Food Policy 115 (2023) 102412

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Employment and wage effects of sugar-sweetened beverage taxes and front-of-package warning label regulations on the food and beverage industry: Evidence from Peru

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ARTICLE INFO

Keywords:
Sugar-sweetened beverage tax
Front-of-package warning labels
Employment impact
Wage impact
Peru

ABSTRACT

Peru increased its sugar-sweetened beverage tax by 8 percentage points (from 17% to 25%) in 2018 and in 2019 imposed front-of-package warning labels on processed and ultra-processed foods and beverages high in sugar, saturated fats, and sodium or containing trans fats. We assess the pre-COVID-19 impacts of these two policies on aggregate formal employment and average wages in the food and beverage industry. In the analysis we use monthly administrative data from the Ministry of Labor in Peru for 127 manufacturing industries from January 2016 through February 2020 and pair an interrupted time series analysis with the synthetic control method. Overall we find that the sugar-sweetened beverage tax increase and the front-of-package label regulations did not result in job or wage losses. These results are consistent with outcomes from previous studies that have separately looked at the effects of sugar-sweetened beverage taxes (in the United States and Mexico) and front-of-package label regulations (in Chile). Our key contribution is that we assess the effects of both policies for the same country. Consistent with the global literature, our findings suggest that, due to industry substitutions and other actions, employment and wages were not impacted even in industries affected by both policies in a short time. The lack of job and wage losses in the Peruvian experience, the scope of the country's policies, and the form of implementation can advise other countries engaging in similar reforms.

1. Introduction

Policies that discourage the consumption of unhealthy foods and beverages may help contain the spread of overweight and obesity. The World Health Organization (WHO) proposes taxing unhealthy foods and beverages to increase their prices and deter consumption (WHO, 2016). The fiscal revenue from these taxes may fund additional measures to correct negative externalities (e.g., increase in health care costs) associated with unhealthy food and beverage consumption. Front-of-package (FOP) warning labels on unhealthy foods and beverages can also influence consumption patterns. In the Latin American context, Chile and Mexico have introduced these tax and label policies and have successfully reduced household expenditures on unhealthy foods and beverages (Pan American Health Organization, 2020a, 2020b; Shekar and Popkin, 2020).

In May 2018 Peru increased its ad valorem tax on beverages with sugar, sweeteners, or flavorings (sugar-sweetened beverages [SSBs]), including fruit drinks, diet sodas, regular sodas, flavored milks, and ready-to-drink coffees, with $\geq$ 6 g of total sugar per 100 ml to 25 % from its previous level of 17 %, an increase of 8 percentage points. All other SSBs below the threshold remained taxed at 17 %. The government declared that this policy was intended to reduce the costs of treating noncommunicable diseases (Cárdenas et al., 2021). The increase in the SSB tax came almost 20 years after its introduction in 1999 as part of the Selective Consumption Tax (Impuesto Selectivo al Consumo [ISC]) levied on luxury goods, such as alcohol, tobacco, new vehicles, fuels, soft

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https://doi.org/10.1016/j.foodpol.2023.102412
Received 21 December 2021; Received in revised form 16 December 2022; Accepted 6 January 2023
Available online 20 January 2023

drinks, and bottled waters.

The Peruvian government issued the Law for the Promotion of Healthy Eating for Children and Adolescents (Law No. 30021) in 2013 and subsequently announced FOP warning labels for processed and ultra-processed foods and beverages in June 2018. Adapting the Chilean experience (Corvalán et al., 2013, 2019; Reyes et al., 2019), Peru introduced four FOP warning labels that identify processed foods and beverages that exceed the limits Supreme Decree No. 017–2017-SA established for sugar, saturated fats, and sodium, three critical nutrients, or that contain trans fats regardless of the amount. These warning labels became mandatory in June 2019 in any form of publicity in addition to on the product itself. Processed foods and beverages containing more than the established limits must display up to four black octagonal warning labels on the fronts of their packages, one for each nutrient limit exceeded, see Fig. 1. Products exceeding the limits on sugar, saturated fats, and sodium must display black octagons declaring "high in" the nutrient next to an "avoid excessive consumption" subhead. Products containing trans fats must display a black octagon declaring "contains trans fats" next to an "avoid its consumption" subhead. The ultimate goal of this information is to guide potential consumers' purchases to prevent overweight and obesity and derived chronic noncommunicable diseases (Popkin et al., 2021).

The increase in the SSB tax and the FOP warning labels would reduce the demand for affected products. This reduction should translate into lower sales, lower production, and ultimately into declines in employment and wages for taxed and labeled products. However, this might not always be the case. The most likely consumer response will be to substitute affected by not affected products produced by the same firms within the foods and beverage industry or by other products and services in the whole economy. Therefore, potential job gains in other unaffected products within affected industries or other sectors can offset potential job losses in affected industries. In addition, Government spending from the additional tax revenue would likely generate new jobs. Even more, affected producers may reformulate not affected products to avoid regulations or reallocate workers between their product lines.

Fig. 1. Front-of-package warning labels implemented in Peru. **Notes**: The figure displays front-of-package warning labels implemented in Peru for foods and beverages high in sugar, saturated fats, and sodium or that contain trans fats.

Our goal in this study is to assess the effects of those two Peruvian policies on two labor market outcomes: employment levels and average wages. We use administrative data from the Ministry of Labor on the number of jobs and average wages in private firms aggregated by class of economic activity. We focus on the pre-COVID-19 period. The first COVID-19 case in Peru was detected in March 2020, thus our data end in February 2020. We combine an interrupted time series analysis (ITSA) and the synthetic control method (SCM) to increase robustness. These are quasi-experimental research designs appropriate for our application. Our results derive from before and after case-control comparisons, a robust research design.

Although still limited, the peer-reviewed empirical evidence on the effects of SSB taxes (Powell et al., 2014; Guerrero-López et al., 2017; Lawman et al., 2019; Marinello et al., 2021a; Marinello et al., 2021b) and FOP warning label regulations (Paraje et al., 2021) show no negative impacts on employment and wages. These results are contrary to concerns food and beverage industry representatives and non–health sector pundits expressed that these taxes and regulations would cause significant increases in unemployment with the loss of thousands of jobs.

The policy debate about economic policy instruments to counter situations of public health concern is ample and complex. Public health and medical organizations have proposed taxes and warning labels as proper policy tools to counter the epidemic of health conditions related to harmful substances such as sugar, tobacco, and alcohol (WHO, 2016; STAX Group, 2018; Corvalán et al., 2019; Muth et al., 2019; Shekar and Popkin, 2020; Mounsey et al., 2022). In a broader context, this debate has to do with the individual versus society-wide approaches to the problem, including obesity (Chater and Loewenstein, 2022), with many of the interventions and the 'blaming' predominantly oriented to individuals as a matter of choice and personal responsibility (Chater and Loewenstein, 2022; Buse et al., 2022). In reality, population-wide interventions have their merits, but they occur less often, and therefore, evaluations of their impacts are not that common (Mounsey et al., 2022). In addition, taxes are not a copy-and-paste type of intervention, and several considerations are required to be taken into account (Miranda et al., 2022). The obvious question is, what is the context in which taxes get implemented? Another equally important question is, what are the key outcomes of interest under study? In this regard, our work provides much-needed evidence providing a robust evaluation of SSB taxes and FOP warning labels as population-wide policy instruments focusing on two key labor outcomes, such as employment and wages, necessary to advance evidence across various settings, the scope of effects including labor and the economy, and beyond public health.

A salient contribution of the paper is the uniqueness of evaluating two policies (SSB taxes and FOP warning labeling) implemented in the same country over a short period, providing evidence underscoring the complexity of the policy environment. In addition, our paper is the first to study the employment and wage impacts of both policies for an upper-middle-income large country with a large proportion of its population living in geographically less accessible areas.

