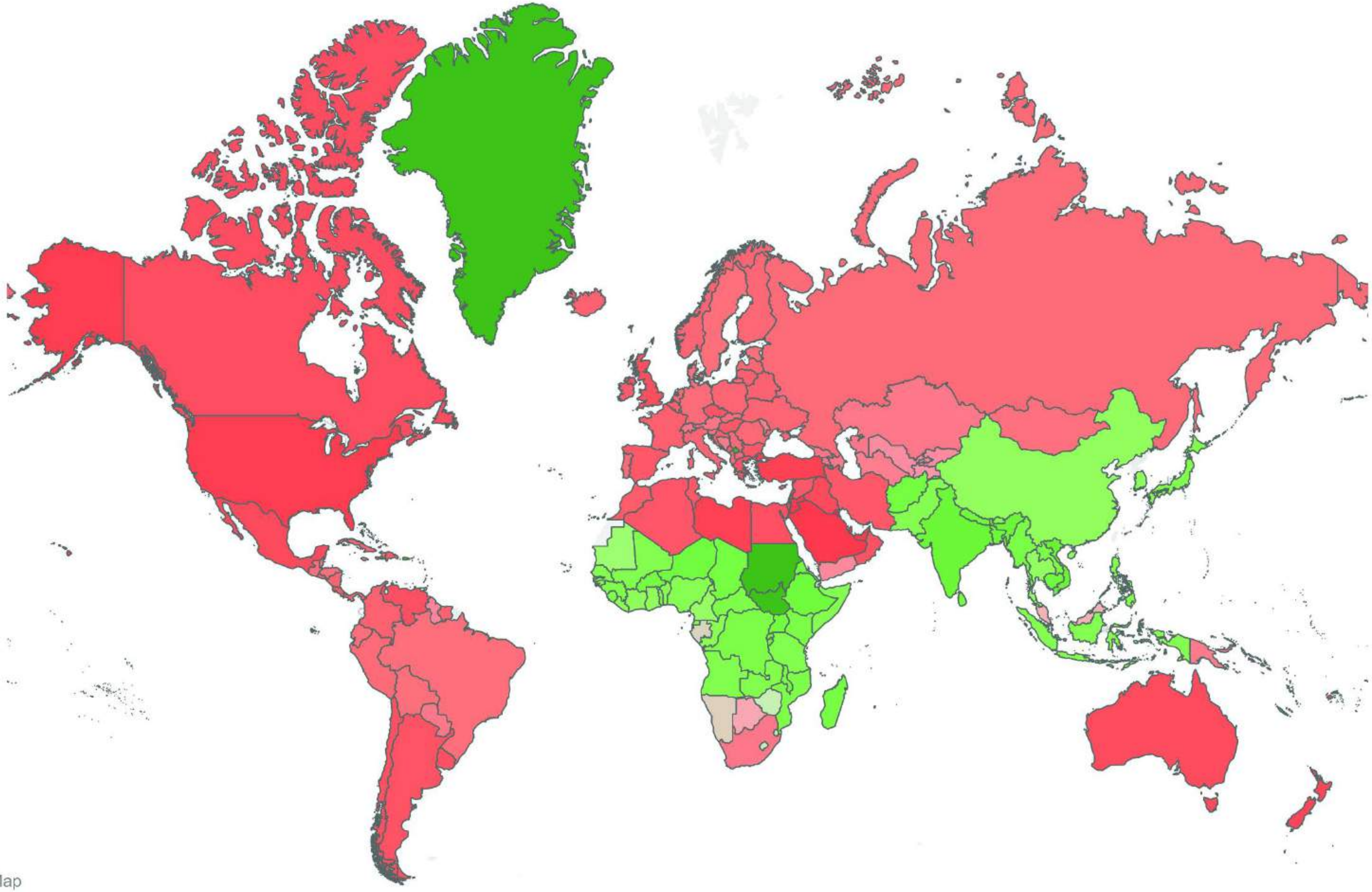
- While the overall **malnutrition** situation in Central Asia has **improved**, overweight and obesity among adults is rising and becoming a significant public health problem (FAO, 2018)

