Intervention time series analysis of the smoking cessation quitline: a 16-years retrospective study in Sweden

Xingwu Zhou[1], Alessio Crippa[1], Rosaria Galanti[2], and Nicola Orsini[1]

[1]*Biostatistics Team, Department of Public Health Sciences, Karolinska Institutet*

[2]*Centre of Epidemiology and Community Medicine*

Abstract

Knowledge about the series of phone calls received by a smoking cessation quitline in response to different interventions aiming at reducing tobacco smoking is currently lacking. Aim of this study is to examine the possible effect of four types of policies on the calling rates to the Swedish smoking cessation quitline: a campaign on passive smoking (Jan 2001); placing larger warnings on cigarette packs (Sept 2002); banning smoking from restaurants (Jun 2005); and a 10% tax increase (Jan 2012). We used 16-years of monthly data collected between January 1999 to December 2014 (192 months) counting a total of 162,978 phone calls. Upon definition of four pre-post intervention intervals, we used intervention time series ARIMA (Auto-Regressive Integrated Moving Average) models where the outcome was defined as calling rates expressed per 100,000 smokers. Rate ratio (RR) at 6 months after intervention together with a 95% confidence interval (CI) were derived from the model. The campaign on passive smoking on Jan 2001 was associated with a 85% higher calling rate (95% CI=1.13-3.04). Larger warnings on cigarette packs in Sept

2002 conferred a 53% increment in the calling rate (95% CI=1.20-1.94). Smoking-free restaurants was associated with a significant 11% (95% CI=1.00-1.1.23) higher calling rate. The 10% tobacco tax increase in Jan 2012 had no significant effect on the calling rate (RR=0.98, 95% CI=0.82-1.15). Within an overall decreasing trend in the population of smokers in Sweden, we were able to detect differential effects of smoking policies on the calling rates to the quitline, the most effective being the campaign on passive smoking and the larger warnings signs on the cigarette packs.

Keywords: Smoking quitline, intervention analysis, ARIMA, ARIMAX.

1 Introduction

National telephone quitlines have the potential to reach large fraction of the smoking population and therefore may play an important role in increasing the chances of smoking cessation (Zhu, Lee, Zhuang, Gamst, and Wolfson, 2012). In addition, quitlines have been shown to be an effective and cost-effective modality for providing tobacco cessation interventions (Tomson, Helgason, and Gilljam, 2004).

To the best of our knowledge, however, no previous national tobacco quitlines have coherently examined the responsiveness of the phone calls to different types of smoking cessation interventions over an extended period of time.

Aim of this study is therefore to investigate the effect of four public health interventions on the number of phone calls received by the Swedish quitline during the last 16 years, namely a campaign on passive smoking, larger warnings on cigarette packs, banning smoking from restaurants, and a tax increase.

2 Methods

2.1 Data

Monthly number of calls to the smoking quitline was available from January 1999 to December 2014. A total of 162,978 phone calls during 16 years (192 months). To take into account the variation over calendar time of the total number of smokers we collected information on the total size of the population and smoking prevalence stratified by age groups and gender. The size of the population was available from Statistics Sweden (http://www.scb.se). The smoking prevalence was available every 2-years from the ULF survey before 2004 and every year from the Public Health National Survey on tobacco use (http://www.folkhalsomyndigheten.se/) after 2004. The outcome of interest was defined as the total number of phone calls divided by the total number of smokers. The calling rate was expressed per $100,000$ smokers.

We identified 4 main interventions aiming at reducing tobacco smoking during the

16-years observation period: 1) campaign on passive smoking in January 2001; 2) larger warnings on cigarette packages in September 2002; 3) banning smoking in restaurants in June 2005; and 4) tobacco tax increase by 10% in January 2012.

2.2 Statistical analysis

We assessed the effect of the 4 interventions on the series of calling rates by using intervention time-series models. We first explain the basic version of a time series model and then its extension to evaluate each intervention. We divided the overall 16-years period into 4 intervals according to the specified intervention months: 1) January 1999 to August 2002; 2) January 2001 to May 2005; 3) September 2002 to December 2008; and 4) January 2009 to December 2014.

