Using a Bayesian Structural Time−Series Model to Infer the Causal Impact on Cigarette Sales of Partial and Total Bans on Public Smoking

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Jaime Pinilla
Universidad de Las Palmas de Gran Canaria

Miguel Negrín
Universidad de Las Palmas de Gran Canaria

Beatriz González López-Valcárcel
Universidad de Las Palmas de Gran Canaria

Francisco José Vázquez-Polo
Universidad de Las Palmas de Gran Canaria

Original Article

Jaime Pinilla, Miguel Negrín*, Beatriz González-López-Valcárcel and Francisco-José Vázquez-Polo

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Abstract: The Bayesian structural time series model, used in conjunction with a state–space model, is a novel means of exploring the causal impact of a policy intervention. It extends the widely used difference–in–differences approach to the time series setting and enables several control series to be used to construct the counterfactual. This paper highlights the benefits of using this methodology to estimate the effectiveness of an absolute ban on smoking in public places, compared with a partial ban. In January 2006, the Spanish government enacted a tobacco control law which banned smoking in bars and restaurants, with exceptions depending on the floor space of the premises. In January 2011, further legislation in this area was adopted, removing these exceptions. The data source used for our study was the monthly legal sales of cigarettes in Spain from January 2000 to December 2014. The potential control series were the monthly tourist arrivals from the United Kingdom, the total number of visitors from France, the unemployment rate and the average price of cigarettes. Analysis of the state–space model leads us to conclude that the partial ban was not effective in reducing the tobacco sold in Spain, but that the total ban contributed significantly to reducing cigarette consumption.

***Corresponding author: Miguel Negrín,** Department of Quantitative Methods, University of Las Palmas de Gran Canaria, 35017 Las Palmas de Gran Canaria, Spain,
E-mail: miguel.negrin@ulpgc.es
Jaime Pinilla: E-mail: jaime.pinilla@ulpgc.es, **Beatriz González-López-Valcárcel:**
E-mail: beatriz.lopezvalcarcel@ulpgc.es, **Francisco-José Vázquez-Polo:**
E-mail: francisco.vazquezpolo@ulpgc.es, Department of Quantitative Methods, University of Las Palmas de Gran Canaria, 35017 Las Palmas de Gran Canaria, Spain

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1 Introduction

Banning smoking in public places is among the most effective public health measures employed in recent years to reduce tobacco consumption in developed countries (WHO 2015). Together with economic measures such as punitive taxation and persuasion–based actions derived from theories of behavioural economics, prohibition has proved to be a major instrument in the anti–smoking armoury of increasing numbers of developed countries (Schaap et al. 2008). Despite low levels of external validity, studies have shown that restrictive policies, based on prohibition and taxation, are both effective and cost–effective (Ranson et al. 2002). However, the incremental effectiveness of an absolute ban on smoking in public places, compared with a partial ban (usually applied to the workplace and with exceptions) remains unknown. It is no easy task to estimate the effectiveness of such measures because they tend to be approved as part of a broader legislative package, and so the study data available are usually observational, which means that appropriate controls are not readily available for comparison.

This paper presents the application of a Bayesian structural time–series (BSTS) model to analyse the impact of two types of smoking ban (partial and total) on tobacco sales in Spain. Spain is an interesting case for study because after five years of partial prohibition, a total ban was then imposed. On 1 January 2006 a partial ban came into force, under Act 28/2005 (Law 28/2005), and this was extended to become a total ban on 1 January 2011 (Law 42/2010). Act 28/2005 was the primary law governing smoking in public places and tobacco advertising, promotion and sponsorship. This legislation banned smoking in all public and work places, with some exceptions in hospitality venues (no ban was applied in premises measuring less than 100 m^2, and a “smoking area” was allowed in larger ones). Five years later, Act 28/2005 was substantially amended by Act 42/2010, which mandated a total ban on smoking in indoor public places and indoor workplaces. In this paper, we measure the impact of each law on tobacco sales.

The causal impact of an intervention can be defined as the difference between the observed value of the response and the (unobserved) value that would have been obtained had the intervention not taken place (Heckman and Vytlacil 2007; Rubin 2008; Kleinberg and Hripcsak 2011). For a time series, the causal impact of an intervention would be the difference between the observed series and the series that would have been observed had the intervention not taken place. In this case, therefore, a counterfactual must be constructed.

