Journal of Agriculture and Food Research 10 (2022) 100439

Contents lists available at ScienceDirect

Journal of Agriculture and Food Research

journal homepage: www.sciencedirect.com/journal/journal-of-agriculture-and-food-research

The impact of agricultural subsidies on obesity

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ARTICLE INFO

Keywords:
BMI
Consumer support estimate
Double-lasso
Machine-learning

ABSTRACT

Farm subsidies are on the rise. Such subsidies can be paid either through transfers from tax payers (PSE) or at the expense of consumers (CSE) or both. As farm subsidies may have an influence on food prices, it makes certain farm commodities more abundant and therefore cheaper. This paper aims to investigate if such subsidies can contribute in explaining rising obesity rates worldwide. We use data on farm subsidies and obesity data from OECD and FAO and distinguish two models to investigate the different effects: on the one hand on overweight (BMI above 25 to 30) and on the other hand on obesity (BMI above 30). Regression analysis shows that farm subsidies may be too low to have an effect on overweight or obesity and conclude that rising obesity is probably better fought on a national level instead trying to fight it on a cross-country level.

1. Introduction

"How much obesity has to be created in a single decade for people to realize that diet has to be responsible for it?" (Robert Atkins, 1996 in [33])

Even though one might get the impression that Atkins knew in 1996 exactly who or what to blame for the rising obesity epidemic, there are many questions left to the issue of rising obesity around the world. A comparison of the obesity rates (in % of the population) between 1980 and 2014 of the OECD countries shows a clear picture of continuously rising obesity rates: Not only the proportion of population that is overweight, which corresponds to a BMI that is above a value of 25, but also the proportion of the obese population – having a BMI that is above 30 – rose over the last decade. From 1975 until 2014 the mean proportion of the population that is overweight of all OECD countries rose by 20% points. Meanwhile, it rose by around 14% points for the obese population [32]. Though, obesity imposes significant individual and social costs, it is still unclear what exactly explains the international rise in obesity (see e.g., [8]).

Comparing the level of overweight and obesity across the OECD countries, the share of overweight in the population developed as follows: In 1980, the Czech Republic had the highest proportion of overweight with more than 50% of its population having a BMI above 25. Nowadays in the United States more than 60% of its population are overweight. Japan is the country with the lowest proportion over overweight: 24% of its population are overweight, which is still eight percentage points higher than in 1980. In comparison to Japan, across the OECD, Austria has the second lowest incidence of obesity with a proportion of 54% being overweight. So why is it that Japanese population is this much thinner than the rest of the OECD countries?

Overall, rising obesity rates are explained by mainly three different approaches: Obesity as an information deficiency problem, obesity as an expression of the weakness of the will and obesity as a rational choice [21]. The relationship between schooling and better health outcomes are long known (see, e.g. [14,25], or [23]) (information deficiency argument). However, information on the triggers of obesity has risen over the years whilst obesity rates are still on the rise [29]. Though physical activity can prevent obesity, it is evident that most populations in developed countries do not meet current recommendations for daily physical activity (see e.g. [16], or [12]) (weakness of the will argument). Under the rational choice argument the role of farm policies plays a decisive role to the process of rising obesity rates: By subsidizing farms, production and therefore prices of certain products are cheapened (see, e.g. [1,2,5,29], or [19]).

Our main interest is to give further insights which aspect – information deficiency, physical inactivity or the rational choice argument – played a role concerning the increase in obesity rates across countries. Hereby, we are especially interested in the rational choice argument: Which role did farm policies play to the process of rising obesity rates by subsidizing farms and therefore cheapen production of certain products? Are farm subsidies probably the one decisive factor to isolate across OECD countries? We aim to extend the previous literature in the direction of understanding more finely the role of farm subsidies on

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https://doi.org/10.1016/j.jafr.2022.100439
Received 23 June 2022; Received in revised form 26 September 2022; Accepted 30 October 2022
Available online 11 November 2022

obesity across countries.

Mainly, we analyze the role of agricultural policy in the obesity epidemic using methods of machine learning (lasso regression). This addresses the problem of the highly dimensional data, that is, the large number of parameters to be estimated relative to the number of observations. We show that the regression techniques used in existing studies are inadequate and produce biased estimators (like in, e.g. [19]). Lasso regression is an effective tool to the problem of principled variable selection for covariates especially in case of high dimensional data.