- **Overweight** and **obesity** are associated with a number of **health problems**, such as hypertension, cardiovascular diseases, musculoskeletal disorders, **diabetes**, depression, and cancer that contributed to high death rates (WHO, 2018)

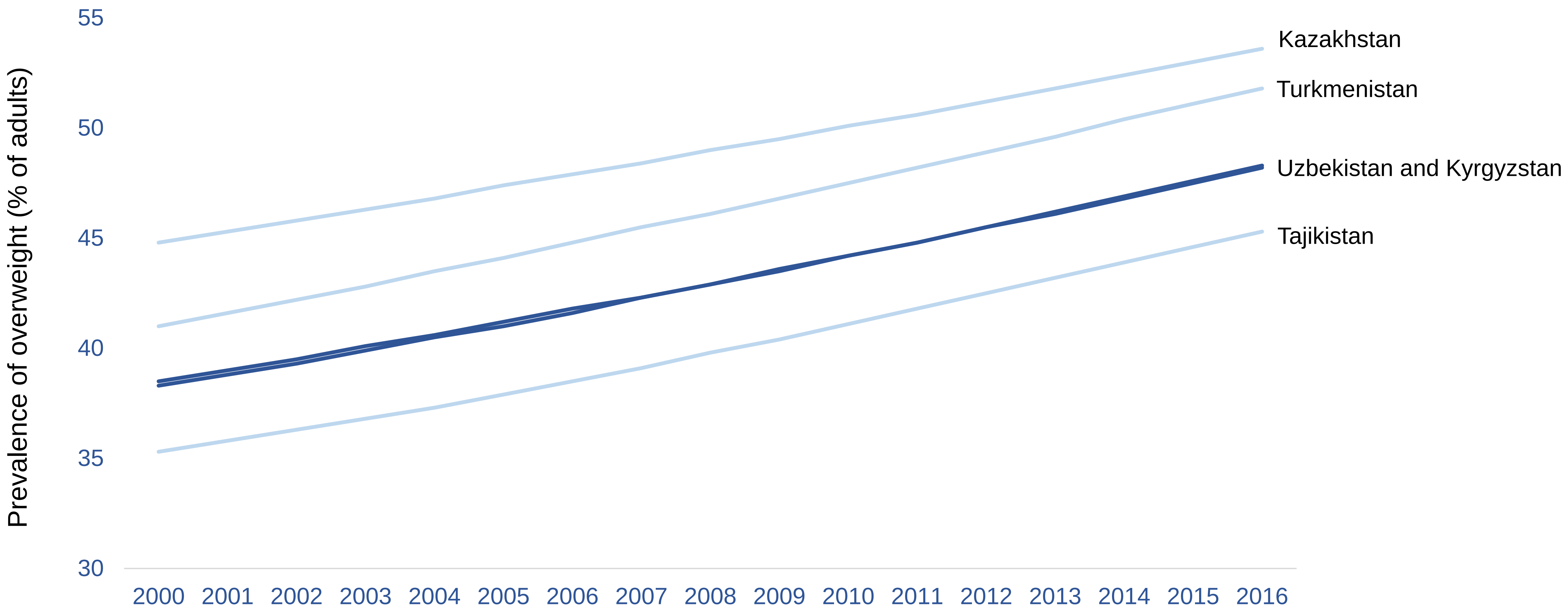
- Obesity **worsen labour market outcomes** – low wages and employment probability – and **increase health care expenditure** considerably (Cawley & Meyerhoefer, 2012; Cawley 2015)
  - Obesity is associated with $2,741 (in 2005 dollars) higher annual medical care costs in USA (Cawley & Meyerhoefer, 2012)
  - Overweight and obesity cost 4.1% of Chinese GNP annually (cited in Ecker, 2019)