2.2.1 Time series model

A Box and Jenkin's Autoregressive Integrated Moving Average (ARIMA)(p,d,q) model can be written as

$$\phi_p(B)(1-B)^d X_t = \theta_q(B)\epsilon_t \tag{1}$$

where X_t represents the monthly (log) calling rate per 100,000 smokers, B is the backshift operator such that $BX_t = X_{t-1}$, d is the degree of differencing in the series X_t, $\phi_p(B)$ and $\theta_q(B)$ are the polynomials in B of order p and q separately. That is $\phi_p(B) = 1 + \sum_{i=1}^{p} \phi_i B^i$ and $\theta_q(B) = 1 - \sum_{j=1}^{q} \theta_j B^j$. If we consider seasonality, an ARIMA(p,d,q)(P,D,Q) can be written as

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D X_t = \theta_q(B)\Theta_Q(B^s)\epsilon_t \tag{2}$$

where D is the number of seasonal differences, s is the seasonal period, and $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are polynomials in B^s of order P and Q, respectively.

2.2.2 Intervention time series model

The intervention time series model introduced by Box and Tiao (1975) is written as follows

$$Y_t = m_t + X_t \tag{3}$$

where the outcome Y_t represents the monthly (log) calling rate per 100,000 smokers. The X_t represents the baseline or background monthly (log) calling rate per 100,000 smokers throughout the selected interval of time. The series X_t is equal to Y_t before the intervention month and it is the predicted calling rate after intervention assuming no effect of the intervention. The m_t represents the additive change in the log calling rate due to the intervention. In other words, m_t is the log rate ratio (or transfer function) at certain time t. Generally, the log rate ratio associated with the intervention can be itself written as an ARMA(r_1, r_2) model of this form $m_t = \frac{\omega(B)}{\delta(B)} I_t$, in which $\omega(B) = \omega_0 + \omega_1 B + \omega_2 B^2 + \cdots + \omega_{r_1} B^{r_1}$, $\delta(B) = 1 - \delta_1 B - \delta_2 B^2 - \cdots - \delta_{r_2} B^{r_2}$, and I_t is an intervention (or dummy) variable. Suppose the intervention takes place at time T_0, then I_t takes value 1 if $t \geq T_0$ and 0 otherwise. Setting $r_1 = 0$ and $r_2 = 1$ provides a flexible yet parsimonious way of defining the intervention effect. In such a case the transfer function m_t becomes an autoregressive process of order 1, with $m_t = \delta m_{t-1} + \omega_0 I_t$. The interpretation of the transfer function can be facilitated by re-writing m_t as follows

$$m_t = \begin{cases} \frac{\omega_0(1-\delta^{t-T_0+1})}{1-\delta} & \text{if } t \geq T_0 \\ 0 & \text{otherwise} \end{cases}$$

The shape of the intervention effect m_t depends on the magnitude and sign of the estimated parameters δ and ω_0.

The estimated rate ratio (RR) k-months after the intervention month T_0 ($k = t - T_0$) is obtained by exponentiating m_k

$$\mathrm{RR}_k = \begin{cases} \exp(\omega_0(1-\delta^{k+1})/(1-\delta)) & \text{if } k \geq 0 \\ 1 & \text{otherwise} \end{cases}$$

The above definition of the intervention effect encompasses a variety of possible functional forms. For example, an immediate and stable intervention effect equal to $\exp(\omega_0)$ is occurring when $\delta = 0$. Furthermore, a smooth increasing rate ratio when moving away from the intervention month is occurring when ω_0 is positive and $0 < \delta < 1$. An oscillating rate ratio is instead occurring when $-1 < \delta < 0$. We identified a priori 6-months period after intervention as a sensible point in time to assess the intervention effect (k=6).

Given the defined model capturing both the underlying trend of the calling rate as well as its change after intervention, we search for the values of the parameters that maximize the joint likelihood of the collected data. A Wald-type test for the null hypothesis of no intervention effect, namely $H_0 : \delta = \omega_0 = 0$, is based on the ratio of the estimates to their variance/covariance matrix. A P-value for the null hypothesis about each parameter defining the shape of the rate ratio after intervention can be obtained by testing $H_0 : \delta = 0$ and $H_0 : \omega_0 = 0$ separately.

A confidence interval (CI) for the rate ratio (RR) k-months after intervention is computed by first estimating the standard error for the log rate ratio k-months after intervention, saying $\mathrm{SE}(m_k)$. Assuming a large-sample normal distribution for the maximum likelihood estimator of the log rate ratio m_k, 95% confidence limits for RR_k are given by $\exp(m_k \pm 1.96 \times \mathrm{SE}(m_k))$.