Various difference–in–differences (DiD) methods have been proposed to identify the causal effects of an intervention, by contrasting the change in pre and post–intervention outcomes for test and control groups. This approach is particularly appropriate for experiments comparing two communities (Abadie 2005; Angrist and Pischke 2009). Under DiD analysis, it is assumed that observations are independent and identically distributed and that the differences between the test and control communities are constant. However, these assumptions rarely hold true for time series data. Bertrand et al. (2004) argued that because of serial correlation DiD analysis may understate the standard deviation of the estimated treatment effects, thus producing an overestimation of the DiD effect. In our own analysis, DiD analysis could have been undertaken by considering another country where no ban has been imposed on smoking in public places. However, we cannot claim that any two countries are truly comparable, due to inherently different properties of their cigarette markets and/or to the presence of different patterns of smoking.

The BSTS method allows a causal impact inference to be drawn for a time series when there is no straightforward candidate for the counterfactual. To construct an adequate synthetic control, we can use the information provided by the behaviour of other time series that are predictive of the response before the intervention and were not affected by the intervention (Abadie et al. 2010). In practice, there are many possible series available, and the challenge facing the researcher is to choose the most significant one, or to combine a set of potential controls using Bayesian model averaging (Hoeting et al. 1999). The BSTS uses a state–space model to approximate the behaviour of the response series when one of the state components is a linear regression on the predictors. The counterfactual is constructed using the prediction of the response series after the intervention, based on the set of candidate controls. The causal effect is then estimated as the difference between the predicted and observed responses after the intervention.

Among other advantages, the BSTS approach enables the fully automatic selection of appropriate covariates; it also includes series properties such as trends and seasonality, provides the implicit capability to demonstrate causality and facilitates impact quantification (Brodersen et al. 2015). Moreover, with this method we can calculate posterior intervals in the magnitude of causal impact and estimate the posterior probability that the causal impact is non–existent.

The remainder of this paper is organised as follows. Section 2 describes the data, which include tobacco sales in Spain as the response time series. The other time series that might be considered as a predictor of the response are the number of visitor arrivals to Spain from the United Kingdom (UK) and France, the Spanish unemployment rate and the average retail price of cigarettes in Spain. Section 3 describes the BSTS model and the choice of diffuse priors. Section 4 presents the results of the BSTS model applied to tobacco sales in Spain, and finally the impact of the two tobacco control laws is discussed in Section 5.

2 Data

Statistics for tobacco sales in Spain (excluding the Canary Islands and the autonomous cities of Ceuta and Melilla) are published by the Tobacco Market Commission of Spain and by the Spanish Tax Agency. In this paper, we use monthly series of cigarette plus hand–rolled sales from January 2000 to December 2014 (T=180). Sales are measured as millions of packs. Thirty grams of hand–rolled tobacco are considered to be equivalent to one pack of 20 cigarettes (Figure 1). Two interventions were sequentially considered: first the partial ban (January 2006) and then the total one (January 2011).

An important proportion of cigarette sales in Spain corresponds to purchases by non-residents (Joossens and Raw 1995; Lakhdar 2008; Nagelhout et al. 2014). Tourism is the country's leading economic activity, and visitors from the

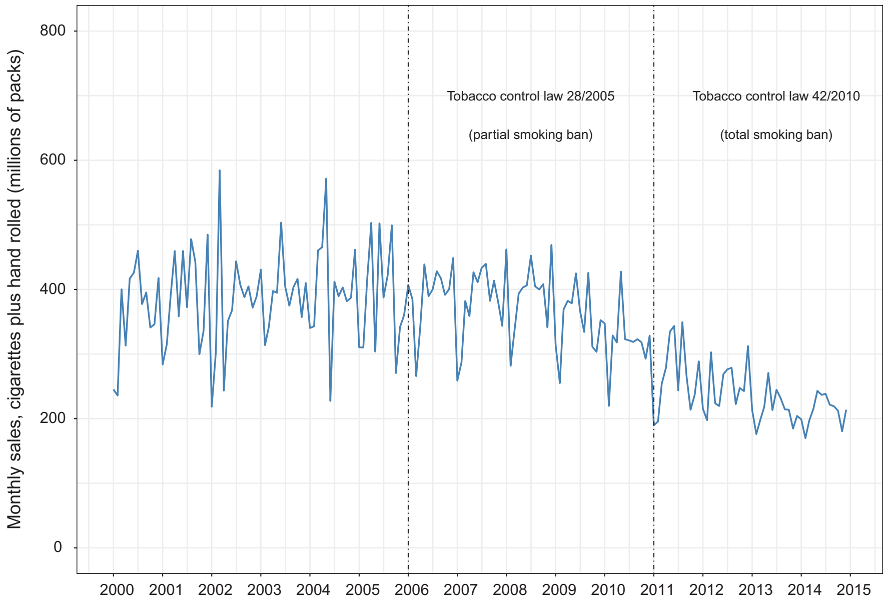

Figure 1: Cigarette plus hand rolled sales (in millions of packs) in Spain 2000–2014.

