Health & Place 70 (2021) 102616

Contents lists available at ScienceDirect

Health and Place

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

Spatial clusters of daily tobacco consumption before and after a smoke-free policy implementation

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ARTICLE INFO

Keywords:
Spatial analysis
Neighborhood environment
Tobacco consumption
Smoke-free policy

ABSTRACT

This study assessed the spatial dependence of daily tobacco consumption and how it is spatially impacted by individual and neighborhood socioeconomic determinants, and tobacco consumption facilities before and after a smoke-free implementation.

Individual data was obtained from the Bus Santé, a cross-sectional survey in Geneva. Spatial clusters of high and low tobacco consumption were assessed using Getis-Ord Gi*.

Daily tobacco consumption was not randomly clustered in Geneva and may be impacted by tobacco consumption facilities independently of socioeconomic factors and a smoking ban. Spatial analysis should be considered to highlight the impact of smoke-free policies and guide public health interventions.

1. Introduction

Tobacco smoking is a major risk factor for several diseases and the preventable behavior that causes more deaths worldwide (National Center for Chronic Disease Prevention and Health Promotion (US) Office on Smoking and Health, 2014; WHO, 2012). Smoke-free policies conceived to prevent this behavior have shown a reduction in cardiovascular outcomes, and to a minor extent, in respiratory diseases (Humair et al., 2014; Jones et al., 2014; Rando-Matos et al., 2017; Tan and Glantz, 2012). However, positive results on smoking cessation and tobacco consumption are not entirely conclusive (Frazer et al., 2016a; IARC, 2009).

In 2009, the state of Geneva in Switzerland implemented a smoke-free policy in all public places including establishments associated with tobacco consumption such as restaurants, bars, cafes, nightclubs, and adult gambling venues (https://www.ge.ch/legislation/rsg/f/s/rsg_K1_18.html). The ban showed an encouraging impact on the smoking prevalence and quit ratios immediately after its implementation, but not in the long-term (Sandoval et al., 2018). Furthermore, the effect of such a ban was mediated by individual socioeconomic factors; less educated individuals were less likely to quit and had a higher smoking prevalence (Sandoval et al., 2018).

Smoking pathways of socioeconomic inequalities have also been described at the neighborhood scale (Glenn et al., 2020; Pearce et al., 2011). Spatial analyses have been helpful to demonstrate that smoking behaviors are geographically associated with the neighborhood environment; individuals socioeconomically deprived and living in unfavorable environments present higher proportions of adverse smoking

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https://doi.org/10.1016/j.healthplace.2021.102616
Received 28 January 2021; Received in revised form 17 June 2021; Accepted 24 June 2021
Available online 3 July 2021

behaviors, while areas with a higher density of tobacco retailers (i.e. stores selling tobacco) show higher smoking rates (Brooks et al., 2021; Caraballo et al., 2019; Galiatsatos et al., 2020; Généreux et al., 2012; Kane and Farshchi, 2019; Xie et al., 2020). Spatial analyses have also assessed the consumption of tobacco overtime (Almeida et al, 2020, 2021; Ciccarelli and Elhorst, 2018) and suggest an interplay between tobacco affordability and smuggling on the spatial pathways of tobacco consumption (Almeida et al, 2020, 2021; Ciccarelli and Elhorst, 2018; Joossens and Raw, 1998). Moreover, the use of spatiotemporal approaches has helped identify a reduction in smoking incidence after the implementation of a smoke-free policy (Lee and Lawson, 2016) and assess the contribution of public policies in reducing the density of tobacco retailers in favor of healthier built environments (Lawman et al., 2020).