To choose among the possible combination of parameters (p, q, d, P, Q, D) for the pre-intervention data, we selected the one with the lowest Akaike Information Criterion corrected by the finite sample size (AICc). The intervention time series model is estimated by function ARIMAX from R package TSA (Cryer and Chan, 2010).

3 Results

A visual inspection of the observed calling rates per 100,000 smokers (Figure 1) suggests an overall increasing trend between 2001 and 2008 with some seasonal variation consisting in high values in January and low values in July. The lowest monthly calling rate occurred in July 2001 (27 calls per 100,000 smokers) and the highest in January 2012 (297 calls per 100,000 smokers). The latter observation was about 4 times larger than the average monthly rate of 80 calls per 100,000 smokers.

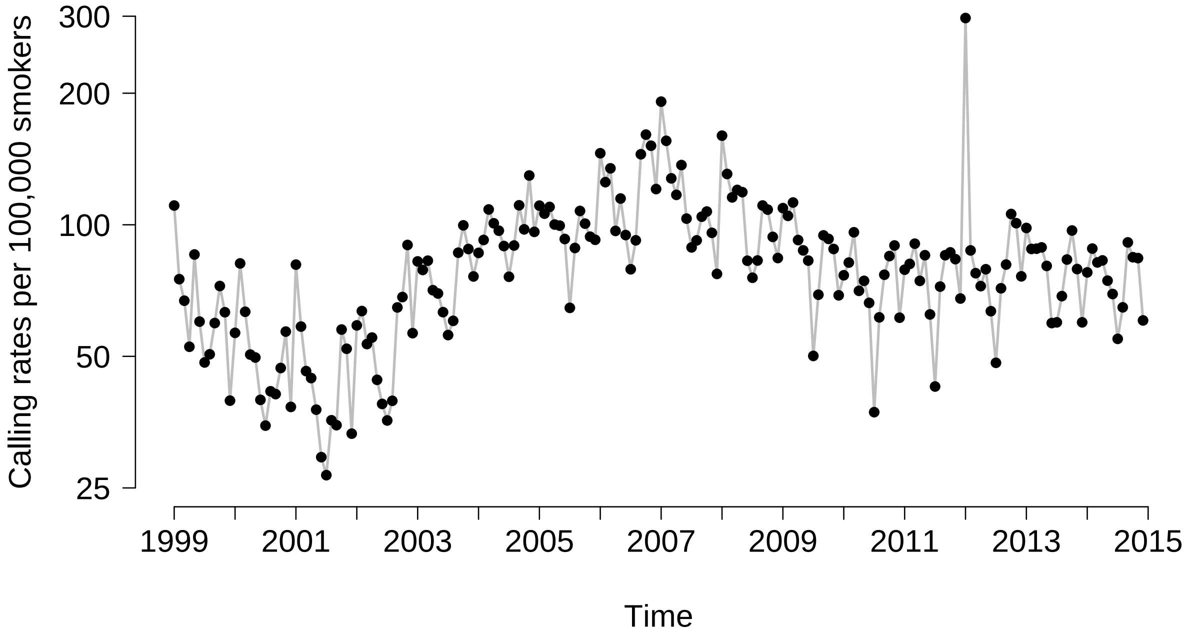

Figure 1: Monthly calling rate per 100,000 smokers to the Swedish smoking cessation quitline between January 1999 and December 2014. The vertical axis is on the log-scale.

3.1 Effect of a campaign on passive smoking (Jan 2001)

During the pre-intervention period between Jan 1999 and Dec 2000, the data were consistent with an ARIMA(0, 1, 0). Neither autoregressive nor moving average coefficients were needed for the first differenced data. The campaign on passive smoking started in Jan 2001 was associated with a higher calling rate (P-value=0.003, Table 1). Compared to the pre-intervention period, the calling rate 6-months after intervention significantly increased by 85% ($\text{RR}_{k=6} = \exp(0.77(1-(-0.24)^{6+1})/(1+0.24)) = 1.85$; 95% CI=1.13-3.04). Figure 2A facilitates the comparison of the observed calling rates after the cam-

Table 1. Defined intervals, types and dates of interventions, estimates of the parameters defining the rate ratios of calling the quitline after intervention using 16-years of data from the Swedish smoking cessation quitline (1999-2014).

