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Article

A spatiotemporal analysis of OECD member countries on sugar consumption and labor force participation

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SUMMARY

Sugar can be classified into two groups, 1) "natural sugars," which come from fruits and plants and provides energy for the cells, or 2) "free sugars," which are any sugars added to food or drinks. Although natural sugars provide an energy supply for workers, free sugars may negatively impact workers' performance. For example, free sugars may contribute to diseases such as obesity and type 2 diabetes. In this study, we examined the impact of sugar consumption on the labor force participation rate. We defined three states of sugar consumption: underconsumption, sufficient consumption, and overconsumption. Underconsumption of sugar decreases productivity; sufficient consumption of sugar makes productivity close to its maximum rate, and overconsumption of sugar worsens productivity. Given these three conditions, we hypothesized that a negative quadratic relationship between sugar consumption and productivity exists. Using data from the Organization for Economic Co-operation and Development countries, we built a random effects model to estimate the effect of sugar consumption on the labor force participation rate (LFPR), accounting for confounders and temporal and spatial heterogeneity. Consistent with our hypothesis, there is a negative quadratic correlation between sugar consumption and LFPR, albeit with a weak R-squared value (0.38685). Potential explanations for the result include the large sample size of the research, the limitation on collected data, and the potential missing confounders. At the policy level, we introduce solutions to mitigate the negative externalities of sugar consumption, such as labeling sugar content on nutrition facts labels, raising health awareness, and enhancing related education.

INTRODUCTION

Sugar is considered a main type of carbohydrate that can be the primary source of energy for the human body, specifically the central nervous system (e.g., brain), muscles, and red blood cells (1,2). However, the overconsumption of sugar can increase the risk of health problems or even diseases, such as cavities, weight gain, obesity, or even type 2 diabetes (T2D) (3). Sugar consumption (per capita sugar food supply) is measured in kilocalories per person per day, which includes the intake of natural sugars and free sugars. Natural sugars come with various nutrients, mostly found in fruit, vegetable, and unsweetened milk, and are often referred to by other names such as honey, syrup, and dextrose (2,4,5). Sugars in general provide energy for cells around the body, supply glucose to the brain, and manage bodily functions (1,2). On the other hand, free sugars, known as added sugars, are mostly found in processed/manufactured sweet products (e.g., cookies, desserts, and sugary drinks) (6). According to the World Health Organization (WHO), it is recommended that the high risk of disease can be prevented by following the mentioned recommended sugar intake (<10%) if individuals reduce the daily intake of free sugars to less than 10% of their total energy intake (7). Having an excess of sugar consumption (free sugar >10% of total energy) can increase weight and body mass index (BMI) and is associated with T2D risk (7).

A study examining people from 175 countries found that the increase in sugar availability was associated with the increase in T2D prevalence (8). If managed poorly, diabetes could lead to severe medical complications, potentially leading to unemployment, early retirement, or a permanent disability pension (9). Thus, T2D imposes social costs with long-term healthcare spending and loss in productivity, requiring substantial healthcare resources and disease management efforts (9). The International Diabetes Federation (IDF) is an umbrella organization focusing on the increase of diagnoses and impact of diabetes from the local to the global level. The Diabetes Atlas reports that, in 2019, for every four people with diabetes, three of them are of working age (20-64 year-olds), which accounted for 352 million people globally (10). This number is expected to reach 417 million by 2030 and 486 million by 2045 (10). The IDF indicates that the high increase in diabetes will severely strain productivity and economic growth over the next few decades (10). It is also possible that sugar consumption affects the labor force participation rate (LFPR), defined as the percentage of workers who are employed or actively seeking employment in the total working-age population (10).

Our study investigated the relationship between overall sugar consumption and LFPR among member states of the Organization for Economic Cooperation and Development (OECD). OECD is an intergovernmental organization that aims to promote policies to improve economics and society (11). The organization has 38 member countries, with high-income economies and a very high Human Development Index (HDI) regarding developed countries, and its databases are based on these nations (11). Sugar consumption includes the consumption of both natural sugar and free sugar, but overconsumption of either form could cause negative impacts on health. Thus, we used overall sugar consumption as our independent variable of interest. We predicted the effect of sugar consumption on LFPR to be three-fold: underconsumption, sufficient consumption, and overconsumption of sugar. Underconsumption of sugar can indicate undernourishment and may be associated with low LFPR. Sufficient consumption of sugar (free sugar <10% of total energy) can contribute to the highest rate of LFPR (7). Overconsumption of sugar (free sugar >10% of total energy) can lead to chronic diseases that decrease LFPR (7). We expected that sufficient sugar consumption makes the LFPR close to its optimal rate. Given the three circumstances, we hypothesized that there existed a negative quadratic relationship between sugar consumption and LFPR among the OECD countries between 1990 and 2013. We used a random effects model to estimate the effect of sugar consumption on LFPR and observed a negative quadratic correlation between sugar consumption and LFPR.