Spatial analyses can therefore be useful to understand better the impact that neighborhood factors and public health interventions may have on smoking. However, to the best of our knowledge, all studies assessing the spatial dependence of smoking are limited by ecological inferences at an aggregated scale (i.e. individual behaviors gathered within counties or other small administrative areas) (Almeida et al., 2020; Brooks et al., 2021; Caraballo et al., 2019; Galiatsatos et al., 2020; Généreux et al., 2012; Kane and Farshchi, 2019; Xie et al., 2020) and no study has assessed neither the spatial dependence of tobacco consumption at an individual level, nor compared - using spatial statistics - the influence of individual and neighborhood characteristics before and after a smoke-free implementation. This is likely to shed new light when evaluating the success of smoke-free policies and to help better design public health interventions at a local scale.

Using individual georeferenced data, we aimed to determine the spatial dependence of daily tobacco consumption and to assess how spatial dependence, if any, is influenced by facilities associated with tobacco consumption and by socioeconomic determinants at the individual and neighborhood level. We ran and compared the analyses before and after the implementation of a smoking ban in Geneva.

2. Materials and methods

2.1. Health data

Individual data were obtained from the Bus Santé study, an ongoing representative cross-sectional survey carried out every year since 1993 in the state of Geneva. The dataset includes health and socioeconomic related information, as well as geolocated data for participants aged 35–74 (20–74 years after 2011). Data are obtained from self-administered standardized questionnaires for sociodemographic and health behavior information, and from measures taken in one of the three study units for anthropometric and laboratory data. Participants are selected using a residential list provided by the local authorities through a random sampling selection stratified by gender and age. Selected individuals are invited by postal mail, and in case of no response, up to seven telephone calls are attempted at different times and days. If unsuccessful, two more postal invitations are sent. Individuals that cannot be reached after these attempts are replaced using the same selection procedure as above, candidates who refuse to participate are not substituted (Guessous et al., 2012). The survey is in line with the Declaration of Helsinki and was approved by the Institute of Ethics Committee of the University of Geneva. All participants signed an informed consent form.

For this study, we selected individuals aged over 35 years to have a similar population age across the period studied. Incomplete data were removed (4% of the sample) and assumed to be missing completely at random. In order to analyze the influence of neighborhood environment on tobacco consumption, we used data from the 2003–2018 period to include information two years before and after neighborhood covariates were available (see below).

2.2. Smoking ban periods

We defined two periods to assess the spatial dependence of daily tobacco consumption. The years 2003–2009 represent the period before the smoking ban, and the years 2010–2018 the period after the ban.

2.3. Tobacco consumption

Daily tobacco consumption was computed as the number of cigarettes (or pipes, cigars, and cigarillos equivalents) that a person smoked or used to smoke per day; a value of 0 was allocated for non-smokers. The tobacco consumption of former smokers was only considered if the consumption happened during the period they were measured (i.e. were smokers at some point between 2003 and 2009 or 2010–2018).

2.4. Socioeconomic and environmental data (covariates)

Individual covariates included gender, age (years), country of birth (Switzerland or other), education level (primary: no education or primary education, secondary: apprenticeship or secondary education, and tertiary: university education), civil status (single, married, divorced, and widow), job status (high, medium or low skilled, and not workers), and cardiovascular risk factors (hypertension, hypercholesterolemia, and/or diabetes).

Environmental covariates consisted of the annual median neighborhood household income (1 CHF = 1.10 USD, in October of 2020) for the years from 2005 to 2016 assigned to each individual based on their corresponding statistical subsector in Geneva (GIRECs) -neighborhood definition by the State of Geneva (Office Cantonal de la Statistique, www.ge.ch/statistique). The household income is only reported for married couples as data from single individuals may not be precise (i.e. they are more likely to live in a shared household). Tobacco consumption facilities were considered as locations directly affected by the smoking ban in Geneva (i.e. tobacco consumption was allowed in these facilities before the smoking ban but prohibited after this policy). Therefore, data labelled as restaurants, cafes, bars, pubs, night clubs, and adult gambling venues were queried from the Registre des Entreprises du canton de Geneve (Central Business Registry, REG) (https://ge.ch/sitg/fiche/2099). The density of tobacco consumption facilities was defined as the total number of these amenities localized within a buffer of 1,200 m around each observation. This distance was chosen to be close to the average diameter (1,133 m) of statistical subsectors.