Global epidemic of overweight and obesity

Prevalence of adult overweight **above** and **below** world average



Prevalence of overweight and obesity has been increasing steadily in Central Asia



Source: WHO, Global Health Observatory Data Repository

Literature

- Changes in global and national food systems in combination with local sociocultural and economic environments seem to drive rising overweight and obesity (Swinburn et al., 2011)
- Evidence suggests statistically significant **positive association** between **sugar-sweetened beverages consumption** and **weight gain** among both children and adults (Malik et al., 2006 & 2015; Bucher Della Torre et al., 2016; Stacey et al., 2017 and Luger et al., 2017)
- Meta analysis of regression studies on the nutritional outcome of SSBs showed that **limiting SSB consumption** decreases probability of obesity and weight gain (Hu, 2013)
- Experimental studies also found that the treatment group that substituted SSBs with non-caloric drinks had slower BMI increase than the control group (Ebbeling et al., 2012)
- Some researchers argued that the effect of SSB consumption on weight gain was ambiguous
  - While there was an increase in body weight in the treatment group with higher SSB intake, the statistical significance of the treatment effect was at the border (Te Morenga et al., 2012 and Kaiser et al., 2013)

Literature

- Consumption of sugar-sweetened beverages has increased worldwide (Basu et al., 2013; Lobstein, 2014)
- Because of heavy marketing campaigns of SSBs organized throughout the world, including developing economies, SSBs sales are growing (Basu et al., 2014; WHO, 2014; Sinclair, 2016; Luger et al., 2017; Du et al., 2018)
- As they are sweetened with various forms of sugars, SSBs add calories to the normal diet and largest contributor to added sugars (USDA and US DHHS, 2010)
  - Sugary beverages contain free sugars that are added to meals and drinks (Stacey, Tugendhaft and Hofman, 2017). Being the source of energy without additional nutrients, free sugars at **high rates negatively affect food nutritional quality** (WHO, 2015)
- Individuals fail to adjust their physical activities in accordance with liquid energy gained from **SSBs**, therefore, **weight gain from fluid intake** is relatively **higher than solid foods** (Woodward-Lopez et al., 2011; Te Morenga et al., 2012; Malik & Hu, 2015)

Research question

How is the consumption of sugar-sweetened beverages related to weight gain in adults in Kyrgyzstan?

Preview of findings

- Our results suggest a statistically significant **link** between **SSBs consumption** and **obesity** in Kyrgyzstan

- We found a **negative relationship** between total calorie intake, share of **staples** in total calorie intake, share of **fruit & vegetables** in total calorie intake, **smoking** and the probability of consuming SSBs

- We observed a **positive association** between household **expenditure**, share of **alcohol** in total calorie intake and the likelihood of consuming SSBs

Data description

- **Kyrgyzstan Integrated Household Survey (KIHS)** provides comprehensive information on **household consumption and spending**
- Food consumption module provides detailed data on individual food items, including staples, fruits and vegetables, **SSB**, etc.
- The data is representative at national and province (urban and rural) levels
- We use the data from 2011 round of the KIHS survey

Descriptive statistics

Variables	*N*	*Mean*	*Median*	*Std.Dev*	*Min*	*Max*
Dependent variables						
Body Mass Index	13,243	24.28	23.74	4.069	13.62	55.47
Overweight (Binary)	13,243	0.275	0	0.447	0	1
Obese (Binary)	13,243	0.0891	0	0.285	0	1
Independent variables						
SSB (Binary)	13,243	0.108	0	0.311	0	1
Age	13,243	40.44	40	17.91	15	105
Urban (Binary)	13,243	0.574	1	0.495	0	1
Male (Binary)	13,243	0.451	0	0.498	0	1
Marital Status (Binary)	13,243	0.591	1	0.492	0	1
Level of education	13,243	2.463	2	0.899	0	4
Visited doctor this year (Binary)	13,243	0.4	0	0.49	0	1
General health status (Very Good = 5)	13,243	3.867	4	0.672	1	5
Exercise habit (at least once a week) (Binary)	13,243	0.239	0	0.426	0	1
Is Smoker (Binary)	13,234	0.159	0	0.366	0	1
# adults in household (>= 18)	13,243	2.955	3	1.233	1	9
Presence of children (< 18) (Binary)	13,243	0.332	0	0.471	0	1
Is Retired (Binary)	13,243	0.212	0	0.409	0	1
Share of alcohol in total calorie intake	13,243	0.00203	0	0.00655	0	0.117
Share of fruit/vegetables in total calorie intake	13,243	0.0775	0.0749	0.0272	0	0.243
Share of staples in total calorie intake	13,243	0.402	0.4	0.109	0	0.785
Total calorie intake	13,243	2,338	2,161	878.4	478.4	11,672
Total household expenditure	13,188	8,864	6,110	13,147	455	268,271