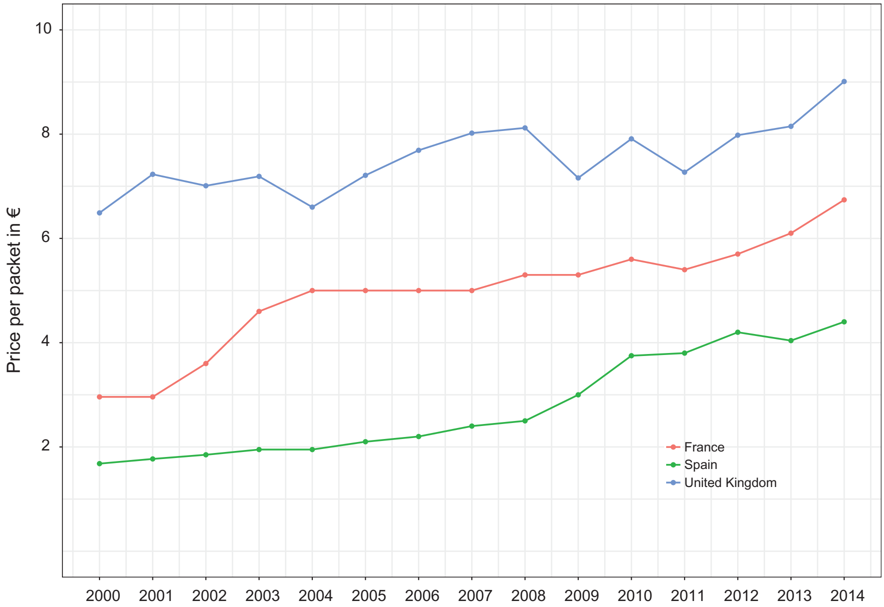

Figure 2: Cigarette Prices in United Kingdom, France and Spain 2000–2014.

European Union, in particular, account for a large proportion of arrivals. In 2014, Spain received 64.9 million inbound tourists (who stayed for at least 24 hours) and 42.6 million excursionists (same–day visitors). The most important source of inbound tourism was the UK (23.1%), while the most important country in terms of inbound excursionists was France (60%), due to its physical proximity. In both the UK and France, there is a considerable price differential with Spain for cigarettes, which has persisted over time (Figure 2), thus encouraging visitors to buy in Spain. To be considered as a candidate predictor variable it is necessary to assume that tobacco sales to non–resident visitors are not affected by the restrictive Spanish legislation. This assumption is based on the fact that most of the cigarettes purchased by visitors will be consumed in their country of origin (Lakhdar 2008).

Despite recent tax increases, Spain continues to have the lowest tobacco prices in Western Europe. Thus, in 2014 a 20–cigarette pack of the most popular brand cost 9.01 in the UK, 6.44 in France and around 4.40 in Spain. By contrast, the price differential with other countries from which tourists come to Spain, such as Italy and Germany, is not so broad. In this study, therefore, we used as a control the monthly series of numbers of tourists entering Spain from the UK and total visitors (tourists + excursionists) from France. Both series were adjusted for the respective prevalence of smoking, obtained by the Organization for

Economic Co–operation and Development (OECD) data (OECD 2015), assuming a linear tendency in order to transform these yearly estimates into monthly series.

To properly analyse the impact of smoking control legislation during the period in question, it is important to incorporate an economic variable to reflect the severe economic crisis that has affected Spain since 2008. This aspect is not sufficiently illustrated by the arrivals of foreign tourists, since in the UK and France the intensity of the crisis was less than that experienced in Spain. Accordingly, the variable considered in this respect was the Spanish unemployment rate.

The fourth candidate predictor variable included in our study is the average price of cigarettes in Spain. This is calculated as the ratio between the value of tobacco sales in Spain in euros and the volume of tobacco sales in millions of packs. These statistics are provided by the Tobacco Market Commission of Spain and the Spanish Tax Agency. The aim of using this variable is to isolate the real effect of the ban on smoking in public places from that of other tax measures that directly affect cigarette prices.