2.5. Statistical analysis

Descriptive data are reported as means ± SD for quantitative variables and frequencies and percentages (%) for categorical data. We performed Welch's t-tests and chi-square tests in numeric and categorical data, respectively, to compare participants' characteristics before and after the smoking ban.

We ran a Hurdle Negative Binomial (HUNB) regression - adequate to analyze data on tobacco consumption - (Pittman et al., 2018) to identify the statistically significant ($p < 0.05$) individual and neighborhood factors related to daily tobacco consumption and to test whether the smoke-free policy was associated with this smoking behavior (Table S1, supplementary materials). The HUNB deals with count data not following an expected Poisson distribution and information showing a high number of zeros (non-smoker population); it is particularly adequate when zeros can only be produced by one process (i.e. only non-smokers produce zeros, tobacco consumers smoke at least one cigarette per day). It is based on a binary regression (whether the outcome is zero or a positive count), and a truncated negative binomial regression (for positive counts in tobacco consumers) (Cameron and Trivedi, 2013; Mullahy, 1986).

We processed local Getis-Ord indices* (Gi*) (Getis and Ord, 1992) to measure the spatial dependence of daily tobacco consumption and identify local spatial clusters of high and low levels of this variable before and after the smoking ban in Geneva. The G* statistic (Getis and Ord, 1992) is calculated as:

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j}$$

This statistic compares the sum of the individual values of daily tobacco consumption within a defined spatial lag in proportion to the sum of the individual values of daily tobacco consumption in the entire study area (Ord and Getis, 1995). The value obtained is a Z score with a statistical p-value associated. Large values of Z indicate hot spots (areas with high values of daily tobacco consumption); low values of Z correspond to cold spots (areas with low values of daily tobacco consumption); non-significant values correspond to neutral zones (no spatial dependence). Additionally, Local Moran's I statistic (LMI) (Anselin, 1995) was calculated to identify discordant observations in hot and cold spots (Fig. S1 and Table S2, supplementary materials). Significance was assessed using a Monte Carlo random procedure (Anselin, 1995) of 999 permutations and an α level of $p \leq 0.1$ with the False Discovery Rate (FDR) correction (Benjamini and Hochberg, 1995; Caldas de Castro and Singer, 2006) for multiple comparisons as suggested by Bradley & Hastie (Efron Bradley and Trevor Hastie, 2016). We used a spatial lag of 1,200 m, a distance close to the mean size of statistical subsectors. Moreover, this spatial lag was previously used in a similar population (Joost et al., 2019). Other spatial lags were also tested and showed similar spatial patterns (Figure S2, supplementary materials). Spatial weights were row standardized due to an unequal number of neighbors in the spatial lag areas (i.e. all individuals within a spatial lag sum a weight of 1, and the weight for each individual is 1/Wi).

After the identification of spatial clusters, we performed Welch's t-tests in cardinal covariates, and chi-square tests in categorical information to compare individual and neighborhood characteristics (e.g. density of tobacco consumption facilities, neighborhood household income, education level) between the hot and cold spots found in the Gi* analysis. We then used the residuals of a HUNB regression to assess the impact of those neighborhood and individual characteristics on the spatial dependence of daily tobacco consumption. If the size of spatial clusters decreases, those covariates are spatially impacting daily tobacco consumption. To do so, we tested two adjusted models, i) a model including the neighborhood household income and individual socioeconomic determinants (gender, age, education level, country of birth, job level, civil status, and cardiovascular risk factors), ii) a model including also the density of tobacco consumption facilities in addition to model 1. As sensitivity analysis, we correlated the density of tobacco consumption facilities with the density of tobacco retailers and implemented a model adjusted only for the density of tobacco consumption (Fig. S3, supplementary materials) and a model adjusted only for the density of tobacco retailers (i.e. supermarkets, kiosks, and tobacco stores) to identify which of these factors was having a higher impact on the spatial dependence of tobacco consumption (Fig. S4, supplementary materials).