1.1. Theoretical background and hypotheses

Relative prices of agricultural commodities decreased dramatically within the last decades. On the one hand due to technical progress and on the other hand due to farm subsidies. Farm subsidies decreased relative prices of agricultural goods by making them more abundant and therefore even cheaper. Lower prices for (especially) fattening foods are discussed to contribute to the problem of obesity as consumers prefer buying low cost (fattening) foods (rational choice argument). [2], e.g., investigate if farm subsidies on the one hand decrease food prices especially of fattening foods and if this, on the other hand, contributes to rising obesity rates in the United States. Overall, they find small evidence that the impact on food prices is high. Furthermore, with food consumption being relatively unresponsive to changes in market prices, the effects on consumption patterns are small [2]. therefore conclude that an elimination of subsidies would not lead to a decrease in overweight. Nevertheless, the correlations between obesity and subsidies paid by the consumer to the farms (Consumer Support Estimate, CSE [28]) show that a larger subsidy from consumers result in lower obesity rates. Although this is only an informal analysis of correlations among obesity and food prices (they use the Big Mac Index as a proxy for prices) it shows that governmental policy can have a direct impact on prices, consumption and therefore obesity. Likewise [30], argues that “the cheap-food farm policy” leads to an intensification of the obesity epidemic. He argues that overproduction in agriculture that is also driven by the government and its subsidies lead to a continuous fall in prices for agricultural commodities in the U.S. and undermines public-health goals by “loosing a tide of cheap calories at home”. Furthermore [1], who analyze price trends between 1960 and 2002 of real farm gate prices find that e.g. the price of white bread has not changed over the past 25 years in real terms. Besides, the price for white sugar has even become cheaper in real terms. They conclude that rising real incomes, smaller households and increasing opportunity costs of time come along with a higher demand for more fast food services [4]. find with data from the Behavioral Risk Factor Surveillance System (BRFSS) for the U.S. that decreasing food prices lead to rising obesity rates. So far, the impact on the role of agricultural subsidies on obesity rates across countries are quite unclear [5]. use empirical methods but only a small size ($N = 9$, respectively $N = 22$) to find a relationship between subsidies, food prices [19]. use a larger data set (N is not known) from 1990 to 2002 of all OECD countries. With help of a generalized least squares random effects model, they show that overall the subsidy, that is paid directly from the consumer to the farmer, has quite a significant influence on obesity rates: The higher this rate, the lower the obesity rate. Though, using a random effects model is - as discussed below - not appropriate for this kind of data. Besides, we argue - in line with the rational choice argument - that higher income may lead to higher obesity rates (as more income can be assigned to food consumption) and a higher agricultural output may lead to lower prices for agricultural commodities.

Overall, based on the literature, our first hypothesis is:

H1. Sinking food prices and a higher income may lead to rising obesity prices.

[25] is the first to examine the relationship between schooling, health knowledge and increasing obesity. He uses data from the 1994 Diet and Health Knowledge Survey (DHKS) from the U.S. Department of Agriculture and concludes that an increase in diet-disease knowledge has an inverted effect on the probability of being obese. That education does play a decisive role in being obese show e.g. [23] for Brazil. They use cross-sectional randomly selected samples of the adult population living in Brazil to show that especially woman but also men – to a lesser extent – profit from education that tends to function protective against overweight and obesity. Concerning the information deficiency argument and in line with, e.g. [23,25], we hypothesize that:

H2. More years of education is associated with lower obesity rates.

Concerning the weakness of the will argument, e.g., physical activity and a higher caloric intake will lead to higher obesity rates. Further, changes in life style such as a higher participation of females in the labor force lead to rising obesity rates (decreasing time resources to prepare meals and more meals consumed away from home) [4,5,18,24,29]. In line with these arguments, we hypothesize:

H3a. Higher intake of calories is associated with higher obesity rates.

H3b. Less physical activity leads to higher obesity rates.

H3c. Life style changes such as a higher proportion of working females may lead to higher obesity rates.

Other factors that are discussed having an influence on overweight are age (see e.g., [15]) – with lower life expectancy there are fewer reasons to eat less and the proportion of smokers – smokers are supposed to be less obese in comparison to the rest of the population (see e.g., [17]).

H4. The higher the proportion of the elderly and a lower proportion of smokers are associated with a higher rates of obesity.