Interval	**Type and date of intervention**	**Estimate (*P*-value) of the intervention model** *
Jan 1999 to Aug 2002	Campaign passive smoking on Jan 2001	$\omega_0 = 0.77(0.002)$, $\delta = -0.24(0.303)$
Jan 2001 to May 2005	Larger warnings on Sept 2002	$\omega_0 = 0.08(0.025)$, $\delta = 0.90(< 0.001)$
Sept 2002 to Dec 2008	Smoking-free restaurants on Jun 2005	$\omega_0 = 0.17(0.048)$, $\delta = -0.74(< 0.001)$
Jan 2009 to Dec 2014	Increase tax 10% on Jan 2012	$\omega_0 = -0.02(0.776)$, $\delta = 0.32(0.673)$

* The time series model specified within each interval describes the rate ratio at k-months after intervention as $\mathrm{RR}_k = \exp(\omega_0(1-\delta^{k+1})/(1-\delta))$.

paign on passive smoking relative to their counterfactual rates had this intervention not occurred. Figure 2B shows the sharp increase in the calling rate after Jan 2001 indicating no further changes beyond 6 months.

3.2 Effect of larger warnings on cigarette packs (Sept 2002)

Before introducing larger warnings on cigarette packs in Sept 2002, saying between Jan 2001 and Aug 2002, the data suggested an ARIMA(0,0,1). The calling rate gradually and significantly (P-value<0.001) increased after the introduction of the larger warnings on the cigarette packs (Table 1, Figure 3A). The calling rate 6-months after intervention was 53% higher ($\mathrm{RR}_{k=6}$=$\exp(0.08(1-0.90^{6+1})/(1-0.9))$=1.53; 95% CI=1.20-1.94). In Sept 2004, 2-years after intervention the calling rate nearly doubled (Figure 3B).

3.3 Effect of banning smoking in restaurants (Jun 2005)

During the pre-intervention period between Sept 2002 and May 2005, we found some evidence of seasonal variation in the calling rates leading to an ARIMA(0,0,1)(0,1,0) with seasonal frequency of 12 months.

We found a significant increased calling rate following introduction of smoking-free restaurants in Jun 2005 (P-value<0.001, Table 1, Figure 4A). Compared with the pre-intervention months, the calling rate significantly increased by 11% after 6 months ($\text{RR}_{k=6}$=$\exp(0.17(1-(-0.74)^{6+1})/(1+0.74))$=1.11; 95% CI=1.00-1.1.23). Of note, banning smoking in restaurants had an oscillating effect (δ has a negative sign) on the calling rate for several months following the intervention (Figure 4B), stabilising about 12 months later (Figure 4B).