Figure 3 shows the correlations between the four candidate predictor variables and tobacco sales. These linear correlations are statistically significant,

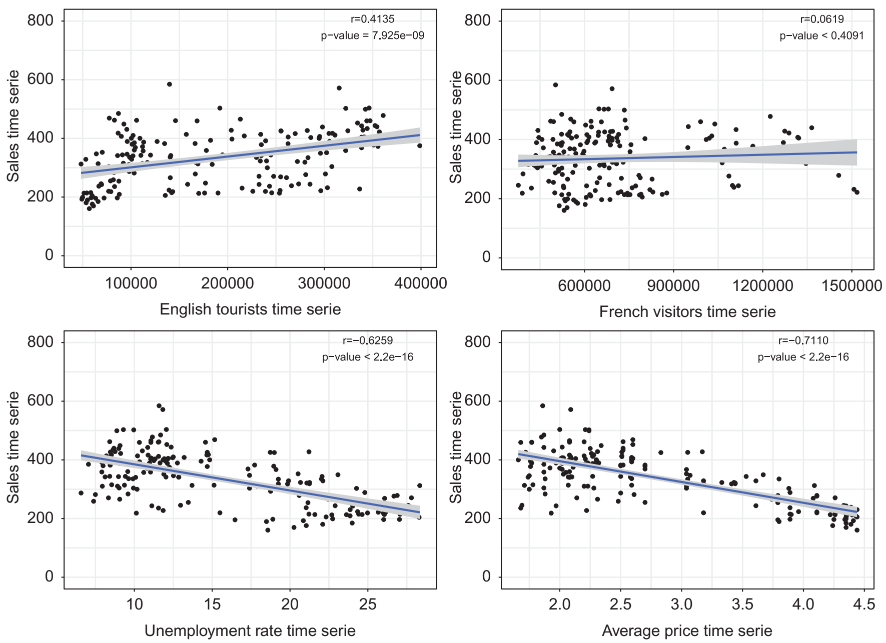

Figure 3: Scatter plot of tobacco sales and the four candidate predictor variables. Pearson correlation coefficient and test for independence.

with the exception of the variable "Total visitors from France", which presents a non-significant correlation (p-value=0.4091) for the full period. However, a partial analysis for the pre–intervention periods (2000 – 2005 and 2000 – 2010) reveals a positive and significant correlation in both cases ($r = 0.2912$, p-value=0.0131 and $r = 0.2573$, p-value=0.0030, respectively).

3 Methods

3.1 Model description

The BSTS model, proposed by Brodersen et al. (2015), is used to infer the causal impact on cigarette sales of the partial and complete bans on public smoking in the period up to May 2015. The BSTS model can be defined as follows:

$$\begin{aligned} y_t &= \mu_t + \tau_t + \beta^T x_t + \epsilon_t \\ \mu_t &= \mu_{t-1} + \delta_t + \upsilon_t \\ \delta_t &= \delta_{t-1} + \nu_t \\ \tau_t &= -\sum_{s=1}^{12-1} \tau_{t-s} + \omega_t \end{aligned} \tag{1}$$

The response variable y_t is the logarithmic transformation of tobacco sales. Equation (1), the observation equation, includes all the components that explain the behaviour of the observed data y_t. The first component, μ_t, is the value of the trend at time t. We assume a local linear trend in which the expected increase in μ between t and $t+1$ (δ) presents a random walk pattern (Brodersen et al. 2015).

Tourist arrivals in Spain are subject to high levels of seasonality, which is reflected in cigarette sales. This seasonality is represented by the state component τ_t, which can be interpreted via a set of 12 dummy variables with dynamic coefficients constrained to have zero expectation over a year.

The vector x_t is a set of potential control series candidate to be predictive of the response. All covariates are assumed to be contemporaneous. In our practical application, the vector x_t is composed of the logarithmic transformation of four time series: numbers of tourists entering Spain from the UK, numbers of visitors entering Spain from France, the Spanish unemployment rate, and tobacco prices in Spain. Note, these are only potential control series; Bayesian analysis allows us to determine which covariates should be considered and how strongly they should influence predictions.

The error terms ϵ_t and $\eta_t = (\upsilon_t, \nu_t, \omega_t)$ follow independent Gaussian random noises, $N(0, \sigma_*^2)$.

3.2 Prior distributions

A genuine Bayesian approach requires us to specify the prior distributions of all the model parameters, i.e. the variances σ^2_ϵ, σ^2_υ, σ^2_ν, σ^2_ω and the regression coefficients β.