Estimation strategy

- In observational studies with non-random treatment assignment, two groups are not comparable as observed and unobserved variables determine the treatment status (Rosenbaum and Rubin, 1983)
- Our estimation strategy is based on PSM technique
- The main issue in PSM technique is how to predict propensity score:
  - **Conventional approaches** − OLS and logistic regression − are **weaker in solving prediction problem** (Kleinberg et al., 2015)
  - PSM models usually don't consider interactions between variables and higher order polynomials, which may lead to misspecification error (Westreich et al., 2010)
  - If propensity score model is misspecified, it may lead to biased estimates of treatment effect (Rosenbaum & Rubin, 1983; Imai & Ratkovic, 2014)
- We use the following methods:
  - Traditional PSM with logit for prediction of propensity scores
  - Covariate balance propensity scores (Imai & Ratkovic, 2014)
  - PSM in tandem with ML methods

Estimation strategy

- Let T_i be binary treatment (SSB intake) indicator for unit i

$$\pi_\beta(X_i) = Pr(T_i = 1|X_i)$$

where X_i is a vector of covariates

- Outcome of interest is

$$Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0)$$

- If CIA holds, i.e.,

$$\{Y_i(1), Y_i(0)\} \perp\!\!\!\perp T_i | \pi_\beta(X_i)$$

- The unbiased estimation of treatment (SSB consumption) effect is feasible by conditioning on the propensity score alone rather than entire covariate vector

Estimation strategy (Classic PS model)

- A parametric propensity score model:

$$Pr(SSB_i = 1|X_i) = \pi_\beta(X_i) = log\left(\frac{p_i}{1-p_i}\right) = \Phi(\cdot)$$

where $\Phi(\cdot) = \frac{exp(X_i'\beta)}{1 + exp(X_i'\beta)}$

- The model fit is maximized

$$\hat{\beta}_{MLE} = arg\max_{\beta\epsilon\theta} \sum_{i=1}^{N} T_i log\{\pi_\beta(X_i)\} + (1 - T_i) log\{1 - \pi_\beta(X_i)\}$$

given that first-order conditions that balance a set of variables hold:

$$\frac{1}{N}\sum_{i=1}^{N} s_\beta(T_i, X_i) = 0 \qquad s_\beta(T_i, X_i) = \frac{T_i \pi'_\beta(X_i)}{\pi_\beta(X_i)} - \frac{T_i \pi'_\beta(X_i)}{\pi_\beta(X_i)} - \frac{(1-T_i)\pi'_\beta(X_i)}{1-\pi_\beta(X_i)}$$

- **Main drawback** of the standard approach is the **PS model** might be **misspecified** leading to biased treatment effect (Imai & Ratkovic, 2014).