2. Data and methods

2.1. Data

We use monthly data on employment (number of jobs) and average wages at formal-sector firms in Peru aggregated by manufacturing industry from January 2016 through February 2020 that the Office of Statistics at the Ministry of Labor provided at our request. The data come from the Ministry of Labor E-Payroll (Planilla Electronica), an administrative registry of employment at formal firms that records employer and employee data. In Peru the formal economy represents 81 % of the total gross domestic product (GDP), but formal-sector employment represents only 39 % of the aggregate employment level (Instituto Nacional de Estadística en Informática, 2019). However, only formal-

sector manufacturers produce processed and ultra-processed products affected by the SSB tax and the FOP warning labels.

In these data the manufacturing industries correspond to classes of economic activity according to the United Nations International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3.1. For confidentiality, the data correspond to the time series of aggregate monthly employment and average monthly wages for each class of economic activity (a four-digit aggregation of the ISIC classification) in the manufacturing sector. We use monthly Consumer Price Index (CPI) data retrieved from the National Bureau of Statistics web page to convert nominal wages from the E-Payroll to wages in real terms. The average value of the CPI in the year 2019 is the reference.

On March 15, 2020, the Peruvian government declared a sanitary emergency in response to the COVID-19 pandemic and imposed a national lockdown restricting citizens' mobility except for essential personnel and essential activities. Nonessential economic activities immediately shut down. Peru suffered a severe recession in 2020, and its GDP declined by 11.1 % (Banco Central de Reserva del Perú, 2021). We do not use data from March 2020 onward to avoid confounding the effects of the SSB tax and FOP warning labels with the impacts of the lockdown and the recession on employment and wages.

The final sample we use in the analysis has a panel (longitudinal) structure with cross-sectional units representing the classes of economic activity (127 units) and time units representing the monthly observations from January 2016 through February 2020 (50 data points in time). We provide additional details in Online Appendix A.1.

Our primary focus is on six manufacturing industries likely affected by the SSB tax increase and the FOP warning labels. The SSB tax increase affects two manufacturing industries: manufacture of soft drinks, mineral water, and bottled water (Class 1554) and processing and preserving fruits and vegetables (Class 1513). The FOP warning labels affect these two plus manufacture of dairy products (Class 1520); bakery products (Class 1541); cocoa, chocolate, and sugar confectioneries (Class 1543); and other food products not elsewhere classified (n.e.c.) (Class 1549). Table 1 provides the means and standard deviations of the employment numbers and average real wages for each affected industry.

We complement these data with monthly employment and wage data from January 2013 through February 2020 but aggregated at the sector of economic activity level (two-digit aggregation of the ISIC Rev. 3.1 classification). This information also comes from the Ministry of Labor E-Payroll registry. We retrieved these data from monthly time series the ministry published in publicly available statistical yearbooks. The data comprise information for 18 sectors of economic activity, including the manufacturing sector. We use these data to assess the effects of the SSB tax increase and the FOP warning labels on employment and wages at the aggregate level of sector of economic activity. In this analysis manufacturing (ISIC Rev. 3.1, Section D) comprises the treatment unit, and the other sectors of economic activity comprise the untreated units.

2.2. Methods

2.2.1. Interrupted time series analysis

We implement a multiple-group ITSA to estimate the effects of the SSB tax increase and FOP warning labels on employment and wages in the manufacturing industry (Campbell and Stanley, 1966; Linden, 2015). ITSA is a quasi-experimental research design appropriate when data are available for an outcome variable observed over multiple periods before and after the introduction of a treatment; the treatment is a well-defined, exogenous intervention implemented at a precise moment in time; and the treated group is an aggregate or large unit, such as a class of economic activity. Intuitively the treatment should "interrupt" the level, the trend, or both of the outcome variable following its introduction if there is a treatment effect. To enhance the internal validity of the design, we include a set of untreated control units to control for potentially confounding omitted variables, hence the term *multiple-group ITSA*.

In our application the outcome variables of interest are the logarithm of the aggregate employment and the average wages in the manufacturing industry measured monthly from January 2016 through February 2020 at the class of economic activity. The treatment is either the SSB tax increase in May 2018 or the imposition of FOP warning labels in June 2019. The treatment units consist of manufacturing industries likely affected by the SSB tax increase or the FOP warning labels. The control units consist of manufacturing industries unlikely to be affected by these treatments. In addition, we include monthly dummies to adjust for seasonality and the aggregate nonmining consumption of electricity to adjust for aggregate economic activity (Pérez et al., 2017). We use a log-level specification to estimate the percent change difference in the levels and slopes between treated and control industries in employment and average wages after the policies went into effect.

The running regression for the ITSA takes the form:

$$Y_{it} = \beta_0 + \beta_1 T_t + \beta_2 X_t + \beta_3 X_t \left(T_t - \widetilde{T}\right) + \beta_4 Z + \beta_5 Z \left(T_t - \widetilde{T}\right) + \beta_6 Z X_t + \beta_7 Z X_t \left(T_t - \widetilde{T}\right) + \sum_{m=2}^{12} \delta_m M_m + \gamma log(Electricity_t) + \varepsilon_{it},$$

Table 1
Means and standard deviations of employment and wages in affected industries.

Class (industry)	Employment (number of jobs)			Average wages		
	Jan. 2016–Apr. 2018	May 2018–May 2019	June 2019–Feb. 2020	Jan. 2016–Apr. 2018	May 2018–May 2019	June 2019–Feb. 2020
Class 1513: Processing and preserving fruits and vegetables	70,018 (15,879)	79,035 (13,914)	90,230 (15,798)	1,567 (78)	1,609 (699)	1,542 (83)
Class 1520: Dairy products	7,563 (347)	7,645 (251)	7,861 (329)	3,539 (227)	3,742 (260)	3,656 (82)
Class 1541: Bakery products	15,222 (607)	16,008 (465)	16,255 (487)	1,470 (47)	1,512 (41)	1,493 (309)
Class 1543: Cocoa, chocolate, and sugar confectioneries	5,188 (235)	5,465 (198)	5,646 (262)	3,008 (250)	2,850 (1,369)	2,740 (91)
Class 1549: Other food products	14,949 (421)	15,452 (109)	15,055 (589)	1,871 (44)	1,927 (409)	1,932 (37)
Class 1554: Soft drinks, mineral water, and bottled water	7,561 (195)	7,298 (229)	7,092 (125)	3,457 (89)	3,571 (145)	3,622 (163)

Notes: Data are from E-Payroll provided by the Office of Statistics at the Ministry of Labor. Real wages are expressed in 2019 PEN (nuevos soles). Standard deviations are in parenthesis.

where Y_{it} is the outcome variable of industry i measured at each period t; T_t is the time since the start of the study; $\widetilde{T}$ is the period when the intervention starts; X_t is a dummy variable that represents the intervention and takes the value of 1 since the onset of the intervention and 0 otherwise; Z is a dummy variable that represents the treatment unit (=1) and the control units (=0); M_m are dummies for calendar month (including quarterly or semi-annual dummies instead does not change our results), $Electricity_t$ represents the aggregate nonmining consumption of electricity at each time t; and ε_{it} is the error term. In the regression β_1 represents the slope of the outcome variable until the introduction of the treatment, β_2 represents the change in the level of the outcome that occurs immediately after the introduction of the treatment, and β_3 represents the pretreatment slope of the outcome trend for the control units.

Coefficients β_4 and β_5 are crucial for assessing the internal validity of the research design. Coefficient β_4 represents the pretreatment difference of the outcome levels between the treatment unit and the control units. Coefficient β_5 captures the pretreatment difference in the slope of the outcome trend between the treatment unit and the control units. Under random assignment of the treatment, treatment and control units should be statistically similar in the pretreatment period. Therefore these coefficients should be statistically equal to 0 if the control units provide a valid counterfactual for the treatment unit in the absence of the treatment. The contrary will raise concerns about establishing a causal relationship between the treatment and the outcome. Our results confirm that these estimated coefficients are statistically nonsignificant, which provides a solid ground for interpreting our estimates.