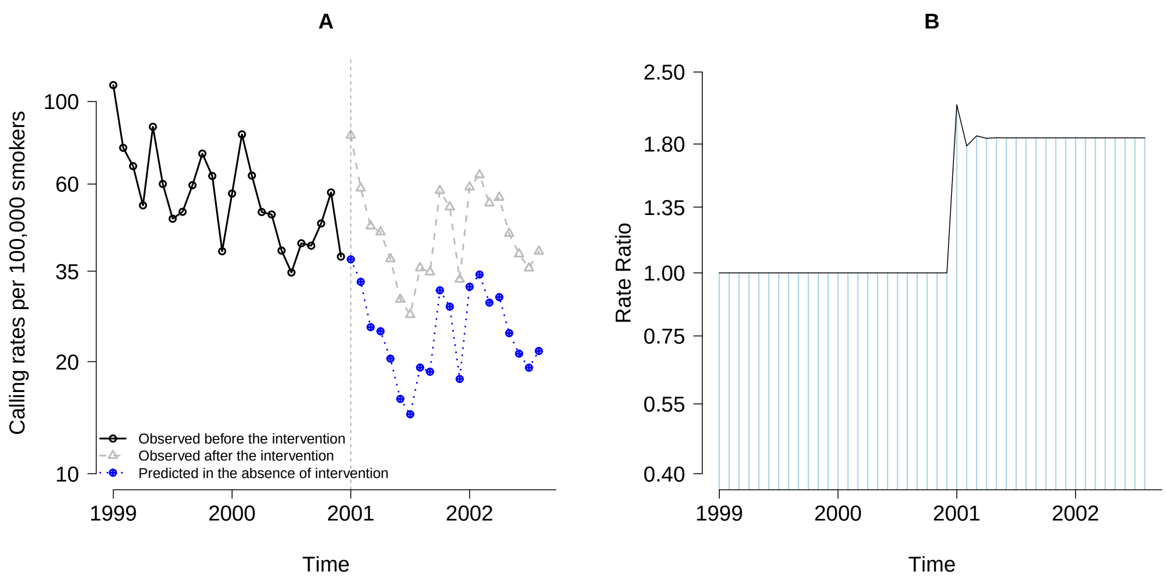

Figure 2: A) Observed and predicted calling rates to the smoking quitline between Jan 1999 and Aug 2002 in Sweden. B) Rate ratio of calling the smoking quitline after the campaign on passive smoking on Jan 2001 (P-value=0.003). Intervention time series model. The vertical axis is on the log-scale.

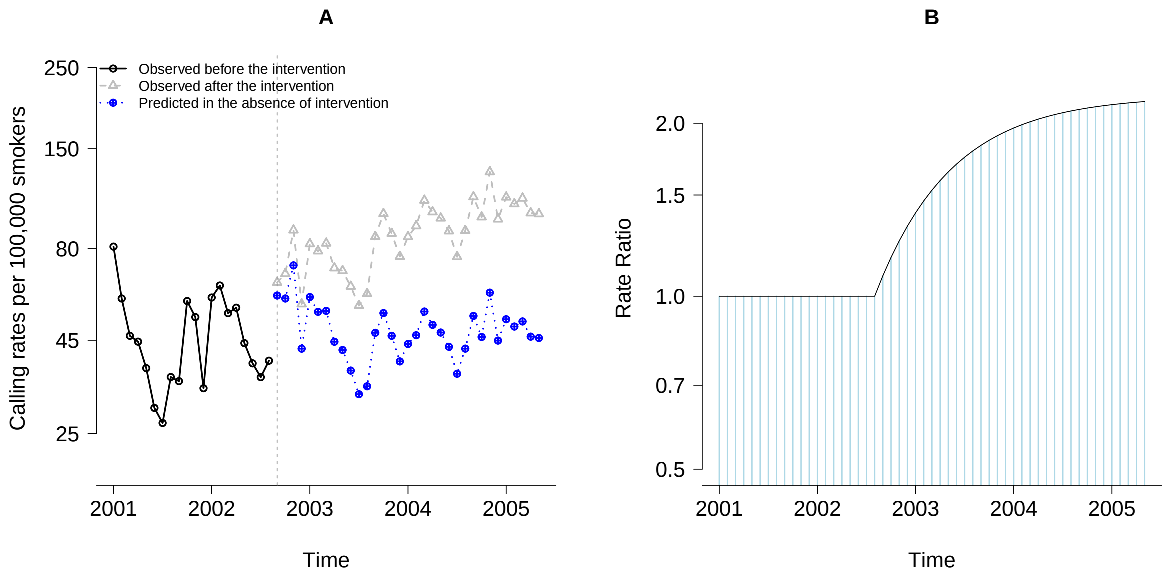

Figure 3: A) Observed and predicted calling rates to the smoking quitline between Jan 2001 and May 2005 in Sweden. B) Rate ratio of calling the smoking quitline after the introduction of larger warnings on the cigarette packs on Sep 2002 (P-value<0.001). Intervention time series model. The vertical axis is on the log-scale.

3.4 Effect of a 10% tobacco tax increase (Jan 2012)

The last intervention consisted in a 10% tax increased on tobacco products on Jan 2012. The interval of time between Sept 2009 and Dec 2014 is characterised by a relatively stable level of the calling rates with one extremely high value (Figure 5A). The calling rate on January 2012 (297 per 100,000 smokers) was particularly influential in assessing the intervention effect and so it was excluded from the analysis. The pre-intervention data suggested an ARIMA(0,1,1)(0,1,0) with seasonal frequency of 12 months. The 10% tobacco tax increase was not significantly (P-value=0.852) associated with a change in the calling rate to the smoking quitline (Table 1). Compared to the pre-intervention period, the calling rate 6-months after intervention decreased by 2% ($RR_{k=6} = 0.98$; 95% CI=0.82-1.15).