This study investigated the effect of sugar consumption on LFPR and we hypothesized that there would be a negative quadratic relationship between the two variables. Elucidating the impact of sugar intake on the labor force may inform policies and future research on reducing the negative externalities of sugar overconsumption.

RESULTS

We investigated the relationship between sugar consumption and LFPR in the OECD countries. We collected data on all 38 member states of the OECD between 1990 and 2013, yielding a sample size of N = 912. Notably, the OECD members have a higher economic development compared to the global average (11). Sugar consumption, the independent variable, is measured by the per capita sugar food supply (kilocalories per person per day in 2011 international dollars). Labor productivity, the dependent variable, is indicated by the LFPR, defined as the ratio of labor force size to total working-age (aged 15 to 64) population (12). Confounding variables, included the employment rate, GDP per capita, health spending total, and mortality of high BMI, were also included in the study. We implemented a fixed effects model and a random effects model to fit quadratic regressions on the data.

We implemented the following formula for our quadratic regression model:

$$LFPR \sim sugar\ consumption^2 + sugar\ consumption + employment\ rate + GDP\ per\ capita + health\ spending\ total + mortality\ of\ high\ BMI + constant$$

First, we fit the data in a Fixed Effects model and a Random Effects model (**Table 1 and 2**). After fitting the data in the two models, we ran a Hausman test to determine which model was appropriate. The Hausman test helps to detect endogenous regressors (similar to dependent variables) in a model and figure out if the predictor variables are endogenous (13). We found that the random effects model was more appropriate for the analysis ($p > 0.05$). In accordance with the results from the random effects model, the coefficient of the square of sugar consumption is -3.750e-05, with a p-value of 0.032. Finally, we ran a sensitivity analysis, a tool that can be used to understand the effect of a set of independent variables on a dependent variable under a given condition, to assess the robustness of our model (14,15).

For the confounders, other than high BMI (r = -9.500e-05), a positive correlation was observed for the employment rate (r = 1.784e-04), GDP per capita (r = 1.873e-04), and health spending total (r = 7.101e-01), with all the confounding variables being statistically significant ($p < 0.05$).

Given the random effect model, the sensitivity analysis reports the partial r-squared of a treatment with an outcome of 0.0669 and the robustness value is 23.44% (**Table 3**). The value explains that 100% of the residual variance of the outcome would need to explain at least 0.0669% of the residual variance of the treatment to fully account for the observed estimated effect. The robustness value is 23.44%, indicating that confounders need to explain at least 23.44% of the variation of the outcome or the treatment variable to bring the point estimate to 0 and explain away the treatment effect.

Variables	*Estimate*	*Std. Error*	*t-value*	*p-value*
Sugar consumption	1.7366e-02	1.4691e-02	1.1821	0.238
Sugar consumption^2	-2.1398e-05	1.8452e-05	-1.1597	0.247
Employment rate	2.3687e-04	7.7735e-05	3.0471	0.002
GDP per capita	1.8101e-04	2.7173e-05	6.6612	<0.001
Health spending total	6.4649e-01	1.0466e-01	6.1773	<0.001
Mortality of high BMI	-1.0702e-04	2.0838e-05	-5.1357	<0.001
R-Squared	0.39407			
F-statistic	51.4859 on 6 and 475 DF		**p-value**	< 2.22e-16

Table 1. Summary of the fixed effects model with a quadratic term for OECD countries between 1990 and 2013.