For the set of variance parameters that govern the diffusion of the individual state components $(\sigma^2_\upsilon, \sigma^2_\nu, \sigma^2_\omega)$, the default prior is assumed to be a non–informative Gamma distribution $1/\sigma^2_* \sim \text{Gamma}(10^{-2}, 10^{-2}s^2_y)$, where $s^2_y = \Sigma_t(y_t - \bar{y})^2/(n-1)$ is the sample variance of the dependent variable. Brodersen et al. (2015) proposed scaling by the sample variance as an effective way to obtain a reasonable scale for the prior.

An appropriate set of controls is selected for our model by placing a spike–and–slab prior over the coefficients (George and McCulloch 1993, 1997; Polson and Scott 2011; Scott and Varian 2014). Such a prior combines point mass at zero (the "spike") with a weakly informative distribution on the nonzero coefficients (the "slab"). The slab is not completely flat, but is a normal distribution with a large variance. We then introduce a new vector $\varrho = (\varrho_1, \varrho_2, \varrho_3, \varrho_4)$, where $\varrho_j = 1$ if $\beta_j \neq 0$ and $\varrho_j = 0$ otherwise. We also define β_ϱ as the nonzero elements of β. The spike–and–slab prior can be factorised as follows:

$$p(\varrho, \beta, \sigma^2_\epsilon) = p(\varrho)p(\sigma^2_\epsilon|\varrho)p(\beta_\varrho|\varrho, \sigma^2_\epsilon) \tag{2}$$

For the spike portion we assume a product of independent Bernoulli distributions with probability π_j. Our practical application adopts a conservative approach, assuming an a priori probability of inclusion of 0.25 for each candidate predictor variable.

For the slab portion, we assume the following conjugate normal–inverse Gamma distribution:

$$\begin{aligned} \beta_\varrho|\sigma^2_\epsilon &\sim N(\beta^0_\varrho, \sigma^2_\epsilon(\Sigma^{-1}_\varrho)^{-1}), \\ 1/\sigma^2_\epsilon &\sim \text{Gamma}\left(\frac{n_\epsilon}{2}, \frac{s_\epsilon}{2}\right) \end{aligned} \tag{3}$$

The vector β^0_ϱ is assumed to be a vector of zeros. To elicit the prior distribution of $1/\sigma^2_\epsilon$, the inverse of the expectation $\left(\frac{s_\epsilon}{n_\epsilon}\right)$ is interpreted as a prior estimate of σ^2_ϵ, and n_ϵ is taken as the prior sample size. In addition, an expected R^2 must be assumed, together with the prior sample size (n_ϵ) used to obtain this prior estimate. Then $s_\epsilon = n_\epsilon(1 - R^2)s^2_y$. Our practical application conservatively assumes $R^2 = 0.6$ and a small prior sample size, $n_\epsilon = 30$, to minimise the impact of the prior distribution on the posterior estimates.

The last parameter, Σ_{ϱ}^{-1}, denotes the rows and columns of Σ^{-1} corresponding to nonzero β. Σ^{-1} is the prior precision over β for the full model. For this matrix, Zellner's g–prior (Zellner 1986; Liang et al. 2008) is assumed, as follows:

$$\Sigma^{-1} = \frac{1}{n}\left(\frac{1}{2}X^T X + \frac{1}{2}diag(X^T X)\right). \tag{4}$$

3.3 Sensitivity analysis

We also analysed the sensitivity of the results obtained to changes in the prior structure. The proposed variations affect the main hyper–parameters that define the prior distribution.

In particular, for the set of variance parameters $(\sigma_{\upsilon}^2, \sigma_{v}^2, \sigma_{\omega}^2)$, the non–informative Gamma distribution is replaced by $1/\sigma_*^2 \sim \text{Gamma}(10^{-3}, 10^{-3}s_y^2)$, in which the hyper–parameter 10^{-2} is replaced by 10^{-3}.

In this sensitivity analysis, the prior probability of inclusion, conservatively assumed as 0.25, varied from 0.5 to 0.8, always considering the same prior probability of inclusion for all candidate predictor variables.

For the prior distribution over the beta coefficients of the model, β_{ϱ}^0 was assumed to be a vector of zeros. However, the hyper–parameters that define the prior distribution of the variance σ_ϵ^2 varied with R^2 values of 0.4 and 0.8, and with prior sample sizes n_ϵ of 10 and 100.