Coefficients β_6 and β_7 capture the effect of the treatment on the outcome of interest when the control units provide a valid counterfactual. Coefficient β_6 represents the difference in the outcome levels between the treatment unit and the control units immediately after the onset of the treatment. Coefficient β_7 captures the difference between the treatment unit and the control units in the slope of the outcome in the posttreatment period.

The control group should provide counterfactual employment and wages that resemble pretreatment employment and wages for treated industries if the SSB tax increase or the FOP warning labels had not been implemented. Following A. Linden (2018), we use the SCM to find control units for each treated industry and outcome (see details in the next subsection). We then implement the multiple-group ITSA with analytic weights for each treated industry. We estimate standard errors adjusted for autocorrelation. We use the Cumby-Huizinga general tests for autocorrelation to determine the lag order to correct for autocorrelated errors. We estimated the ITSA regressions in Stata 17 using the "itsa" command (Linden, 2015).

2.2.2. Synthetic control method

We use the SCM to generate a suitable control group (Abadie, 2021; Abadie et al., 2011, 2010). The SCM is a quasi-experimental research design appropriate to conduct comparative case studies under similar conditions described earlier for the ITSA. In our application the SCM selects untreated units that provide counterfactual employment and wages for treated industries, that is, the employment and wages in treated industries if the SSB tax increase or the FOP warning labels had not been implemented.

The SCM selects units from the donor pool of untreated units such that the pretreatment discrepancy in covariates between the treated unit and the selected untreated units is minimized. The covariates are predictors of the outcome of interest in the absence of treatment, including the preintervention values of the outcome variable as they are themselves unaffected by the intervention. In our application we only use the preintervention values of the outcomes as our predictors.

Each untreated unit selected by the SCM receives a weight that is nonnegative and no greater than one. Then it is possible to obtain a weighted average of untreated units in the donor pool that reproduces the trajectory of the outcome of interest for the treatment unit in the pretreatment period, hence the label *synthetic control*. We use the weights provided by the SCM as analytic weights in the multiple-group ITSA (Linden, 2018).

We provide additional evidence by estimating treatment effects using only the SCM. We implemented the SCM in Stata 17 using the "synth" command (Abadie et al., 2011).

2.2.3. Assessing the treatment effects of the SSB tax increase

To assess the effects of the SSB tax increase we define two treated units: manufacture of soft drinks, mineral water, and bottled water (Class 1554) and processing and preserving fruits and vegetables (Class 1513). We compare the evolution of employment and wages in these industries to their counterfactuals obtained by applying the SCM. Data from January 2016 through April 2018 comprise the preintervention period, and data from May 2018 through May 2019 comprise the postintervention period. Data from June 2019 onward do not enter the analysis since the FOP warning labels that affect SSB manufacturers took effect that month. FOP warning labels may also generate effects on employment and wages for SSB manufacturers (Paraje et al., 2021), but our methods cannot separate them. In June 2019 Peru decreased the tax on SSBs with $<$ 0.5 g total sugar per 100 ml to 12 % (e.g., diet sodas). Other SSB taxes either remained at 17 % (0.5 g–6 g total sugar/100 ml) or 25 % ($\geq$6 g total sugar/100 ml). This change has no impact on our results, because our analysis does not include data after May 2019.

A concern with the estimation of the effects of the SSB tax increase is that we can confound them with the potential anticipatory impact of the imposition of FOP warning labels. FOP warning label regulations also include SSBs and became effective in June 2019, yet the government announced the labels' specific requirements one year in advance. Law No. 30,021 dates back to 2013 and its regulation (Supreme Decree No. 017–2017-SA) to 2017, and the government issued a label manual that formally announced the FOP warning labels in June 2018. Thus the posttreatment period of the SSB tax increase and the FOP warning label anticipation period overlap from June 2018 through May 2019. If the imposition of FOP warning labels generated anticipatory effects, we cannot separate them from the SSB tax increase effects. For this reason in this part of the analysis we drop from the sample those manufacturing industries affected by the FOP warning labels to avoid confusion with potential anticipation effects on these industries.

2.2.4. Assessing the treatment effects of the FOP warning labels

To assess the effects of the FOP warning labels we define four industries as the treated units: manufacture of dairy products (Class 1520); manufacture of bakery products (Class 1541); manufacture of cocoa, chocolate, and sugar confectioneries (Class 1543); and manufacture of other food products (Class 1549). We compare the evolution of employment and wages in these industries to their counterfactuals derived from the SCM. Data from January 2016 through May 2019 comprise the preintervention period, and data from June 2019 through February 2020 comprise the postintervention period. For this analysis we exclude from the sample the two industries also previously affected by the SSB tax increase: manufacture of soft drinks, mineral water, and bottled water and processing and preserving fruits and vegetables.

In a complementary analysis we concentrate on data from May 2018 onward, when the effects of the SSB tax increase should be in place. Then we replicate our analysis using data from June 2019 through February 2020 as the postintervention period to assess the effects of the FOP warning labels on employment and wages in manufacture of soft drinks, mineral water, and bottled water and in processing and preserving fruits and vegetables. The complementary analysis provides estimates of the effects of the FOP warning labels on employment and wages for these industries on top of the effects of the SSB tax increase.

2.2.5. Robustness checks

We implement two more estimations to check the robustness of our analysis. First, we concentrate on the food and beverage industry as a whole (corresponding to ISIC Rev. 3.1, Division 15) as the treated unit instead of the likely affected industries individually. Second, we report results considering the whole manufacturing sector (corresponding to ISIC Rev. 3.1, Section D) as the treated unit and the other sectors of economic activity as the untreated units. We provide details for these two approaches in Online Appendix A.2.

3. Results

3.1. Main results

Table 2 reports the results of the multiple-group ITSA on employment and wages for the industries affected by the SSB tax increase. Table 3 reports analogous results for the industries affected by the FOP warning labels. Figs. 2 and 3 plot the actual and predicted trajectories of the employment and wage outcomes for the industries affected by the SSB tax increase and the FOP warning labels, respectively. The vertical dashed lines indicate the date the policy went into effect. In all cases the control group for each affected industry and outcome in the multiple-group ITSA comes from the SCM. Each untreated unit in the control group enters the analysis with the weight the SCM assigned. Online Appendix Tables B1 through B5 provide the composition of the control groups and the weights for each control industry and outcome variables. The SCM provides control groups for all affected industries and outcomes with only one exception: for the analysis of the impact of the SSB tax increase on employment in the class processing and preserving fruits and vegetables. Employment in this industry follows a marked seasonal pattern that other manufacturing industries do not match.

Table 2
ITSA estimated effects of the SSB tax increase.

	Class 1554: Soft drinks, mineral water, and bottled water		Class 1513: Processing and preserving fruits and vegetables
	Employment (1)	Wages (2)	Wages (3)
β_1 Pretreatment outcome trend	0.002	0.000	0.002
	(0.030)	(0.003)	(0.004)
β_2 Change in the outcome immediately after the treatment	0.007	−0.007	−0.014
	(0.785)	(0.077)	(0.110)
β_3 Pretreatment outcome trend for control units	−0.001	0.001	0.002
	(0.097)	(0.010)	(0.014)
β_4 Pretreatment difference of the outcome between treated and control units	−0.001	0.001	−0.001
	(0.448)	(0.049)	(0.061)
β_5 Pretreatment difference of the outcome trend between treated and control units	0.000	−0.000	0.000
	(0.029)	(0.003)	(0.004)
β_6 Difference in outcome levels between treated and control units immediately after the treatment	−0.090	0.045	0.014
	(0.768)	(0.076)	(0.108)
β_7 Posttreatment difference of the outcome trend between treated and control units	0.002	−0.006	−0.003
	(0.093)	(0.009)	(0.014)
Electricity (logs)	−0.125	0.361	−0.125
	(6.966)	(0.719)	(0.997)
Constant	9.921	5.223	8.321
	(56.121)	(5.795)	(8.041)
Observations	533	697	615

Notes: We use data on employment and wages from January 2016 through February 2020. The employment and wage figures are in logs. All regressions include monthly dummies to adjust for seasonality. Standard errors adjusted for autocorrelation are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.10.