Estimation strategy (CBPS model)

- Imai & Ratkovic (2014) developed Covariate Balance Propensity Scores method that is **robust to mild misspecification of PS model**
- Robustness was achieved using dual characteristics of propensity score: a covariate balancing score & conditional probability of treatment assignment
- Covariate balancing was done using Inverse Propensity Score Weighting:

$$\mathbb{E}\left\{ T_i \tilde{X}_i - \frac{\pi_\beta(X_i)(1-T_i)\tilde{X}_i}{1-\pi_\beta(X_i)} \right\} = 0$$

- By incorporating score & covariate balancing conditions, they suggested:

$$\hat{\beta}_{\mathrm{GMM}} = \arg\min_{\beta \in \Theta} \bar{g}_\beta(T,X)^{\mathrm{T}} \Sigma_\beta(T,X)^{-1} \bar{g}_\beta(T,X)$$

where $\bar{g}_\beta(T, X)$ is sample mean of moment conditions

- Even if there are unobserved confounders, CBPS improve covariate balancing

PSM results suggest no significant link between SSB consumption and BMI in Kyrgyzstan

Model	*Control group*	*Treatment group*	*ATT*	*t-statistics*	*p-value*	*Accuracy*
Logit	24.167	24.267	0.100	0.749	0.454	
CBPS	24.160	24.267	0.106	0.797	0.426	
Machine-learning models:						
Deep Neural Network	24.082	24.267	0.184	1.383	0.167	0.809
CART	24.378	24.267	-0.112	-0.874	0.382	0.766
Bagged CART	24.155	24.267	0.111	0.870	0.385	0.934
Naive Bayes	23.996	24.267	0.271	2.147	0.032	0.789
Random Forest	24.228	24.267	0.038	0.297	0.766	0.941

Note: All models control for individual, household, location characteristics and regional fixed effects.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

PSM results suggest no significant link between SSB consumption and overweight in Kyrgyzstan

Model	*Control group*	*Treatment group*	*ATT*	*t-statistics*	*p-value*	*Accuracy*
Logit	0.275	0.263	-0.012	-0.870	0.385	
CBPS	0.264	0.263	-0.002	-0.109	0.913	
Machine-learning models:						
Deep Neural Network	0.264	0.263	-0.001	-0.085	0.933	0.809
CART	0.286	0.263	-0.023	-1.736	0.083	0.766
Bagged CART	0.267	0.263	-0.005	-0.363	0.717	0.934
Naive Bayes	0.267	0.263	-0.005	-0.346	0.730	0.789
Random Forest	0.275	0.263	-0.012	-0.897	0.370	0.941