The remainder of the paper is structured as follows: Section 2 describes our empirical strategy. Section 3 presents the data used for the empirical application, detailing how we selected the studied sample and reporting descriptive statistics. Section 4 introduces the results, investigating the main drivers of the rising obesity rates across countries. Section 5 concludes by summing-up the main results, discussing the limitations of the study and providing possible lines of future research.

2. Empirical strategy

Overall, the most common methods for estimating unobserved effects when using panel data are the random effects model or the fixed effects model. The distinction between both models is whether the unobserved individual effect is correlated with the regressors in the model or not [10]. Usually, conducting a Hausman-Test, which tests if the predictor variables are exegenous and therefore, if there is a correlation between the errors and the regressors, gives insights on whether fixed or random effects are appropriate. The null hypothesis is that the preferred model is random effects (e.g. no correlation between unique errors and regressors). In our case, we prefer a fixed effects model.

A fixed effects model assumes that within country factors impact the predictors and therefore the outcome variable:

$$y_{it} = \beta x_{it} + \alpha_i + u_{it} \tag{1}$$

Furthermore a fixed effects model assumes that the country-specific characteristics of one country are not correlated with other country-specific characteristics (of other countries). α_i is the unknown intercept for each country, that affects obesity rates but that does not change over time (like a specific government policy or gender and age, that are roughly constant over time). The error term and the constant should not be correlated with the predictors. Fixed effects removes the effect of time-invariant characteristics and therefore, we can asses the net effect of the predictor on the outcome variable which is in our case the proportion of population being overweight or obese.

However, in our case and as described below, most variation in our data is across time whereas only little variation is across countries. This raises the suspicion of running spurious regressions. If most of the variation used to identify the effect of agricultural policy on BMI comes from variation over time, we should be concerned with the stationarity of the data. The issue of stationarity should be ameliorated by using first-differences which is another option to control for unobserved effects and eliminating the α_i. Using first differences can lead to large standard errors if we have little variation in Δx_i but if u_{it} are not serially uncorrelated, using first differences can be more efficient.

We use the Wooldridge test for serial correlation in panel-data models to check which model we should prefer [34]. The tests shows that in our case using first differences is the most efficient model.

To extent our analysis, we use the Least Absolute Shrinkage and Selection Operator (LASSO) to decide on the selection of covariates that should be included in the dataset [3]. Lasso regression is an effective tool to the problem of principled variable selection for covariates especially in case of high dimensional data. Analysis that do not take into account all valid predictors of the dependent variable may suffer from, e.g., the omitted variables error and can cause bias in estimated parameters due to correlations of the predicted dependent variable and correlated focal independent variable(s) [6,22]. In doing so, we are able to include controls not only in a linear way but also in form of simple transformations and a variety of interaction terms. Double lasso regression in comparison to other data mining methods is doing better in terms of false discovery and overfitting. It helps searching and selecting the variables that should be included in the analysis but also helps avoiding errors of Type 1 (rejecting H_0 although it is true). Furthermore, it can be applied even when the number of observations is small in comparison the number of predictors [3]. Instead of estimating a linear regression model and finding the coefficients that minimize the sum of squared errors, lasso regression finds coefficients that minimize the sum of squared errors in the regression equation with an additional penalty term. Therefore, the standard OLS model $y_i = \beta_0 + \beta_1 x_i + \beta_2 w_{i1} \ldots + \beta_{k+1} w_{ik} + \varepsilon_i$ finds the coefficients beta that minimize the sum of squared residuals. Lasso additionally includes the penalty term $\lambda \sum_k |\beta_k|$, which penalizes the inclusion of many coefficients that are close to zero in absolute value and minimizes $min[\sum_i (y_i - \beta_0 + \beta_1 x_i + \beta_2 w_{ik} + \ldots. + \beta_{k+1} w_{ik})^2 + \lambda \sum_k |\beta_k|]$. Hereby, x_i is the focal independent variable of interest which is in our case the CSE: We want to know if the proportion of overweights' is really determined by the agricultural policy. By setting some variables to zero, variable selection is undertaken implicitly [31]. [3] suggest using "double-lasso" variable selection as lasso regression can lead to underestimation of coefficients that are not equal to zero and cause inference about β_1. Furthermore, coefficients mistakenly set to zero cause omitted variable bias especially when those predictors are relevant for the variable of interest. Using double-lasso regression, in a first step, we fit a lasso regression predicting the dependent variable without the focal variable. In a second step, the focal independent variable is predicted (retaining all variables with non-zero estimated coefficients). Then, the final regression model is estimated: this model includes the focal independent variable as well as all other predictors that were selected to be non-zero in the first two steps [31]. Overall, we use the baseline model as described above with first differences and consider nonlinear trends interacted with observed country-specific characteristics. The choice of variables is based on [3] and allws checking for the development of obesity rates over time: The included independent variables include (initial) levels, (initial) differences, within country averages of the country-specific time varying observables, the initial level and initial difference of subsidy rates, quadratics in each of the preceding variables, interactions of all the aforementioned variables with t and t^2 and the main effects t and t^2. This procedure is helpful as the "baseline model" only provides good estimates if time-varying and country-specific factors that are correlated to both subsidy rates and obesity are captured by a small set of characteristics.