We find that the estimated coefficients corresponding to pretreatment outcome level differences between treatment and control units (β_4) and differences in pretreatment outcome trends between treatment and control units (β_5) are statistically nonsignificant both for the SSB tax increase and for the FOP warning labels. These results imply that the control groups provide valid counterfactuals.

Our multiple-group ITSA results suggest that the SSB tax increase and FOP warning label regulation did not affect employment or wages (see Tables 2 and 3). Neither case shows evidence of differences in the outcome levels between the treatment unit and the synthetic control units immediately after the onset of the treatment, as the estimated coefficient β_6 is statistically nonsignificant. There is no evidence of differences in the slopes of the outcomes in the posttreatment period between the treatment unit and the control units, as the estimated coefficient β_7 is statistically nonsignificant. Figs. 2 and 3 show graphic evidence consistent with these findings. None of the predicted trajectories before the intervention of interest differ between the treatment and the control units.

Table 4 reports the complementary analysis on the potential effects of the FOP warning labels for the industries previously affected by the SSB tax increase. We find no evidence of changes in employment or wages attributable to the FOP warning labels, estimated coefficients β_6 and β_7 in all columns are statistically nonsignificant.

As we mentioned, the government announced the FOP warning labels in June 2018, one year before their imposition, and firms in affected industries might have modified their behaviors based on that information. To incorporate the possibility of anticipation effects we conduct an additional analysis using data from January 2016 through May 2018 as the preintervention period and data from June 2018 through May 2019 as the postintervention period. As before, we exclude the two industries affected by both the SSB tax increase and the FOP warning labels. Online Appendix Table C1 and Figure C1 report the results of the multiple-group ITSA for the anticipation effects of the FOP warning labels. As before, the control units and their corresponding weights come from the SCM. There is no evidence of anticipatory effects following the announcement of the FOP warning labels.

3.2. Additional evidence from the SCM

Online Appendix D reports the estimated treatment effects from the SCM and inference results from permutation distributions. Overall we find no evidence of changes in employment or wages in affected industries after implementation of the SSB tax increase or the FOP warning labels.

3.3. Robustness: Zooming out to more aggregated treatment units

Table 5 and Fig. 4 report the results of the multiple-group multiple-treatment ITSA on employment and wages for the SSB tax increase and the FOP warning labels. In Table 5 the first and second columns report results for employment and wages when the treatment unit is the food and beverage industry. The third and fourth columns report the results when the treatment unit is the whole manufacturing sector. The corresponding control group in each case comes from the SCM. Each untreated unit in the control group enters the analysis with the weights assigned by the SCM.

For both robustness checks we find the two policies have no effects on employment or wages. There is no evidence of change in the outcome levels between the treatment unit and the control units immediately after the SSB tax increase or the FOP warning label implementation provided that the estimated coefficients on the interactions between the treatment unit dummy and the treatment date dummies are statistically nonsignificant. Similarly we find no evidence of changes in the trends of the outcomes between the treatment unit and the control units in the posttreatment period. The estimated coefficient on the triple interaction terms between the treatment unit dummy, the treatment date dummies,

Table 3
ITSA estimated effects of the FOP warning labels.

	Class 1520: Dairy products		Class 1541: Bakery products		Class 1543: Cocoa, chocolate, and sugar confectioneries		Class 1549: Other food products	
	Employment (1)	Wages (2)	Employment (3)	Wages (4)	Employment (5)	Wages (6)	Employment (7)	Wages (8)
β_1 Pretreatment outcome trend	0.001	0.003	0.002	0.002	0.002	0.001	0.001	0.001
	(0.012)	(0.003)	(0.009)	(0.002)	(0.010)	(0.003)	(0.015)	(0.002)
β_2 Change in the outcome immediately after the treatment	0.022	−0.019	0.009	−0.042	0.018	−0.008	−0.025	−0.049
	(0.504)	(0.104)	(0.344)	(0.069)	(0.386)	(0.098)	(0.592)	(0.080)
β_3 Pretreatment outcome trend for control units	−0.006	0.000	−0.006	−0.003	−0.010	0.005	−0.008	−0.002
	(0.097)	(0.019)	(0.065)	(0.013)	(0.075)	(0.019)	(0.111)	(0.016)
β_4 Pretreatment difference of the outcome between treated and control units	−0.000	−0.003	−0.006	−0.001	−0.003	0.018	0.001	−0.000
	(0.226)	(0.048)	(0.171)	(0.033)	(0.176)	(0.044)	(0.285)	(0.032)
β_5 Pretreatment difference of the outcome trend between treated and control units	0.000	0.000	0.000	0.000	0.000	−0.001	0.000	0.000
	(0.010)	(0.002)	(0.007)	(0.001)	(0.008)	(0.002)	(0.012)	(0.001)
β_6 Difference in outcome levels between treated and control units immediately after the treatment	−0.038	0.002	−0.013	−0.004	0.003	−0.025	0.023	0.013
	(0.489)	(0.101)	(0.333)	(0.067)	(0.375)	(0.096)	(0.573)	(0.079)
β_7 Posttreatment difference of the outcome trend between treated and control units	0.012	−0.004	0.003	0.007	0.005	0.002	−0.004	0.008
	(0.093)	(0.018)	(0.062)	(0.012)	(0.073)	(0.019)	(0.106)	(0.015)
Electricity (logs)	−0.124	0.032	−0.069	−0.062	0.159	−0.640	0.332	−0.048
	(3.389)	(0.734)	(2.465)	(0.489)	(2.631)	(0.719)	(4.080)	(0.524)
Constant	9.897	7.860	10.150	7.758**	7.218	13.152**	6.935	7.889*
	(27.275)	(5.908)	(19.832)	(3.932)	(21.172)	(5.789)	(32.825)	(4.216)
Observations	650	800	500	900	600	700	650	1,200

Notes: We use data on employment and wages from January 2016 through February 2020. The employment and wage figures are in logs. All regressions include monthly dummies to adjust for seasonality. Standard errors adjusted for autocorrelation are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.10.