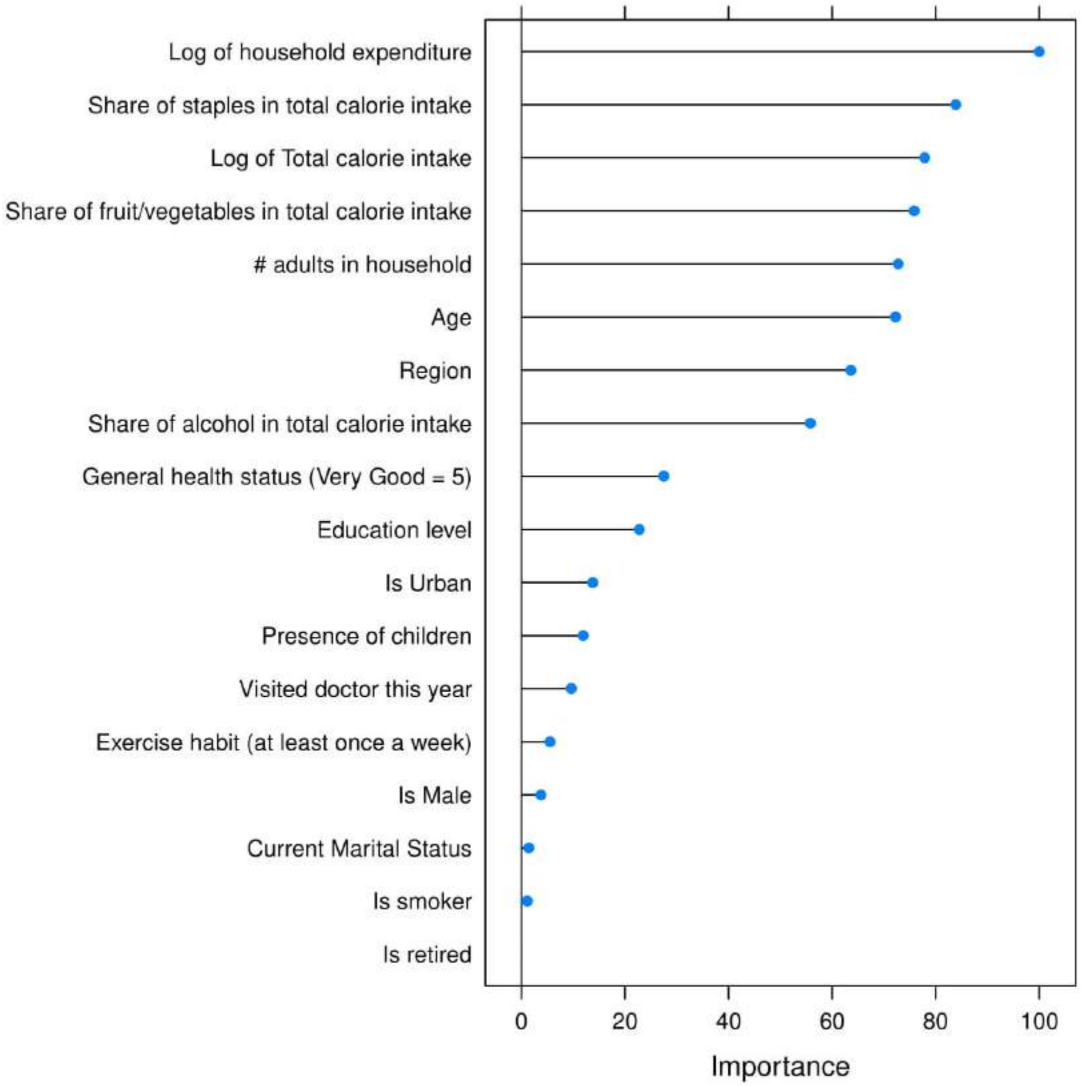
Note: All models control for individual, household, location characteristics and regional fixed effects.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