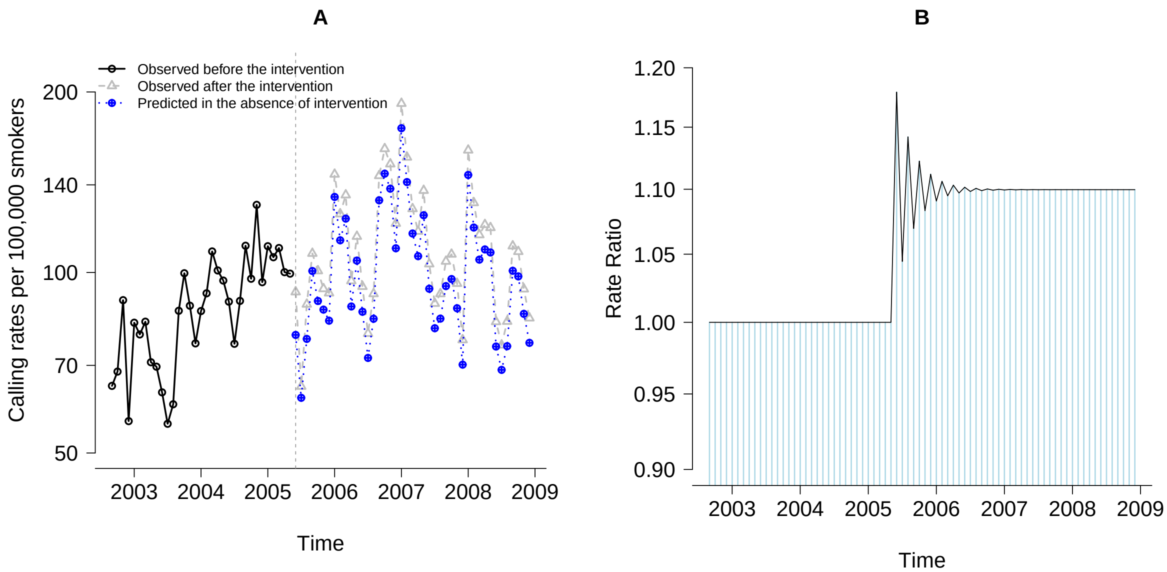

Figure 4: A) Observed and predicted calling rates to the smoking quitline between Sept 2002 and May 2005 in Sweden. B) Rate ratio of calling the smoking quitline after the banning of smoking in restaurants on Jun 2005 (P-value$<$0.001). Intervention time series model. The vertical axis is on the log-scale.

4 Discussion

In this retrospective study of 16-years of monthly phone calls to the Swedish smoking cessation quitline we found differential effects of the policies used to reduce tobacco smoking. The campaign on passive smoking in Jan 2001, larger warnings on cigarette packs in Sept 2002, and banning smoking from restaurants in Jun 2005 were all associated with a 6-months significantly higher calling rates. The increment by 10% of the tobacco products in Jan 2012 had, however, no impact on the calling rates to the quitline.

Major strength of this study is the relatively large number of phone calls accumulated over a long period of time. This unique source of data allowed a consistent and homogeneous assessment of diverse interventions. We employed advanced time-series models to distinguish the effect of the intervention from the background and seasonal variation. The functional form specified to capture the intervention effect was sufficiently general to describe a variety of possible shapes expressed in terms of just two