3. Material and methods

We want to understand the complex links between social, cultural and political factors causing rising obesity rates across OECD countries. But, as mentioned earlier, we are especially interested in the question to what extent agricultural policy is to blame for the obesity. Governmental policies mainly influence agricultural policy in two ways across the OECD countries: Overall, the total support estimate (TSE) consists of the producer support estimate (PSE) that are transfers to agricultural producers and the CSE that measures transfers to consumers of agricultural commodities. Market price support, budgetary payments and the cost of revenue foregone by the government and other economic agents are all combined in the PSE that sums all policy transfers to agricultural producers measured at the farm gate. In contrast, the CSE measures the gross transfers from or to consumers of agricultural products at the farm gate level. Therefore, we are mainly interested in the effects of the CSE. Usually, the CSE is negative which indicates a transfer from the consumer (implicit tax on market price) to the agricultural producer. If it is positive, it indicates a subsidy and therefore a lower price for the consumer [28]. Data on the CSE (the share of CSE in consumption expenditure, net of taxpayer transfers to consumers (%)) is taken from [27], starting in 1986–2014. At that time still, there were 34 OECD member states. The variation in those subsidies is small across countries. Switzerland and Japan have quite high rates of CSE in comparison to the other nations. Meanwhile – besides having the highest proportion of overweight population – the United States are the only nation having a positive CSE from time to time and therefore subsidizing the consumers. Overall, there is no high variation over countries due to the common agricultural policy (CAP) in the EU countries (see Fig. 1): Due to the CAP, the CSE is the same for all EU countries. Nevertheless, there is some variation over the years. Overall, the indirect tax on consumers decreased in the OECD over the years, meanwhile overweight rates increased (see Fig. 2) [28]. Data on obesity rates (BMI over 25 and BMI over 30) is provided by [32] starting in 1975.

Based on the literature research and our hypotheses, we include GDP per capita and agricultural output per worker in our analysis (H1). A higher income may lead to higher obesity rates as well as a higher agricultural output may lead to lower prices for agricultural commodities and therefore higher obesity rates. The variable output per worker is calculated by using the agricultural output level from FAO [7] divided by the proportion of working population working in agriculture from the World Bank [35]. The agriculture gross production value from [7] is measured in 2004–2006 million USD starting from 1961 for most

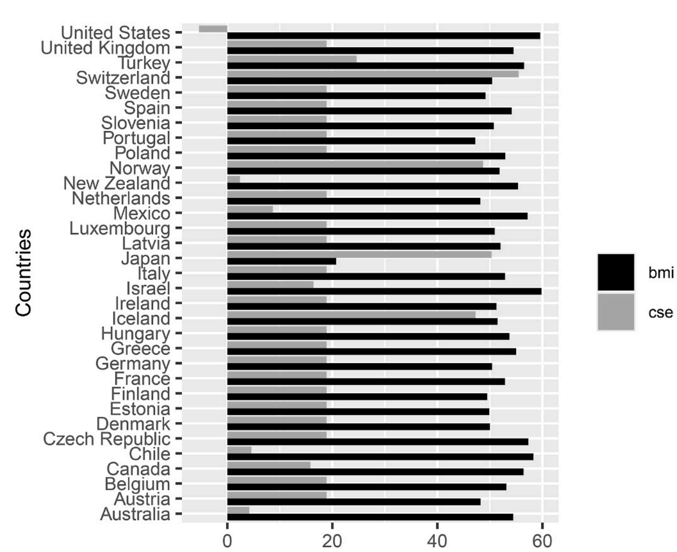

Fig. 1. Development of the mean of the CSE in comparison to the development of the BMI above 25 to 30, mean over 1986–2014 [27,32].