3.4 Posterior distribution

The Gibbs sampler is used to simulate the parameters of the model and the posterior predictive distribution over the counterfactual time series, given the observed pre–intervention activity. The data–augmentation step used to simulate the model parameters is defined in Brodersen et al. (2015). Taking into account that conditionally–conjugate priors exist in the class of state space models, Gibbs sampling was performed to produce a Markov chain with a length of 40,000, after a burn–in of 40,000 simulations. Bayesian structural time–series models were then modelled using the CausalImpact and BSTS R Packages.

4 Results

Table 1 shows the estimates obtained for the effects of each intervention, according to the model. Figures 4 and 5 illustrate the outcomes of the partial ban and

Table 1: Results of the Bayesian structural time–Series models.

	Partial ban		Total ban	
Coefficient	**Mean (sd)**	**Prob**	**Mean (sd)**	**Prob**
β_1	0.3791 (0.4618)	47.85%	0.5095 (0.2809)	81.81%
β_2	0.2087 (0.3477)	33.17%	0.0149 (0.0916)	4.40%
β_3	−0.0037 (0.0394)	4.21%	−0.0199 (0.0698)	8.55%
β_4	−0.0035 (0.0454)	4.51%	−0.0232 (0.0891)	7.82%
R^2	0.6050		0.4744	
MSE	0.0167		0.0216	
MAE	0.0939		0.1086	
MAPE	1.5931%		1.8477%	
Relative effect	Mean (sd)	Prob	Mean (sd)	Prob
$\ln(y_t)$	−0.063%(0.72%)	52%	−6.3% (0.97%)	99.999%
y_t	−0.048%(0.076%)	52%	−30.232% (3.81%)	99.999%

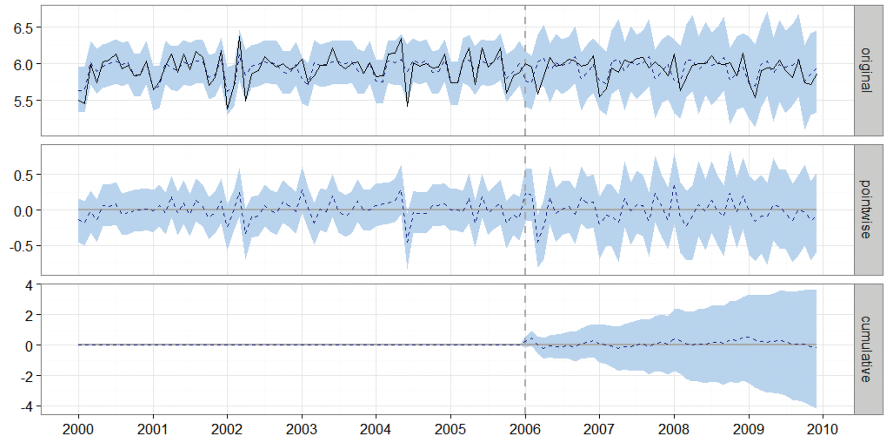

Figure 4: Causal impact analysis for tobacco sales: model results for the effects of the partial ban, which came into force in January 2006.

of the complete ban, respectively. In each of these figures, in the top graph, the solid line represents the actual data for tobacco sales and the dotted line is the baseline what–if forecast obtained from the model fit. The middle graph shows the difference between the actual and the fitted values. The bold horizontal line represents zero. The bottom graph shows the cumulative effect produced since the start of the intervention. In all the graphs, the blue region represents the 95% credible interval.

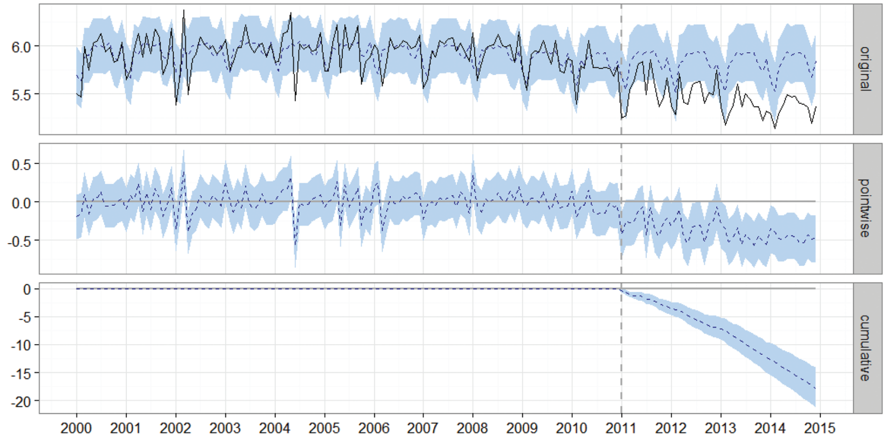

Figure 5: Causal impact analysis for tobacco sales: Model results for the effects of the total ban, which came into force in January 2011.