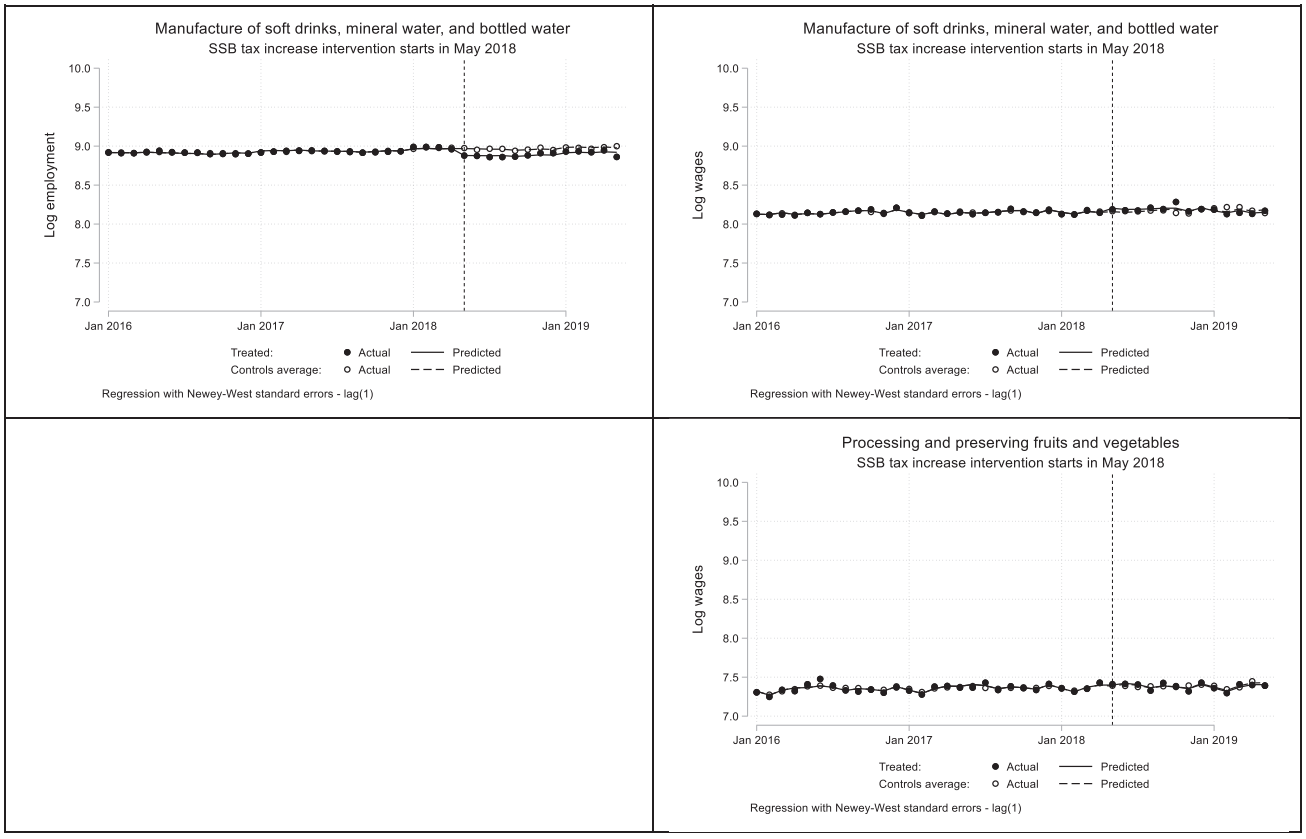

Fig. 2. ITSA estimated effects of the SSB tax increase on employment and wages. **Notes**: We use data on employment and wages from January 2016 through June 2019. The figure plots actual and predicted employment and wages for the treatment unit and the comparison units. Predicted values are from the multiple-group ITSA. The vertical dashed line in May 2018 indicates the date the SSB tax increase went into effect.

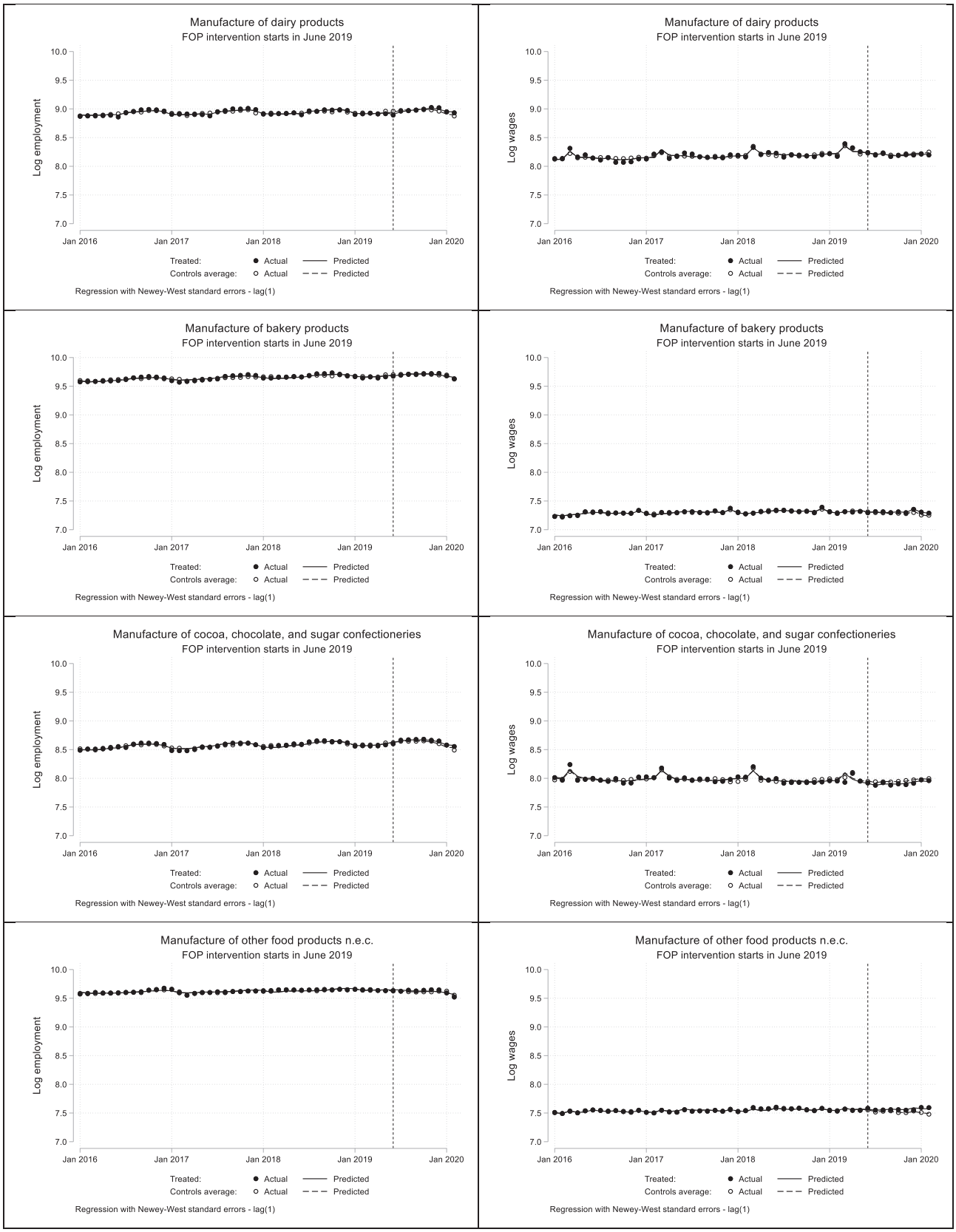

Fig. 3. ITSA estimated effects of the FOP warning labels on employment and wages. **Notes**: We use data on employment and wages from January 2016 through February 2020. The figure plots actual and predicted employment and wages for the treatment unit and the comparison units. Predicted values are from the multiple-group ITSA. The vertical dashed line in June 2019 indicates the date the FOP warning labels went into effect.

Table 4
ITSA estimated effects of the FOP warning labels on SSB tax–affected industries.

	Class 1554: Soft drinks, mineral water, and bottled water		Class 1513: Processing and preserving fruits and vegetables
	Employment (1)	Wages (2)	Wages (3)
β_1 Pretreatment outcome trend	−0.000	−0.005	−0.002
	(0.113)	(0.007)	(0.022)
β_2 Change in the outcome immediately after the treatment	0.049	−0.011	−0.003
	(1.073)	(0.069)	(0.207)
β_3 Pretreatment outcome trend for control units	−0.012	0.000	−0.007
	(0.195)	(0.013)	(0.038)
β_4 Pretreatment difference of the outcome between treated and control units	0.003	0.004	0.005
	(0.677)	(0.035)	(0.129)
β_5 Pretreatment difference of the outcome trend between treated and control units	0.000	−0.001	−0.001
	(0.094)	(0.005)	(0.018)
β_6 Difference in outcome levels between treated and control units immediately after the treatment	−0.047	0.033	0.000
	(1.015)	(0.065)	(0.199)
β_7 Posttreatment difference of the outcome trend between treated and control units	0.008	0.002	0.002
	(0.187)	(0.013)	(0.037)
Electricity (logs)	−0.183	0.893	0.596
	(18.603)	(1.373)	(3.699)
Constant	10.429	0.931	2.528
	(150.898)	(11.145)	(30.011)
Observations	242	176	198

Notes: We use data on employment and wages from June 2018 through February 2020. The employment and wage figures are in logs. All regressions include monthly dummies to adjust for seasonality. Standard errors adjusted for autocorrelation are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.10.

and the posttrend variable are statistically nonsignificant.