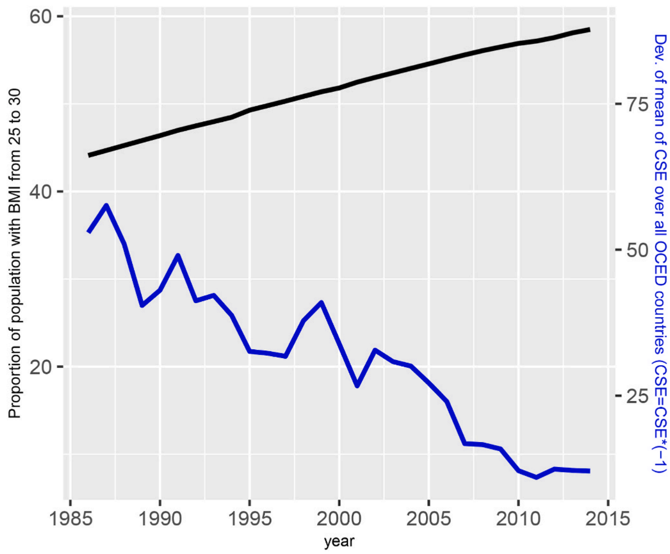

Fig. 2. Proportion of population with BMI above 25 to 30 in comparison to the CSE (CSE = CSE*(-1)), mean over 1986–2014 [27].

countries. GDP per capita is given at constant 2005 USD and is provided by the World Bank [35].

Accordingly to H2, as a proxy for the population's information level, we use the percentage of GDP dedicated to education from [35]. In line with H3, we include calories eaten per capita and day from [7]. As a proxy for changed life style and extent of physical activity we include kilometers driven (data starting in 1956) [26] and data on per capita volume of environmental emissions including sulphur, oxide, nitrogen oxide, and carbon monoxide from the OECD Environmental Statistics [26] (starting in 1990) as well as the percentage of rural populations per country and year from the World Bank [35] (starting in 1960). The proportion of the female labor force is from [35] starting in 1990. In line with H4, we further include the proportion of population over 65 (proxy for age) as well as the proportion of smokers (data from [26].

While the CSE is our focal variable, it is influenced by several factors. Agricultural politics is mainly influenced by the governmental budget: The GDP as well as expenditures in other sectors like education influence the budget for agricultural policy. Furthermore, the significance of the agricultural sector is a main driver for the agricultural policy. The proportion of people living in rural areas could indicate that significance. The proportion of the elderly is a factor for the role of agriculture in policy as well: The elderly usually bear a higher relation to the agricultural sector. Contrary, more females in the workforce might weaken the role of agriculture within society as the role of traditional cooking decreases. Overall, we can conclude that our covariates are adequate to further investigate the role of agricultural policy on obesity.

Table 1 shows the summary statistics of the control variables of our data set.

4. Results

The results for the fixed effects model as well as the first difference model are shown in Table 2.

In the fixed effects model, we observe the intake of calories, the proportion of population living in rural areas, the proportion of the population over 65, the proportion of the female workforce, the emissions variable as well as the proportion of smokers and the variable that measures agricultural productivity as being significant while the CSE is not significant. Especially the effect of the agricultural productivity is high. Nevertheless, we observe a high R^2 which indicates that we are overfitting the model. This is a problem of high-dimensional data.In the model with first differences caloric intake is no longer significant for

Table 1
Summary statistics.

	Mean	Standard Deviation
Calories: Calories per capita and day	3283.69	(262.95)
Rural: Proportion of population living in rural areas	25.65	(10.99)
Older: Proportion of population over age of 65	13.27	(3.08)
Female_work: Proportion of females working	42.59	(4.75)
GDP: GDP per capita at constant 2005 USD	31.90	(18.52)
Expend_Educ: Gov. expend. on education (% of GDP)	5.08	(1.29)
Km driven by private vehicles (in 1000 km)	9.18	(3.33)
Emissions: Per capita volume of environemntal emissions (in kg)	0.22	(0.17)
Smokers: Proportion of smokers above age 15	27.17	(5.27)
Output per worker: Gross Prod. Value per worker (const. 2004–2006 USD in 1000)	19.06	(12.73)
CSE: Agricultural transfers from consumers (% of total support)	24.34	(14.08)

Table 2
Fixed Effects Regressions and Regressions using First Difference Models including year dummies Modeling the Incidence of Overweight and Obesity.