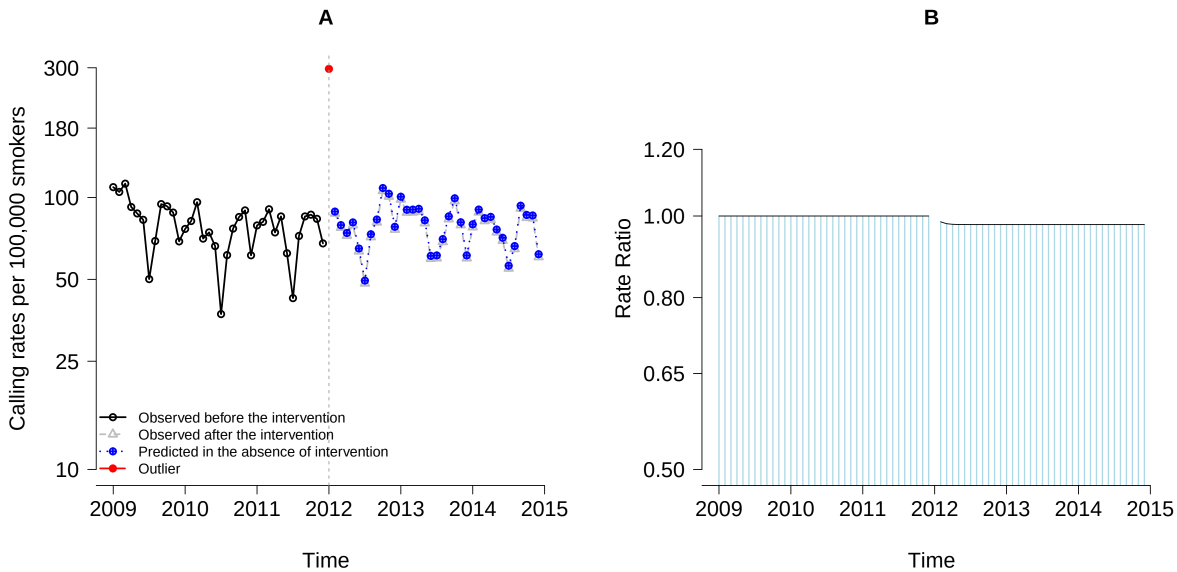

Figure 5: A) Observed and predicted calling rates to the smoking quitline between Sept 2009 and Dec 2014 in Sweden. B) Rate ratio of calling the smoking quitline after the introduction of a 10% tax increase on Jun 2012 (P-value=0.852). Intervention time series model. The extreme observation on Jan 2012 (red circle) was not included in the analysis. The vertical axis is on the log-scale.

parameters. To facilitate the interpretation of the specified complex statistical models some effort was placed on providing both graphical comparisons of observed and predicted calling rates and closed formulas to make inference on the rate ratio associated with the intervention at any time after intervention.

Main limitation of this investigation refers to the varying amount of pre-intervention data points available for each intervention. In particular, we could use only 24 and 20 months before the first and second intervention respectively. The consequence being probably the limited power to detect seasonality prior to the the first two interventions. Given that knowledge about the pre-intervention series defines the comparison group (or counterfactual) to evaluate the post-intervention series, it should ne noted that limited data and/or a poor model for the pre-intervention period may result in a poor assessment of the public health measures of intervention effect. Comparison of likelihood of the data arising from alternative ARIMA models guided us in selecting the most appropriate yet parsimonious model given the available data.

To evaluate multiple interventions we decided to split the 16 years of follow-up into multiple intervals. This approach offered the practical advantage of facilitating the visualization of observed and predicted rates within a narrower interval of calendar time. On the other hand, this strategy of focusing on an interval of time around the intervention month may exaggerate the intervention effect. Indeed, we noticed some sensitivity of the estimated intervention effects in case of sudden changes, typically a high increase, occurring exactly during the first month of intervention. The extremely high number of phone calls on Jan 2012 following the introduction of the tobacco tax is an example of this scenario. The inclusion of this single data point would have incorrectly overestimated the magnitude of the intervention effect.

During the 16-years of the study going from 1999 to 2014 the smoking behaviour in the Swedish population has likely changed. This may explain the variation in the number of phone calls over time with or without the investigated public health interventions. Actually the prevalence of smoking in the general population nearly halved during our observation period. This change has been, however, smooth and gradual over almost two decades. Although we cannot rule out this alternative explanation in our observational study, it is unlikely that the changes in smoking prevalence over the 6 months after each intervention would have been so strong and sudden to fully explain the magnitude of the rate ratio estimated in our analysis. Indeed, we tried to take into account the gradual decreasing size of the smoking population directly in the definition of the outcome. Rather than modelling number of calls per month, we modelled number of calls per months divided by number of smokers that during each month could have been potentially interested in calling the smoking quitline.

In conclusion, we evaluated the possible effects of four public health interventions aiming at reducing tobacco smoking on the calling rate to the Swedish smoking cessation quitline. We found the series of phone calls particularly responsive to the campaign on passive smoking in Jan 2001 and the introduction of larger warnings on cigarette packs in Sept 2002. Banning smoking from restaurants in Jun 2005 was associated only with a modest increment in the calling rate. The 10% higher tobacco tax in Jan 2012 had instead no impact on the calling rates to the quitline.

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