4. Discussion

We provide evidence that in Peru SSB taxes and FOP warning labels do not generate job or wage losses in the policy-affected industries or in the whole manufacturing sector. We use administrative data from the Ministry of Labor E-Payroll, an administrative registry of employment and wages of firms in the formal sector of the economy in Peru and estimate these effects using a combination of ITSA and the SCM. Our results derive from before and after case-control comparisons, thus affording a robust research design.

Our results are consistent with previous peer-reviewed studies of SSB taxes and FOP warning label regulations, but the key difference is that our study is the first that looks at both policies implemented in the same country. In particular our results are consistent with studies of the effects of SSB taxes on citywide aggregate employment levels for Philadelphia and San Francisco (Marinello et al., 2021a; Marinello et al., 2021b) and statewide aggregate employment levels for California and Illinois (Powel et al., 2014) and a study of the effects of FOP warning label regulations on industry-level employment and wages in Chile (Paraje et al., 2021). Furthermore, our results are consistent with other peer-reviewed studies of policies to reduce the consumption of unhealthy products, including taxes on tobacco and alcohol (Chaloupka et al., 2019).

At least four explanations may address the lack of effects of the SSB tax increase and FOP warning labels on employment levels and average wages (Powell et al., 2014; Guerrero-Lopez et al., 2017; Paraje et al., 2021; Marinello et al., 2021a). First, multiproduct firms in affected industries may internally reallocate their labor forces to products unaffected by these policies. Second, beverages have nonnutritive sweetener options that allow firms to quickly reformulate, as research in Chile and South Africa has shown. Reformulation allows firms to sidestep the tax and retain most consumer demand (Essman et al., 2021; Reyes et al., 2020). As a result they have no need to reduce employment or change wages. Third, if the demand for affected products does not decline or declines slightly after these policies go into effect, manufacturing firms feel no need to adjust employment. Fourth, consumers may substitute untaxed or unregulated products for the taxed or warning-labeled products produced by the same firms, and the increase in the demand for unaffected products may offset the decline in demand for affected products.

Table 5
Robustness checks.

	Foods and beverages		Manufacturing sector	
	Employment (1)	Wages (2)	Employment (3)	Wages (4)
β_1 Pretreatment (tax) outcome trend	0.000	0.001	0.000	0.001
	(0.028)	(0.010)	(0.004)	(0.003)
β_2 Change in the outcome immediately after the treatment (tax)	0.027	−0.075	0.019	0.000
	(0.724)	(0.248)	(0.263)	(0.197)
β_3 Pretreatment (tax) outcome trend for control units	−0.004	0.000	0.001	−0.002
	(0.088)	(0.031)	(0.034)	(0.025)
β_2' Change in the outcome immediately after the treatment (FOP labels)	0.061	−0.052	0.035	0.009
	(0.894)	(0.327)	(0.357)	(0.266)
β_3' Pretreatment (FOP labels) outcome trend for control units	−0.016	−0.013	−0.002	−0.001
	(0.160)	(0.058)	(0.060)	(0.046)
β_4 Pretreatment (tax) difference of the outcome between treated and control units	−0.004	−0.021	0.013	−0.002
	(0.437)	(0.146)	(0.094)	(0.084)
β_5 Pretreatment (tax) difference of the outcome trend between treated and control units	−0.000	0.001	−0.000	−0.000
	(0.027)	(0.009)	(0.003)	(0.002)
β_6 Difference in outcome levels between treated and control units immediately after the treatment (tax)	0.009	0.081	−0.002	0.009
	(0.706)	(0.246)	(0.261)	(0.195)
β_7 Posttreatment (tax) difference of the outcome trend between treated and control units	0.003	−0.010	−0.001	0.001
	(0.085)	(0.031)	(0.034)	(0.025)
β_6' Difference in outcome levels between treated and control units immediately after the treatment (FOP labels)	−0.047	0.083	−0.013	−0.020
	(0.852)	(0.317)	(0.352)	(0.261)
β_7' Posttreatment (FOP labels) difference of the outcome trend between treated and control units	0.013	0.009	0.004	−0.000
	(0.158)	(0.058)	(0.059)	(0.045)
Electricity (logs)	0.626	1.027	0.222	0.099
	(6.125)	(2.148)	(1.059)	(0.835)
Constant	4.387	−0.452	11.321	6.936
	(49.349)	(17.310)	(8.417)	(6.643)
Observations	400	550	348	609

Notes: The table reports the results of the robustness checks. Columns (1) and (2) zoom out to the food and beverage industry as the unit affected by the SSB tax increase and the FOP warning labels. For this we use data from January 2016 through February 2020. Columns (3) and (4) zoom out to the manufacturing sector as the affected unit. For this we use published E-Payroll data from January 2013 through February 2020 retrieved from the Ministry of Labor statistical yearbooks.