	Fixed Effects Model		First Difference Model	
	(BMI>25)	(BMI>30)	(BMI>25)	(BMI>30)
Calories	0.001*	0.002***	0.000	−0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Rural	−0.108***	−0.080***	−0.053	0.009
	(0.025)	(0.026)	(0.053)	(0.041)
Older	−0.510***	−0.617***	−0.474***	−0.557***
	(0.060)	(0.062)	(0.133)	(0.137)
Female_work	0.377***	0.273***	0.141**	0.116**
	(0.047)	(0.049)	(0.051)	(0.048)
GDP	25.534	14.847	12.509	8.339
	(22.042)	(22.857)	(17.958)	(10.734)
Expend_Educ	0.013	0.083	0.005	0.040
	(0.083)	(0.086)	(0.033)	(0.031)
km driven by private vehicles	−0.093	−0.012	−0.037	−0.047
	(0.062)	(0.065)	(0.030)	(0.039)
Emissions	−0.003***	−0.005***	−0.001	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Smokers	0.057***	0.094***	−0.005	−0.006
	(0.019)	(0.020)	(0.006)	(0.006)
Agr. Productivity	26.088***	33.501***	0.944	−0.575
	(9.263)	(9.605)	(2.448)	(2.464)
CSE	0.003	0.009	−0.001	−0.002
	(0.012)	(0.012)	(0.002)	(0.002)
Constant	33.293***	1.458	0.519***	0.341***
	(3.459)	(3.586)	(0.061)	(0.028)
Observations	263	263	181	181
Adjusted R^2	0.979	0.967	0.512	0.462
Standard errors in parentheses				

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

both models with BMI>25 and BMI>30. The same applies to the share of the rural population, emissions, the proportions of smokers. Even the variable that measures agricultural productivity is no longer significant and its value decreases a lot. However, the effect of *Older* and *Female_work* is significant in the first difference models as well: On the one hand, an increase in the percentage of the population older than 65 decreases the proportion of the overweight/obese population. On the other hand an increase in the share of working females, increases the proportion of the overweight/obese population. The effects of almost all other variables are mainly zero in the models with first differences. Indeed, this is also true for our focal variable – the CSE – that has a very small (almost zero) and non-significant effect on the proportion of population being overweight or obese.

Especially when the number of observations is small while including many predictors, regression can lead to spurious results. Accordingly to [9] a good rule of thumb is for multiple regression to have at least a number N of observations that fulfill: $N \geq 50 + 8\,m$ with m being the number of covariates but *m* not being larger than seven or correlation results may result in values being too large. Especially when using high-dimensional data, using many potential predictors, it can be difficult to extract those predictors that have an effect on the outcome [3]. As this is the case for our data set and as we want to find the predictors that do impact the proportion of population being overweight or obese, we further apply double lasso regression.

Table 3 provides the result for the double-lasso approach. As described above, we use double-lasso regression for a model with first differences with country-specific and time-specific effects to eliminate unobserved effects constant over time (i.e., fixed effects). The baseline model is the model with first differences. The model "all controls" shows the results for the CSE with all the controls aforementioned. Likewise, the results for the "double-lasso" regression shows no significant effect on obesity of CSE rates and even changes the sign of the influence.

Table 3
Effect of CSE on proportion of population being overweight and obese: Baseline model with first differences and double-lasso regression in comparison.

	BMI>25			BMI>30		
	Baseline Model	(All controls)	Double-lasso	Baseline	All controls	Double-lasso
CSE	−0.001 (-0.94)	0.0 (.)	0.109 (0.87)	−0.002 (-0.86)	0.0 (.)	0.0659 (0.53)

5. Discussion

Overall, we can resume that there is no significant effect of the CSE on the proportion of population being overweight or obese. Neither in a fixed effects model, nor in the model with first differences nor the lasso regression, the CSE is significant. This is in contrast to our main hypothesis. The effect of the CSE on prices may be too small to influence consumers behavior. Therefore, the CSE does not have an effect on the proportion of population being overweight or obese. This result is in line with [2] who find small evidence as well that food consumption patterns are responsive to changes in market prices. They conclude that an elimination of subsidies will not have an effect on overweight or obesity rates. Nevertheless, our results is contrary to other studies like, e.g. [19], who find a significant effect of the CSE on the BMI. Though they make use of a similar data set, however [19] make use of a generalized least squares random effects model although the data does not offer much variability in the predictors – especially with respect to country differences.Our study shows that in the case of low variability in the predictors, a model with first is much more reliable and hinders running spurious regression that is only picking up underlying time trends in the variables. Further, having a small data set and a high number of predictors, the results of the double-lasso regression supports our results of the models with first differences.