Data analysis was carried out in R 3.6.3 (R Core Team, 2020R Core Team, 2020). Additionally, we used the libraries of rgeoda (Xun Li, 2019) for spatial analyses, pscl (Jackman, 2020) for the HUNB regressions, sf (Edzer Pebesma, 2018) to calculate the distance of tobacco consumption facilities, and ggplot2 (Hadley Wickham, 2016) to draw the maps.

3. Results

The dataset for the 2003–2018 period included 14,170 individuals, of whom 12,267 remained after removing individuals below 35 years. From this sample, 11,723 participants with complete data were selected. Additionally, 21 participants were removed as they were geographically isolated from the sample population (they lived at a distance >1,200 m from their closest neighbor). Therefore, 11,702 observations were retained in the dataset: 4,388 before the ban (2003–2009) and 7,314 after (2010–2018).

3.1. Participants' characteristics

The dataset contains 5,993 (51%) women and the mean age of the sample is 51.8 (±10.8). There were 2,953 (25%) participants with positive daily tobacco consumption, smoking around 14 (±10) cigarette equivalents per day. The mean of the neighborhood household income was 146,858 (±47,010) USD, and each individual was surrounded by approximately 163 (±235) tobacco consumption facilities in a radius of 1,200 m (Table 1).

We observed a significant decrease ($p < 0.001$) of around 3 cigarettes consumed per day after the smoking ban. Additional differences between the two periods were also observed. The sample population after the ban was older (52.0 ± 10.8 *vs* 51.4 ± 10.9), included a higher proportion of participants with a tertiary education level (47% *vs* 39%), widow individuals (6% *vs* 3%), and with cardiovascular risk factors (58% *vs* 51%), and a lower proportion of swiss (47% *vs* 52%). Similarly, after the ban, a higher number of tobacco consumption facilities was observed (209 ± 273 *vs* 86 ± 117), and the neighborhood household income was higher (150,194 ± 48,203 *vs* 141,296 ± 44,402) (Table 1).

3.2. Spatial patterns of raw daily tobacco consumption

We found spatial clusters of high and low daily tobacco consumption in the state of Geneva. Before the smoking ban period (Fig. 1A), a predominant concentration of high daily tobacco consumption clusters (hot spots) was located in the central area of the state (landmarks 1 and 2). In contrast, concentrations of low amounts of daily tobacco consumption

Table 1
Population characteristics (overall and stratified by smoking ban period).

Population characteristics	Overall (2003–2018)	Before the ban (2003–2009)	After the ban (2010–2018)	P-value[a]
N	11,702	4,388 (38%)	7,314 (62%)	
Tobacco consumers	2,953 (25%)	1,170 (27%)	1,783 (24%)	0.006
Daily tobacco consumption (tobacco consumers)	14 ± 10	16 ± 11	13 ± 9	<0.001
Density of tobacco consumption facilities	163 ± 235	86 ± 117	209 ± 273	<0.001
Neighborhood household median income (USD)	146,858 ±47,010	141,296 ±44,402	150,194 ±48,203	<0.001
Age (years)	51.8 ± 10.8	51.4 ± 10.9	52.0 ± 10.8	0.002
Women	5,993 (51%)	2,238 (51%)	3,755 (51%)	0.74
Born in Switzerland	5,700 (49%)	2,289 (52%)	3,411 (47%)	<0.001
Education level				
Primary	2,821 (24%)	795 (18%)	2,026 (28%)	<0.001
Secondary	3,722 (32%)	1,894 (43%)	1,828 (25%)	
Tertiary	5,159 (44%)	1,699 (39%)	3,460 (47%)	
Civil status				
Single	1,206 (10%)	453 (10%)	753 (10%)	<0.001
Married	7,830 (67%)	3,044 (69%)	4,786 (66%)	
Divorced	2,128 (18%)	780 (18%)	1,348 (18%)	
Widowed	538 (5%)	111 (3%)	427 (6%)	
Job status				
High skilled	2,631 (22%)	930 (21%)	1,701 (23%)	0.06
Medium skilled	3,585 (31%)	1,384 (31%)	2,201 (30%)	
Low skilled	1,687 (15%)	638 (15%)	1,049 (15%)	
Not working	3,799 (32%)	1,436 (33%)	2,363 (32%)	
Cardiovascular risk factors	6,460 (55%)	2,236 (51%)	4,224 (58%)	<0.001

[a] Before *vs* after the smoking ban.