Variables	*Estimate*	*Std. Error*	*t-value*	*p-value*
Sugar consumption	3.2431e-02	1.3760e-02	2.3569	0.018
Sugar consumption^2	-3.7501e-05	1.7537e-05	-2.1384	0.032
Employment rate	1.7841e-04	5.3807e-05	3.3158	<0.001
GDP per capita	1.8729e-04	2.4568e-05	7.6233	<0.001
Health spending total	7.1007e-01	1.0236e-01	6.9371	<0.001
Mortality of high BMI	-9.4996e-05	1.8241e-05	-5.2079	<0.001
R-Squared	0.38685			
Chi-squared	317.503 on 6 DF		**p-value**	< 2.22e-16

Table 2. Summary of the random effects model with a quadratic term for OECD countries between 1990 and 2013.

Partial r-squared of treatment with the outcome	0.0669
Robustness Value	0.2344

Table 3. Summary of sensitivity analysis.

DISCUSSION

We found out that there was a negative quadratic relation between sugar consumption and LFPR, hence the relationship of the two variables can be shown as a quadratic regression, a downward-concaving curve (**Table 2 and Figure 1**). In other words, LFPR rises as the sugar consumption increases for the low value of the sugar consumption (underconsumption)

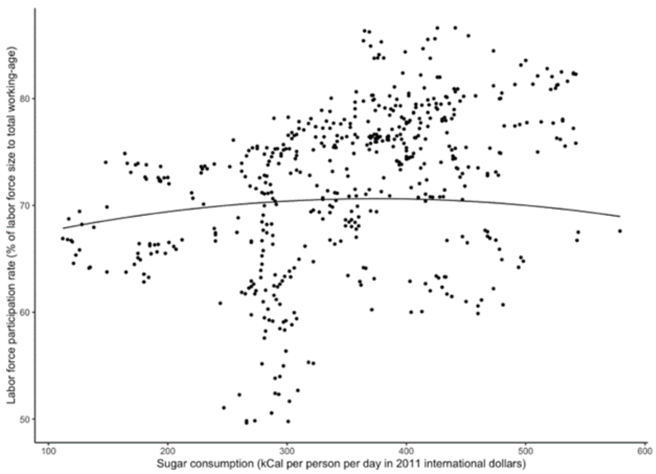

Figure 1. Relationship between sugar consumption and labor force participation rate. The black dots show a scatterplot of sugar consumption on the x-axis and LFPR on the y-axis for OECD countries between years 1990 and 2013. The line shows a quadratic regression fitted to the data, given by the equation: LFPR = -0.00005 SC2 + 0.03 SC + 52.5.

and falls as the sugar consumption increases for the high value of sugar consumption (overconsumption).

For the confounders, all the confounding variables are statistically significant with a p-value smaller than 0.05. The positive correlations, the employment rate, GDP per capita, and health spending total, can be interpreted as that LFPR increases as the employment rate increases; the GDP per capita grows as the LFPR rises; the LFPR increases as the health spending total rises due to the more investment in individual's health care. Mortality of high BMI was shown to have a negative correlation, therefore an increase in high BMI can be explained by the effects on the labor force, thus leading to a decrease in LFPR.

Despite that the coefficient of all the variables from the random effect model being statistically significant ($p < 0.05$), the r-squared (39%) shows that the model does not explain much of the variation or why there is a weak correlation between the independent (sugar consumption) and dependent (LFPR) variables. Given the above results, we propose three possible reasons for the moderate R-squared value (0.38685). The first possibility is due to the large sample size of the research. This research collected data on the OECD countries between 1990 and 2013 (N = 912). Each country has its own relationship between sugar consumption and LFPR because of the differences in economic development and living standard. Thus, the model showed an overall correlation between the two variables but may not represent the conditions of all the OECD countries. Besides, with the large database, there might be an increased number of outliers. Compared to linear regression, quadratic regression is even more sensitive to outliers, hence the presence of outliers might badly affect the performance of the model and result in a low r-squared value (16). The second possibility is the limitation of the collected data. Since there is no database recording free sugar intake, we can only use the measure of sugar consumption per capita as a substitute for the data. However, sugar consumption includes both natural sugar and free sugar so we cannot specify the amount of intake of either kind of sugar. In our research, we assumed that the amount of sugar intake can be divided into three conditions which are underconsumption, sufficient consumption, and overconsumption. However, we could not tell the proportion of natural and free sugar in total sugar consumption. As a result, the standard for classifying the three sugar intake conditions might not be ideal as we thought for the presentation of a quadratic relationship. The third possibility is the missing confounders. Only four confounders are accounted for in our model. However, there are a variety of factors that can influence LFPR directly or indirectly. For instance, retirement, health conditions, labor insurance, and other labor-related policies. By adding more confounding variables, the result would also change. In addition, sugar consumption could only be considered as an indirect factor that has little effect on LFPR. Hence, it can be hard to show a clear relationship between sugar consumption and LFPR, which might explain the low r-squared value.