However, the proportion of female in the labor force as well as the proportion of the elderly in the population has a significant effect on overweight/obesity rates. More females in the labor force means less time to prepare meals at home and more food is consumed away from home when females work leading to a higher proportion of overweight in the population, which supports the results from [24] or [4]. The proportion of the elderly in the population has in both models – the fixed effects models as well as in the models with first differences – a significant negative effect on the BMI over 25 or 30. This result is in contrast ot the literature, see, e.g. [15] who argue that with lower life expectancy eating habits change, consuming more foods.

Besides, the study is restricted due to data limitation, which is why we had to use many proxy variables. Even using the BMI as a proxy for the health status of a population has been discussed in the past [13,20]. Socio-economic determinants seem to play a high role on the national level concerning obesity levels (see, e.g, [11]. Using the CSE as our focal variable has limits as well. As mentioned above, due to the CAP, the variation across OECD countries is low as the EU member states have the same levels of CSE and we can only observe some variation over the years.

Overall, we resume that it is hard to explain overweight/obesity rates across countries with low variability in the predictors, especially with respect to country differences.Further, on the base of our analysis, we conclude that given such a complex problem as overweight and obesity it might just not be the right approach to use cross-country analysis. It is more probable that fighting the obesity problem is a problem that is triggered in a better way on a national level and further analysis should concentrate on national levels. On the national level, the socio-economic status, seems to play a high role concerning obesity (see, e.g. [11].

6. Conclusion

Overweight and obesity are on the rise across the world but until now there is little understanding for the main reasons. We try to shed some lights on the reasons using a first difference model and double-lasso and are hereby mainly interested in the impact of agricultural policies.

From our analysis, we can conclude that the effect of farm subsidies – measured with help of the CSE – may be too small to influence consumers behavior via prices and therefore, the CSE does not have an effect on the proportion of population being overweight or obese. In the end, the higher contribution from consumers to support the agricultural sector are not successful in controlling the spread of the overweight-related problems.

For a further understanding of the topic, future research could, e.g., add waist circumference as a better proxy for overweight/obesity. Besides an extension with a dynamic model specification would be interesting to control for the dynamics of the CSE impact on the obesity.

However, as mentioned above, we conclude, that it is probably better to understand the rise in overweight and obesity on a national level instead of using the cross-country perspective.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data availability

Data will be made available on request.

References

[1] J.M. Alston, D.A. Sumner, S.A. Vosti, Are agricultural policies making us fat? likely links between agricultural policies and human nutrition and obesity, and their policy implications, Rev. Agric. Econ. 28 (3) (2006) 313–322.
[2] J.M. Alston, D.A. Sumner, S.A. Vosti, Farm subsidies and obesity in the United States: national evidence and international comparisons, Food Pol. 33 (2008) 470–479.
[3] A. Belloni, V. Chernozhukow, C. Hansen, High-dimensional methods and inference on strucutral and treatment effects, J. Econ. Perspect. 28 (2) (2014) 29–50.
[4] S. Chou, M. Grossman, H. Saffer, An economic analysis of adult obesity: results from the behavioural risk factor surveillance system, J. Health Econ. 23 (3) (2004) 565–587.
[5] D.M. Cutler, E.L. Glaeser, J.M. Shapiro, Why have americans become more obese, J. Econ. Perspect. 17 (3) (2003) 93–118.
[6] R.B. Darlington, Regression and Linear Models, 1990. *Chapters 4 and 8)*.
[7] FAO, Data from faostat, Available at, https://www.fao.org/faostat/en/#data, 2019, 09-20-2019.
[8] E.A. Finkelstein, W.C.K. Graham, R. Malhotra, Liftime direct mdeical costs of childhood obesity, Pediatrics 133 (5) (2014) 854–862.
[9] S.B. Green, How many subjects does it take to do a regression analysis, Multivariate Behav. Res. 26 (1991) 499–510.
[10] W.H. Greene, Econometric Analysis, Prentice Hall, Upper Saddle River, N.J, 2008.
[11] P. Guallar-Castillón, , Áurea Redondo Sendinoa, J. Banegas, E. López-García, F. Rodríguez-Artalejoa, Differences in quality of life between women and men in the older population of Spain, Soc. Sci. Med. 60 (6) (2005) 1229–1240.
[12] R. Guthold, G.A. Stevens, L.M. Riley, F.C. Bull, Global trends in insufficient physical activity among adolescents: a pooled analysis of 298 population-based surveys with 1.6 million participants, Lancet 4 (1) (2020) 23–35.