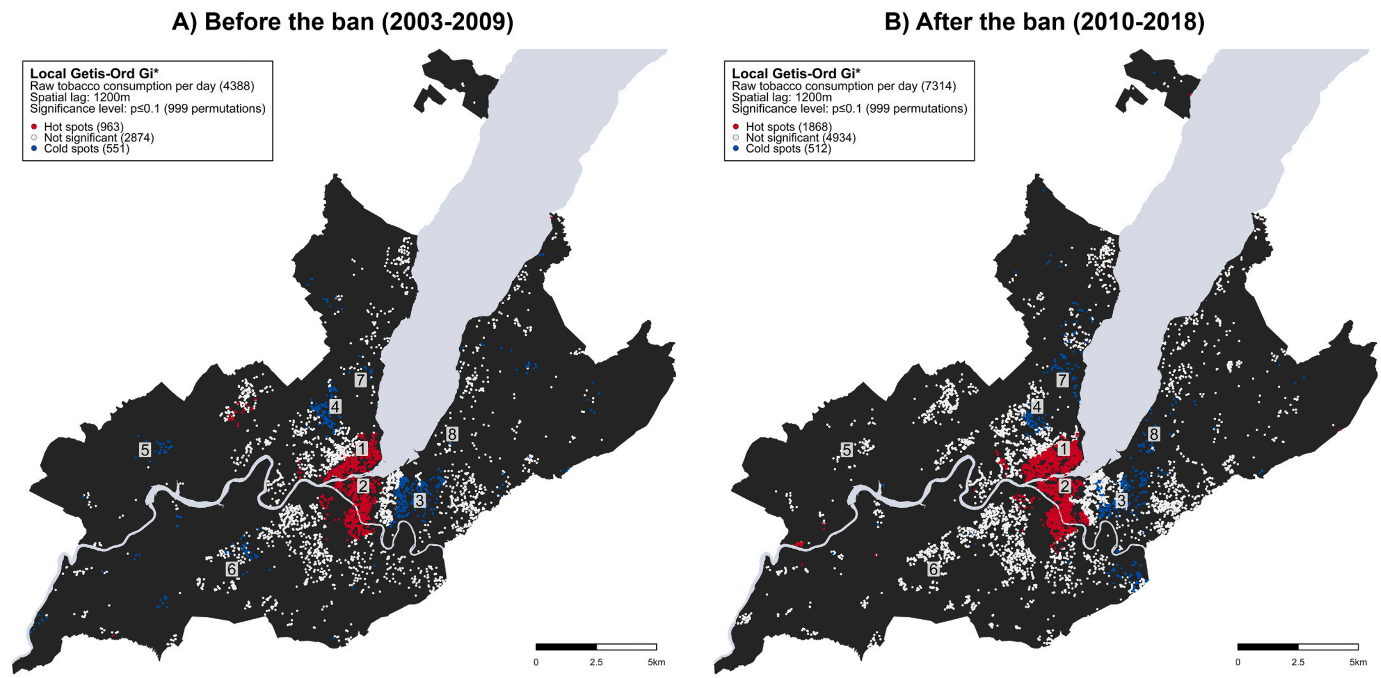

Fig. 1. Spatial distribution of raw daily tobacco consumption before (A) and after (B) the smoking ban in Geneva (Getis-Ord Gi*). Statistical significance is assessed at an α threshold of $p \leq 0.1$ FDR correction included. Red dots (hot spots) indicate individuals in areas showing high values of daily tobacco consumption, blue dots (cold spots) indicate individuals in areas showing low values of daily tobacco consumption, white dots indicate individuals in areas where tobacco consumption is not spatially dependent. Numbers 1–8 in the maps represent landmarks to support the description of the results.