4.1. Limitations

We acknowledge that our study has some limitations. First, our

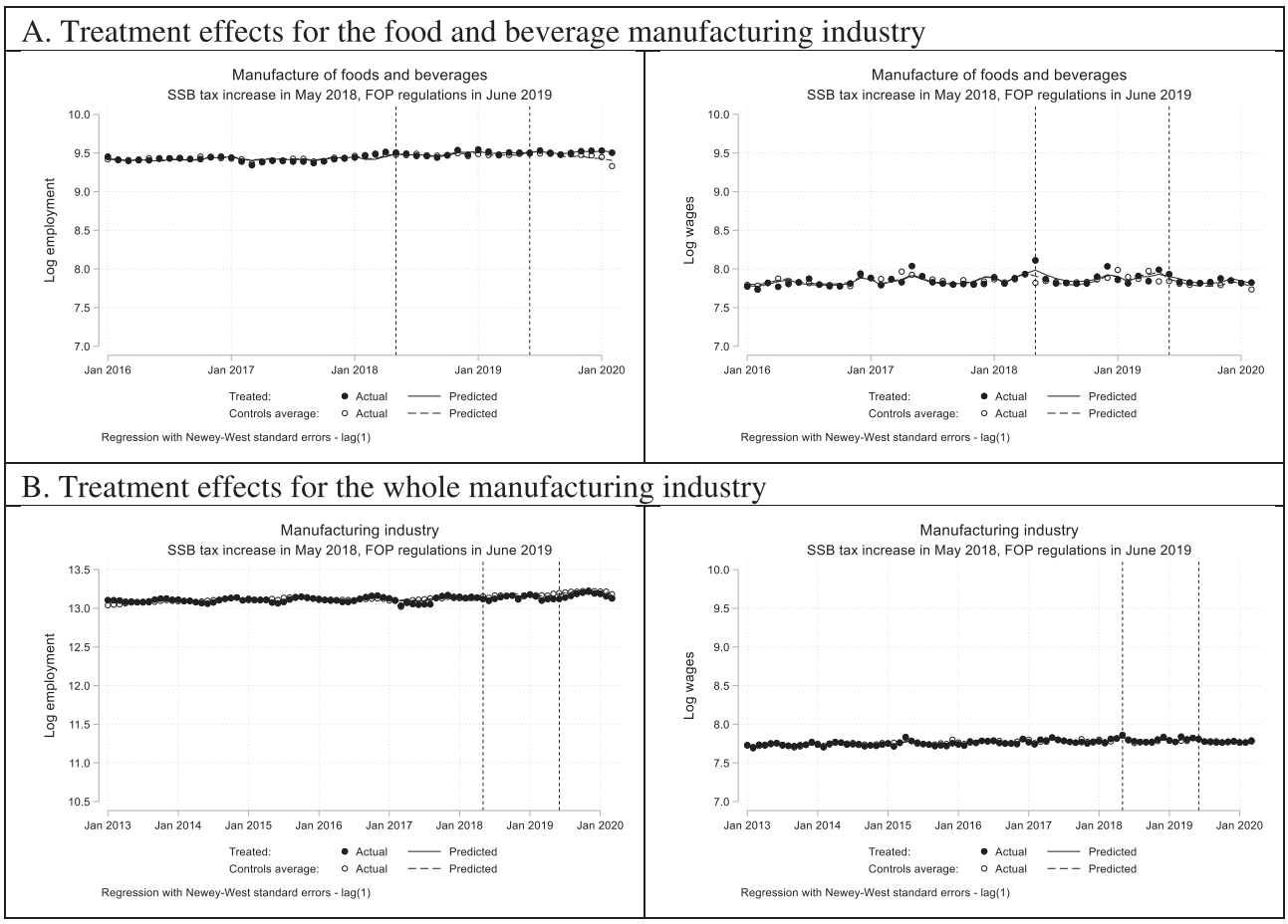

Fig. 4. Robustness checks on ITSA estimated effects of the SSB tax increase and the FOP warning labels. **Notes**: In panel A we use data by industry on employment and wages from January 2016 through February 2020. In panel B we use aggregate data by sector of economic activity on employment and wages from January 2013 through February 2020. The figure plots actual and predicted employment and wages for the treatment unit and the comparison units. Predicted values are from the multiple-group ITSA. The vertical dashed lines in May 2018 and June 2019 indicate the dates the SSB tax increase and the FOP warning labels went into effect.

assessment cannot identify the effects of the policies at the firm level. We only have access to industrywide and sectorwide aggregate data on employment and wages. However, most firms that produce drinks affected by the SSB tax increase also manufacture unaffected products. Similarly firms that manufacture processed foods and beverages subject to FOP warning labels also manufacture unaffected products. Thus our estimates on industrywide and sectorwide aggregate outcomes may provide valuable insights into the effects of the policies.

Second, our assessment cannot identify the effects of the policies on the number of hours worked. A possible response to declining demand at affected firms is to reduce the hours their labor forces work instead of reducing the number of jobs. Unfortunately our data do not include hours of work but only the total number of jobs. However, the lack of effects on the employment levels and average wages are compatible with no changes in the hours worked.

Third, the estimation of the SSB tax effect calls for a warning. The key limitation is the interpretation of the SSB tax effect. It is combined with the potential anticipatory effects of FOP warning labels announced at the time of the SSB tax increase. Thus we essentially combine that year of anticipation of the FOP warning labels with the SSB tax increase. The FOP warning labels and the SSB tax increase can both be linked with reformulation, as we noted above (Essman et al., 2021; Reyes et al., 2020). However, the lack of estimated effects on employment and average wages is reassuring in this regard.

Fourth, our assessment only provides evidence of the effects of the policies on employment and wages for the formal sector of the economy. The E-Payroll data we use only record information from firms that comply with the requirements of the Peruvian regulation. However, firms in the formal sector of the economy account for most of the volume of the industrial products affected by the SSB tax and the FOP warning labels. Thus our estimates using E-Payroll data may provide valuable insights into the effects of the policies.

4.2. *Strengths*

The strengths of our study reside in the use of a solid research design and reliable data. We use a combination of an ITSA to detect changes in the levels and the trends of the outcomes of interest and the SCM to generate synthetic control groups providing counterfactuals that resemble the situation in the absence of the assessed policies. We use E-Payroll administrative data that cover formal employment in the Peruvian labor market. We provide the best possible assessment before the onset of the COVID-19 pandemic, which indeed has further affected patterns and will merit further evaluations in the future.

5. Policy implications

Policies to control the spread of obesity and noncommunicable diseases are expanding worldwide; in particular, SSB taxes and FOP warning labels have gained momentum. Over 45 countries, cities, and regions globally have instituted SSB taxes (Pan American Health Organization, 2020a; Popkin and Ng, 2021). In the Americas, Chile, Mexico, Peru, and Uruguay have adopted mandatory FOP warning labels, and Brazil and Canada have proposed their mandatory use; outside the

Americas, Israel also adopted FOP warning labels (Pan American Health Organization, 2020b).

With nuances, to date the evidence on SSB taxes suggests this policy might discourage SSBs consumption, particularly in the short run, and encourages reformulations by the beverage industry (Popkin and Ng, 2021). The evidence on FOP labeling suggests that nutritional warnings, such as those implemented in Peru following the Chilean model, perform better than other labeling systems and effectively decrease consumers' intent to purchase processed and ultra-processed food products containing excessive amounts of critical nutrients (Pan American Health Organization, 2020b). However, the food and beverage industry around the world opposes these policies arguing, among other considerations, that they will harm the economy by causing job losses.

This study is the first to investigate the impacts of these two policies in the same country on employment and wages. Between June 2018 and June 2019, Peru introduced an SSB tax increase and imposed FOP warning labels on processed and ultra-processed foods and beverages. We find these policies had no impact on the assessed labor market outcomes. The lack of effects of the SSB tax increase and FOP warning labels on employment and wages in the Peruvian context supplements the literature showing that these policies do not generate massive job losses or wage declines, as some industry advocates have predicted. The absence of job losses and wage declines might be the consequence of employment reallocation within firms or industries, the reformulation of affected products to avoid drops in sales, the absence of reductions in consumption of affected products, and changes in consumption that increase the demand for products not affected produced by affected firms. Our results coincide with evidence previously presented in this journal, showing that FOP warning labels in Chile did not affect employment and wages (Paraje et al., 2021). Similarly, our results coincide with the evidence presented elsewhere showing that SSB taxes did not affect employment in Mexico (Guerrero-López et al., 2017) and U.S. cities (Lawman et al., 2019; Marinello et al., 2021a and 2021b). Moreover, our results widen the evidence supporting policies to reduce the consumption of processed and ultra-processed foods and beverages (Pagliai et al., 2021; Popkin et al., 2021).

The Peruvian case provides a real-world example of policy implementation in a complex environment characterized by multiple interventions and industry opposition relevant for other low- and middle-income countries considering similar policies. Our results suggest that it is possible to introduce policies to reduce the incentives to consume unhealthy foods and beverages without hurting employment and wages in the affected industries or the whole manufacturing sector.

6. Conclusion

In 2018 and 2019 the Peruvian government implemented two health-related policies to prevent obesity and other noncommunicable diseases. The first policy was the increase in the tax rate on SSBs from 17 % to 25 % implemented in May 2018. The second policy, implemented in June 2019, was the imposition of FOP warning labels for processed foods high on saturated fats, sodium, and sugar or containing trans fats.

Our results suggest that neither the SSB tax increase nor the imposition of FOP warning labels generated changes in employment levels or average wages. In addition, we do not find evidence of the possible anticipatory effects of the early announcement of FOP warning labels on these outcomes. Our results are consistent with previous peer-reviewed studies of the impacts of these policies on employment and wages. The differing policy time frames, the scope of the policies, and the form of implementation in Peru can advise similar policies in other settings.