[13] I. Gutin, In bmi we trust: reframing the body mass index as a measure of health, Soc. Theor. Health 16 (2018) 256–271.
[14] D. Kenkel, Health behavior, health knowledge, and schooling, J. Polit. Econ. 99 (1991) 287–305.
[15] I. Kiefer, M. Kunze, Adipositas beim alternden mann: epidemiologie, auswirkungen, Blickpkt. Mann 3 (1) (2005) 19–22.
[16] B.-Y. Kim, D.-H. Choi, C.-H. Jung, S.-K. Kang, J.-O. Mok, C.-H. Kim, Obesity and physical activity, J Obes Metab Syndr 26 (1) (2017) 15–22.
[17] R.C. Klesges, K.D. Ward, J.W. Ray, G. Cutter, D.R. Jacobs, L.E. Wagenknecht, The prospective relationships between smoking and weight in a young, biracial cohort: the coronary artery risk development in young adults study, J. Consult. Clin. Psychol. 6 (1998) 978–993.
[18] D. Lakdawalla, T. Philipson, The growth of obesity and technological change, Econ. Hum. Biol. 7 (3) (2009) 283–293.
[19] M.L. Loureiro, R.M. Nayga, International dimensions of obesity and overweight related problems: an economics perspective, Am. J. Agric. Econ. 5 (2005) 1147–1153.
[20] E. Mahase, Stop using body mass index as measure of health, say mps, BMJ Br. Med. J. (Clin. Res. Ed.) 373 (2021) 256–271.
[21] S. Mann, Framing obesity in economic theory and policy, Rev. Soc. Econ. 66 (2) (2008) 163–179.
[22] R. Mauro, Understanding love (left out variables error): a method for estimating the effects of omitted variables, Psychol. Bull. 108 (2) (1990) 314.
[23] C.A. Monteiro, W.L. Conde, B.M. Popkin, Independent effects of income and education on the risk of obesity in the brazilian adult population, J. Nutr. 131 (3) (2001) 881–886.
[24] R.M. Nayga, Wife's labor force participation and family expenditures for prepared food, food prepared at home, and food away from home, Agric. Resour. Econ. Rev. 25 (1996) 179–186.
[25] R.M. Nayga, Schooling, health knowledge and obesity, Appl. Econ. 32 (7) (2000) 815–822.
[26] OECD, Health statistics open data, Available at, https://stats.oecd.org/index.aspx?themetreeid=9, 2004, 06-18-2022.
[27] OECD, Agricultural Support (Indicator), 2017, https://doi.org/10.1787/6ea85c58-en, 23 November 2019.
[28] OECD, Agricultural Policy Monitoring and Evaluation 2017, 2017.
[29] T. Philipson, The world-wide growth in obesity: an economic research agenda, Health Econ. 10 (1) (2001) 1–17.
[30] M. Pollan, The (Agri)cultural Contradictions of Obesity, New York Times, 2003. October 12.
[31] O. Urminsky, C. Hansen, V. Chernozhukov, Using Double-Lasso Regression for Principled Variable Selection. Working Paper, University of Chicago, 2015.
[32] WHO, Global database on body mass index, 2017. Available at http://apps.who.int/gho/athena/data/gho/ncd_bmi_25a?filter=agegroup:*;country:*;sex:*&format=xml&profile=excel, 06-18-2022.
[33] A. Witchel, Refighting the Battle of the Bulge, The New York Times, 1996.
[34] J.M. Wooldridge, Econometric Analysis of Cross Section and Panel Data, The MIT Press, Cambridge, Massachusetts, 2002.
[35] World Bank, World Bank open data, Available at, https://data.worldbank.org/indicator, 2017, 06-18-2022.