4.1 Effects of the partial ban

The partial ban started in January 2006. The post–intervention period is defined as the next four years (January 2006 to December 2009), the analysis being limited to this period in order to avoid possible noise from factors other than the prohibition, not included in the model variables.
Of the four potential control variables, those related to tourist visits from the UK and France show higher probabilities of inclusion in the predictive model of tobacco sales, at 47.85% and 33.17%, respectively. The Spanish unemployment rate and the retail price of tobacco have less than 5% probability of being predictive of sales.

As expected, the estimated coefficients are positive for tourist visits from the UK and France, and negative for the unemployment rate and the price. None of the coefficients are statistically significant, which is in line with their low probabilities of inclusion. As measures of goodness of fit, the R^2 was 0.6050, with a mean squared error (MSE) of 0.0167, a mean absolute error (MAE) of 0.0939 and a mean absolute percentage error (MAPE) of 1.5931%.

The mean difference between the response variable and its counterfactual prediction was found to be −0.05 per year, with a 95% credible interval of (−0.34, 0.25), resulting in a cumulative effect of −0.18. In relative terms, the response variable showed a cumulative decrease of −0.063%. The 95% interval of this percentage is (−1.51%, 1.33%). These results are based on the logarithmic transformation of the tobacco sales. The estimated effect for the original response variable is a decrease of −0.048%.

Although the intervention may seem to have exerted a negative effect on tobacco sales over the whole intervention period, this effect is not statistically significant. The posterior probability of a causal effect, measured as the posterior probability of there being a negative cumulative effect, is 52%.

4.2 Effects of the total ban on smoking in public places

The total ban started in January 2011. Due to the non-significant effect on sales of the partial ban, we define as pre–intervention the period from January 2000 to December 2010. The comparison is then established between the total ban and the previous period of no ban or partial ban. However, the measured impact of the total ban is somewhat reduced by the negative (although non-significant) impact of the partial ban.

For this study period, Bayesian analysis shows that the number of tourist visits from the UK is a clear predictor of tobacco sales in Spain, with a probability of inclusion of 81.81%. The unemployment rate is also a good predictor, with a probability of 8.55%, followed by the retail price, with a probability of 7.82%. However, the number of visitors from France has less than 5% probability of being predictive of sales.

The coefficients obtained show that for each 1% increase in the number of tourists from the UK, tobacco sales increase by an average of 0.51%. The impact of the remaining coefficients is close to zero due to their low probabilities of inclusion.

The goodness of fit of this model is a little worse than that obtained for the partial ban. The R^2 is 0.4744, and the MAPE is 1.8477%.

In contrast to the case of the partial ban, the model shows that the total ban on smoking in public places is related to a significant reduction in cigarette sales, of 30.232%, with a 95% credible interval of (−34.598%, −19.052%). Thus, the effect is highly significant, with a posterior probability of a causal effect of 99.999%.

Figure 5 shows that the reduction in cigarette sales mainly took place in the first two years following the introduction of the ban. Subsequently, sales stabilised and the difference between predicted and actual sales remained constant.

4.3 Sensitivity analysis

Table 2 shows the results of the sensitivity analysis performed. Variations in the prior structure of the model have been proposed, but no significant differences

Table 2: Sensitivity analysis.

	Partial ban		Total ban	
Relative effect (y_t)	Mean (sd)	Prob	Mean (sd)	Prob
$n_*/2 = 10^{-3}$	−0.040% (0.072%)	56%	−30.177% (3.98%)	99.999%
$\pi_j = 0.5$	−0.059% (0.074%)	54%	−29.542% (3.90%)	99.999%
$\pi_j = 0.8$	−0.036% (0.073%)	52%	−27.960% (4.05%)	99.999%
$R^2 = 0.4$	−0.064% (0.079%)	52%	−30.481% (3.98%)	99.999%
$R^2 = 0.8$	−0.065% (0.072%)	57%	−30.773% (4.03%)	99.999%
$n_\epsilon = 10$	−0.026% (0.073%)	57%	−30.636% (4.07%)	99.999%
$n_\epsilon = 100$	−0.044% (0.074%)	58%	−30.227% (3.64%)	99.999%

in this respect in the final results are observed. For the partial ban, the posterior probability of a causal effect ranges from 52% to 58%. For the total ban, all the models reflect a significant impact, ranging from −27.960% to −30.773%, with a posterior probability of 99.999%.