(cold spots) were dispersed across different locations in the region (landmarks 3–7). The spatial distribution of daily tobacco consumption after the ban implementation (Fig. 1B) showed similar patterns; hot spots were in the central region (landmarks 1 and 2), and cold spots were distributed in different zones of the state (landmarks 3, 4, 7 and 8).

3.3. Individual and environment characteristics between hot and cold spots for the raw distribution of daily tobacco consumption

Differences in individual and neighborhood characteristics between the spatial distribution of daily tobacco consumption in hot and cold spots were found in both periods (Table 2).

Table 2
Population characteristics in hot and cold spots before and after the ban (raw daily tobacco consumption).

Population characteristics	Before the ban				After the ban			
	Hot spots	No spatial dependence	Cold spots	P-value[a]	Hot spots	No spatial dependence	Cold spots	P-value[a]
N	963 (22%)	2,874 (65%)	551 (13%)		1,868 (26%)	4,934 (67%)	512 (7%)	
Tobacco consumers	325 (34%)	732 (25%)	113 (20%)	<0.001	546 (29%)	1,119 (23%)	118 (23%)	0.007
Daily tobacco consumption (tobacco consumers)	17 ± 12	15 ± 10	15 ± 11	0.03	13 ± 9	13 ± 9	11 ± 10	0.04
Density of tobacco consumption facilities	239 ± 129	43 ± 70	43 ± 52	<0.001	540 ± 280	98 ± 155	62 ± 84	<0.001
Neighborhood household median income (USD)	115,662 ± 23,601	146,835 ± 47,002	157,211 ± 40,588	<0.001	121,111 ± 26,022	157,660 ± 48,602	184,371 ± 56,345	<0.001
Age (years)	49.8 ± 10.6	51.7 ± 10.9	52.4 ± 10.8	<0.001	50.7 ± 10.8	52.4 ± 10.7	53.1 ± 11.2	<0.001
Women	482 (50%)	1,470 (51%)	286 (52%)	0.52	941 (50%)	2,546 (52%)	268 (52%)	0.46
Born in Switzerland	457 (47%)	1,539 (54%)	293 (53%)	0.04	761 (41%)	2,419 (49%)	231 (45%)	0.08
Education Level								
Primary	183 (19%)	1,079 (38%)	82 (15%)	<0.001	527 (28%)	1,409 (29%)	90 (18%)	<0.001
Secondary	425 (44%)	1,265 (44%)	204 (37%)		447 (24%)	1,257 (25%)	124 (24%)	
Tertiary	355 (37%)	530 (18%)	265 (48%)		894 (48%)	2,268 (46%)	298 (58%)	
Civil status								
Single	169 (17%)	240 (8%)	44 (8%)	<0.001	306 (16%)	404 (8%)	43 (8%)	<0.001
Married	576 (60%)	2,062 (72%)	406 (74%)		1,069 (57%)	3,366 (68%)	351 (69%)	
Divorced	184 (19%)	512 (18%)	84 (15%)		390 (21%)	872 (18%)	86 (17%)	
Widowed	34 (4%)	60 (2%)	17 (3%)		103 (6%)	292 (6%)	32 (6%)	
Job status								
High skilled	192 (20%)	586 (20%)	152 (28%)	<0.001	427 (23%)	1,132 (23%)	142 (28%)	<0.001
Medium skilled	313 (32%)	905 (32%)	166 (30%)		574 (31%)	1,475 (30%)	152 (30%)	
Low skilled	172 (18%)	410 (14%)	56 (10%)		294 (15%)	712 (14%)	43 (8%)	
Not working	286 (30%)	973 (34%)	177 (32%)		573 (31%)	1,615 (33%)	175 (34%)	
Cardiovascular risk factors	456 (47%)	1,489 (52%)	291 (53%)	0.05	1,051 (56%)	2,883 (58%)	290 (57%)	0.91

[a] Hot spots *vs* cold spots.