Our data collected has both advantages and disadvantages. We gathered country-level data sets from the OECD, Our World in Data (OWID), and World Bank (WB). This enables us to investigate the topic at the macroeconomics level. Therefore, we may suggest policy implications corresponding to different countries. Nevertheless, the country-level data did not incorporate individual information so we were unable to show the correlation at the individual level. However, information at the individual level could play a role in personalized medicine.

In contrast to the ordinary least squares, the study applied both fixed effects and random effects models which take time and location into account. After processing the aforementioned models, we ran a Hausman test in order to determine the model that better demonstrates our data. Apart from the independent variable and dependent variable, the study accounted for confounding variables. The more confounders that are taken into consideration, the more significant the estimate. However, possible missing confounders still might cause bias in our model.

Through the overall discussion and analysis, the study posits that excess sugar consumption leads to negative impacts on various aspects, especially health concerns and the labor force. To ameliorate the adverse condition, we recommend diminishing the consumption of products with added sugar, such as sugary beverages and cookies. The following are some possible suggestions that have been implemented in certain countries. First, it is recommended that governments could make regulations for the particular labeling of sugar content on nutrition facts labels. Therefore, consumers can easily notice how much added sugar is contained in products. In this way, we could prevent the impacts due to asymmetric information. Furthermore, warning labels on products alert consumers to the risk of sugar exposure and may even discourage buyers from purchasing the products (17). As a result, the consumption of products with added sugar may decrease. Second, raising health awareness and enhancing education can also be relevant to mitigating the issue. The government or some organizations should help to disseminate the recommendation for sugar intake: a maximum of 50 grams of sugar per day, according to the WHO (18). In addition, promoting healthy diets and lifestyles could improve public health. Eating habits are essential for children and adults alike, so educational efforts should not be limited to school. Last but not least, the above policy changes are general suggestions based on our research so each country would have to implement policies individually and make appropriate adjustments according to their conditions.

Our research focused on the overall relationship between sugar consumption and LFPR. Therefore, for further research, we would suggest comparing the models of the two variables between developing countries and developed countries. Each country might have its own relationship between sugar consumption and LFPR owing to the differences in economic development and living standard. Hence, it might be interesting to find out the models for different countries and make comparisons between models.

Our study found a negative quadratic correlation between sugar consumption and LFPR. Notably, overconsumption was associated with decreased labor force participation. Our findings provide evidence for a negative externality of the overconsumption of sugar. Policies such as nutrition facts labeling, health awareness enhancement, and local policy-making may improve population health and the economy.

MATERIALS AND METHODS

We extracted 20 years of data (1990-2013) for all 38 member states of the OECD (N = 912). The Our World in Data (OWID), the Organization for Economic Co-operation and Development (OECD), and the World Bank (WB) are the data sources of this paper (11, 19, 20). The independent variable is sugar consumption, measured by the per capita sugar food supply (kilocalories per person per day in 2011 international dollars). The dependent variable is the labor force participation rate, defined as the ratio of labor force size to the total working-age (aged 15 to 64) population (12). Confounding variables, including the employment rate, GDP per capita, health spending total, and mortality of high BMI, were also included in the study.

The analyses were implemented in R using RStudio. Of note, we used the plm and sensemakr packages from Comprehensive R Archive Network (21,22). Fixed effects and random effects models are standard methods for conducting panel data analysis, where the data is cross-sectional and time-series (23). The Hausman test determines the more appropriate model between the fixed and random effects models (23). Quadratic regression was chosen to accommodate our hypothesis of an initial positive correlation and eventual negative correlation. We ran a sensitivity analysis to determine the robustness of our model by testing the impact of possible missing confounders. The sensemakr package was chosen as it was an extension of traditional sensitivity analysis methods (24).

Source code is found at https://gist.github.com/YIYUN0119/de47406e97652610d675f59ed2de2bc0.

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