CRediT authorship contribution statement

Juan-José Díaz: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Alan Sánchez:** Conceptualization, Methodology, Writing – review & editing. **Francisco Diez-Canseco:** Conceptualization, Funding acquisition, Project administration, Writing – review & editing. **J. Jaime Miranda:** Conceptualization, Funding acquisition, Writing – review & editing. **Barry M. Popkin:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We are grateful to Peru's Ministry of Labor for providing access to the data that made this study possible. Additionally, we thank Guillermo Paraje for his comments on an early version of this document.

Funding: This work was supported by Bloomberg Philanthropies, grant number 46129.

Appendix. Supplementary data

Supplementary material to this article can be found online at https://doi.org/10.1016/j.foodpol.2023.102412.

References

Abadie, A., 2021. Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. Journal of Economic Literature 59, 391–425.
Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. Journal of the American Statistical Association 105, 493–505.
Abadie, A., Diamond, A., Hainmueller, J., 2011. SYNTH: Stata module to implement Synthetic Control Methods for comparative case studies, Statistical Software Components S457334, revised. Boston College Department of Economics.
Banco Central de Reserva del Perú, 2021. Memoria 2020. Banco Central de Reserva del Perú. ISSN, Lima, pp. 0067–3242.
Buse, K., Bhaumik, S., Miranda, J., Hunnisett, C., Batz, C., Feeny, E., 2022. Individual responsibility: a red herring that lets the fossil fuel industry off the climate catastrophe hook. BMJ. Jul 5; 378, o1656.
Cárdenas, M.K., Cazzulino, P., Popkin, B.M., Miranda, J., 2021. Sugar-sweetened beverages tax in Peru: A tax nested in history in the last two decades. osf.io/preprints/socarxiv/9y67w.
Campbell, D., Stanley, J., 1966. Experimental and Quasi-Experimental Designs for Research. Rand McNally, Chicago, IL.
Chaloupka, F.J., Powell, L.M., Warner, K.E., 2019. The Use of Excise Taxes to Reduce Tobacco, Alcohol, and Sugary Beverage Consumption. Annu. Rev. Public Health, 40 (1), 187-201.
Chater, N., Loewenstein, G., 2022. The i-frame and the s-frame: How focusing on individual-level solutions has led behavioral public policy astray. Behav. Brain Sci. 1–60.
Corvalán, C., Reyes, M., Garmendia, M.L., Uauy, R., 2013. Structural responses to the obesity and non-communicable diseases epidemic: the Chilean Law of Food Labeling and Advertising. Obes Rev 14 (Suppl 2), 79–87.
Corvalán, C., Reyes, M., Garmendia, M.L., Uauy, R., 2019. Structural responses to the obesity and non-communicable diseases epidemic: Update on the Chilean law of food labelling and advertising. Obes Rev 20, 367–374.
Essman, M., Taillie, L.S., Frank, T., Ng, S.W., Popkin, B.M., Swart, E.C., 2021. Taxed and untaxed beverage intake by South African young adults after a national sugar-sweetened beverage tax: A before-and-after study. PLOS Medicine 18, e1003574.
Guerrero-López, C.M., Molina, M., Colchero, M.A., 2017. Employment changes associated with the introduction of taxes on sugar-sweetened beverages and nonessential energy-dense food in Mexico. Preventive Medicine 105, S43–S49.
Instituto Nacional de Estadística e Informática, 2019. Producción y empleo informal en el Perú. Cuenta Satélite de la Economía Informal 2007-2018. Lima, Perú.
Lawman, H.G., Bleich, S.N., Yan, J., LeVasseur, M.T., Mitra, N., Roberto, C.A., 2019. Unemployment claims in Philadelphia one year after implementation of the sweetened beverage tax. PLOS ONE 14, e0213218.
Linden, A., 2015. Conducting interrupted time-series analysis for single- and multiple-group comparisons. Stata Journal 15 (2), 480–500.
Linden, A., 2018. Combining synthetic controls and interrupted time series analysis to improve causal inference in program evaluation. Journal of evaluation in clinical practice 24, 447–453.
Marinello, S., Leider, J., Powell, L.M., 2021a. Employment impacts of the San Francisco sugar-sweetened beverage tax 2 years after implementation. PLOS ONE 16, e0252094–e.

Marinello, S., Leider, J., Pugach, O., Powell, L.M., 2021b. The impact of the Philadelphia beverage tax on employment: A synthetic control analysis. Econ Hum Biol 40, 100939.

Miranda, J., Thow, A.M., Cárdenas, M.K., Corvalán, C., Barrientos-Gutiérrez, T., Kaufman, J.S., 2022. Nutrition-related health taxes: setting expectations. Lancet Diab. Endocrinol. 2022 Feb; 10(2), 93-94.

Mounsey, S., Veerman, L., Jan, S., Thow, A.M., 2020. The macroeconomic impacts of diet-related fiscal policy for NCD prevention: A systematic review. Econ Hum Biol. 2020 May; 37, 100854.

Muth, N.D., Dietz, W.H., Magge, S.N., Johnson, R.K., 2019. AMERICAN ACADEMY OF PEDIATRICS; SECTION ON OBESITY; COMMITTEE ON NUTRITION; AMERICAN HEART ASSOCIATION. Public Policies to Reduce Sugary Drink Consumption in Children and Adolescents. Pediatrics 143(4), e20190282.

Pan American Health Organization, 2020a. Sugar-sweetened beverage taxation in the Region of the Americas. PAHO, Washington DC.

Pan American Health Organization, 2020b. Front-of-package labeling as a policy tool for the prevention of noncommunicable diseases in the Americas. PAHO, Washington DC.

Pagliai, G., Dinu, M., Madarena, M.P., Bonaccio, M., Iacoviello, L., Sofi, F., 2021. Consumption of ultra-processed foods and health status: a systematic review and meta-analysis. British Journal of Nutrition 125, 308–318.

Paraje, G., Colchero, A., Wlasiuk, J.M., Sota, A.M., Popkin, B.M., 2021. The effects of the Chilean food policy package on aggregate employment and real wages. Food Policy 100, 102016.

Pérez, F., Ghurra, O., Grandez, R., 2017. Un Indicador Líder de Actividad Real para el Perú. Banco Central de Reserva del Perú. Serie de Documentos de Trabajo. DT No., 2017–001.

Popkin, B.M., Ng, S.W., 2021. Sugar-sweetened beverage taxes: Lessons to date and the future of taxation. PLoS Med 18 (1), e1003412.

Popkin, B.M., Barquera, S., Corvalan, C., Hofman, K.J., Monteiro, C., Ng, S.W., 2021. Towards unified and impactful policies to reduce ultra-processed food consumption and promote healthier eating. The Lancet Diabetes & Endocrinology.

Powell, L.M., Wada, R., Persky, J.J., Chaloupka, F.J., 2014. Employment impact of sugar-sweetened beverage taxes. Am J Public Health 104, 672–677.

Reyes, M., Garmendia, M.L., Olivares, S., Aqueveque, C., Zacarías, I., Corvalán, C., 2019. Development of the Chilean front-of-package food warning label. BMC public health 19, 906.

Reyes, M., Smith Taillie, L., Popkin, B.M., Kanter, R., Vandevijvere, S., Corvalán, C., 2020. Changes in the amount of nutrient of packaged foods and beverages after the initial implementation of the Chilean Law of Food Labelling and Advertising: A nonexperimental prospective study. PLOS Medicine 17, e1003220.

Shekar, M., Popkin, B.M., 2020. Obesity: Health and Economic Consequences of an Impending Global Challenge. the World Bank, Washington DC.

Sugar, Tobacco, and Alcohol Taxes (STAX) Group, 2018. Sugar, tobacco, and alcohol taxes to achieve the SDGs. Lancet. 2018 Jun 16; 391(10138), 2400-2401.

WHO, 2016. Fiscal policies for diet and prevention of noncommunicable diseases: technical meeting report, 5-6 May 2015. WHO Technical Report. World Health Organization, Geneva, Switzerland.