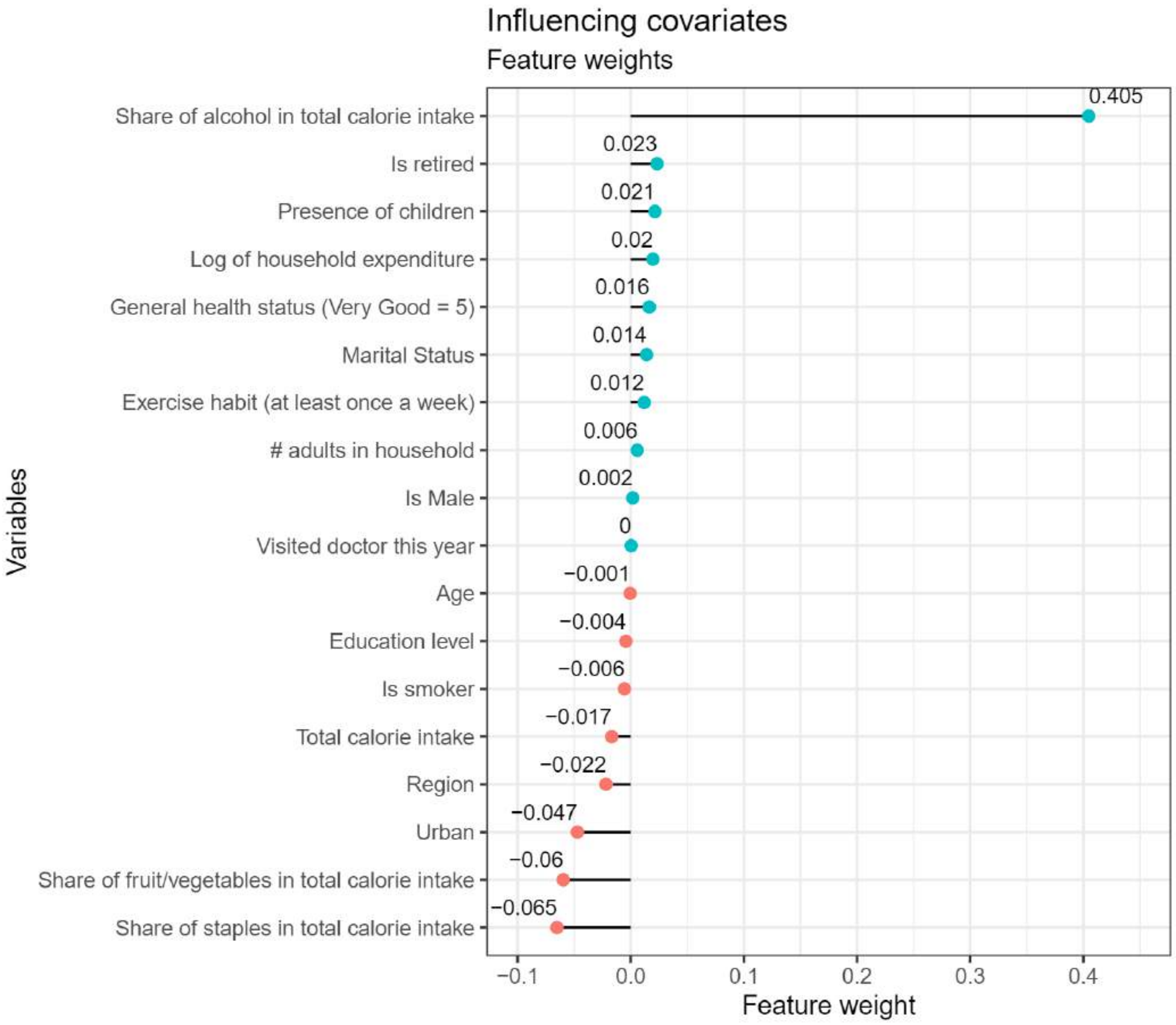
PSM results show significant link between SSB consumption and obesity in Kyrgyzstan

Model	*Control group*	*Treatment group*	*ATT*	*t-statistics*	*p-value*	*Accuracy*
Logit	0.079	0.101	0.022**	2.382	0.017	
CBPS	0.085	0.101	0.016*	1.700	0.089	
Machine-learning models:						
Deep Neural Network	0.082	0.101	0.019**	2.054	0.040	0.809
CART	0.085	0.101	0.016*	1.776	0.076	0.766
Bagged CART	0.084	0.101	0.016*	1.829	0.068	0.934
Naive Bayes	0.070	0.101	0.031***	3.541	0.000	0.789
Random Forest	0.086	0.101	0.015*	1.698	0.090	0.941

Note: All models control for individual, household, location characteristics and regional fixed effects.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Influential covariates





Conclusion

- Our results suggest a statistically significant **link** between **SSBs consumption** and **obesity** in Kyrgyzstan

- We found a **negative relationship** between total calorie intake, share of **staples** in total calorie intake, share of **fruit & vegetables** in total calorie intake, **smoking** and the probability of consuming SSBs

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The contribution of SSB intake to obesity in Kyrgyzstan appears to be significant

Therefore, limiting SSB consumption may help to mitigate the emerging public health challenge in the country

Policy implications

- **SSB warning labels** to reshape people's perception and reduce SSB consumption (VanEpps & Roberto, 2016)
- **Increasing public awareness** on the negative effects of sugar-sweetened beverages' consumption (Kansagra et al., 2015)
- **Regulation of marketing campaigns** promoting SSBs (WHO, 2019)
- **Taxation** of SSB consumption (Jou & Techakehakij, 2012; Cawley, 2015; Battakova et al., 2017)

Thank you for your attention!