5 Conclusions and discussion

The main conclusion to be drawn from our results is that the partial ban imposed was not effective in reducing the volume of tobacco sold in Spain, while the total ban on smoking in public places contributed significantly to reducing cigarette consumption. These results are not surprising, as they are in line with other sources of information, such as the Spanish National Health Survey and the Household Budget Survey 2006–2014.

An important advantage of our method is that it allows us to examine the short–term impact of the interventions, thanks to the monthly frequency of the data considered. Our method, based on a composite counterfactual playing the role of control group, has been used successfully in other areas and is a promising new avenue for generalising the DiD approach in the classical regression framework (Chun et al. 2016; González and Hosoda 2016). Of course, a key point in our analysis is that of the validity of the assumptions made, particularly the independence between the controls and the intervention.

Although compliance with partial bans is high in the United States, Canada, the UK and Australia (Borland et al. 2006), in Spain the partial restrictions on smoking imposed in 2006 were not universally respected. According to the Healthcare Barometer 2006 (CIS 2015) around half of the population perceived that smokers were not respecting the law, which in addition had other shortcomings such as the lack of a plan for evaluation (Galán and López 2009). This might be one of the reasons why the partial ban had no significant effect in Spain, according to our own research and other studies (López et al. 2012). A cohort study showed that the partial ban of 2006 did not protect the workers of the hospitality sector in Spain (Fernández et al. 2009).

The present analysis has some limitations. As controls, we used the monthly data of arrivals of visitors to Spain from two selected countries, the UK and France. This choice was based on two arguments: (i) The price gap for cigarettes between Spain and both France and the UK remained substantial throughout the observation period, and therefore we assume that tourists have an incentive to purchase cigarettes in Spain for suitcase export. Accordingly, the series of monthly arrivals of tourists, adjusted by smoking prevalence in the respective countries, seems to be correlated with the outcome variable and, therefore, it is a plausible control. (ii) We also assumed that the ban on cigarettes did not reduce cigarette sales to tourists. This assumption may be controversial. It is more plausible for many of the visitors from France, who only cross the border in order to buy in Spain, and do not remain in the country (thus, they are excursionists, or same–day visitors); it is plausible, then, that their consumption in Spain is not affected by the Spanish ban. However, British tourists remain in Spain for at least several days and the ban may affect their consumption, and therefore the amount of tobacco purchased. If the ban did in fact influence their behaviour while in Spain, then our results might be biased upwards, although this bias would affect only tobacco purchased to consume in Spain, and not tobacco purchased for export to the purchasers' country of origin.

The price gap between Spain and UK and France varied during the analysis period. In particular, as shown in Figure 2, the price gap between Spain and France has narrowed significantly since 2006. In February 2006, Spain introduced a minimum excise tax for manufactured cigarettes, which acted as a tax floor and led to price increases. This may be one of the reasons why the arrival of visitors from France is considered a predictor of tobacco sales, with a probability of 33.17% in the period 2000–2006 (before the partial ban), which decreased to 4.09% in the period 2000–2010 (before the total ban).

The price of cigarettes was introduced as an additional control in the model. There is no doubt that this aspect is an important determinant of consumption, at least in the long term and for beginner smokers, who present greater price elasticity. As cigarette prices were affected by the interventions (via increased taxes), our estimation represents the net effect of the bans after adjusting for the tax effect. However, the smoking legislation contains other measures, affecting tobacco advertising, promotion and sponsorship, that may also have affected sales. In our model, their effect is included in the estimated effect of the prohibition.

We estimate that the total ban led to a reduction in tobacco sales of −30.232% in the four years following its introduction. Our analysis compares the period before and after the total ban (January 2011), with the period before the total ban including the period of partial ban. The estimated reduction in sales might have been even greater if the period of total prohibition were compared with the period prior to the partial prohibition since, as shown in Figure 1 and Table 1, during the partial ban, tobacco sales fell, although not significantly.

To the best of our knowledge this is the first study to apply this new and promising Bayesian modelling approach to estimate the effects of partial and total bans on smoking in public places. Our conclusions are clear: in order to significantly reduce cigarette smoking, partial bans are not effective. In contrast, a total ban on smoking in public places is an effective tool for health policy.

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