We observed a younger population in hot spots (49.8 ± 10.6) than in cold spots before the ban (52.4 ± 10.8, p < 0.001). Moreover, in this same period, there were lower prevalence of swiss (hot spots: 47 *vs* cold spots: 53%, p = 0.04), people with a tertiary education level (hot spots: 37% *vs* cold spots: 48%, p < 0.001), and high skilled workers (hot spots: 20% *vs* cold spots: 28%, p < 0.001) in hot spots. Similarly, hot spots presented a lower proportion of married individuals (60% *vs* 74%, p < 0.001).

The age of the population considered after the ban was also lower in hot spots (50.7 ± 10.8) than in cold spots (53.1 ± 11.2, p < 0.001). Likewise, for this period, there were lower proportions of people with tertiary education (hot spots: 48% *vs* cold spots 58%, p < 0.001) and with a high skilled job (hot spots: 23% *vs* cold spots 28%, p < 0.001) in hot spots. Married individuals were also less concentrated in hot spots (57% *vs* 69%, p < 0.001).

The distribution of neighborhood factors presented statistical differences (p < 0.001) between hot and cold spots. Before the ban, the neighborhood income was lower in hot spots (115,662 ± 23,601) in comparison to cold spots (157,211 ± 40,588) and the number of tobacco consumption facilities was higher in hot spots (239 ± 129) than in cold spots (43 ± 52). Similar patterns were found after the ban; the neighborhood income was lower in hot spots (hot spots: 121,111 ± 26,022 *vs* cold spots: 184,371 ± 56,345), while the density of tobacco consumptions facilities was higher (hot spots: 540 ± 280 *vs* cold spots: 62 ± 84).

3.4. Spatial patterns of daily tobacco consumption adjusted for individual and neighborhood socioeconomic factors

Adjustment for individual and neighborhood socioeconomic factors strongly reduced the number of clusters compared to those identified in the raw model (Fig. 2). Compared to the raw model (Fig. 1A), the adjusted model (Fig. 2A) reduced the number of hot spots from 22% to 7% of the individuals, and the cold spots from 13% to 1% before the ban. The adjusted model, after the implementation of the ban (Fig. 2B), also showed a decrease of spatial clusters in comparison to the raw model (Fig. 1B); hot spots were reduced from 26% to 8% of the individuals and cold spots from 7% to 1%. In both periods, the remaining concentrations of clusters were mainly located in the central (hot spots) and central-east (cold spots) regions (landmarks 2 and 3, respectively).

3.5. Spatial patterns of daily tobacco consumption adjusted for socioeconomic factors and the density of tobacco consumption facilities

Further adjustment from model 1, including also the density of tobacco consumption facilities, made all remaining clusters disappear in both periods (Fig. 3).

4. Discussion

We found spatial clusters of high and low daily tobacco consumption in the state of Geneva, and they were similar before and after the implementation of a smoking ban. In both periods, spatial areas of high daily tobacco consumption were located downtown, while clusters of low daily tobacco consumption were mostly distributed in the bounds of the metropolitan area. After adjustment for neighborhood and socioeconomic factors, the spatial clusters presented a significant decrease in the number of their members (between 68% and 92% decrease). Adjusting for the density of tobacco consumption facilities in the previous model made all clusters disappear. Such results suggest that individual and neighborhood socioeconomic determinants may have an impact on the spatial dependence of daily tobacco consumption, and that tobacco consumption facilities, may also spatially influence this smoking behavior independently of socioeconomic factors. Besides, our results suggest that the smoking ban in Geneva is not influencing the spatial distribution of daily tobacco consumption.

Hot spots showed a lower neighborhood household income, a lower proportion of highly educated individuals and highly skilled workers, and a higher prevalence of unmarried participants, a finding consistent with other studies that detected a relationship between individual and environmental socioeconomic inequalities with the geographic

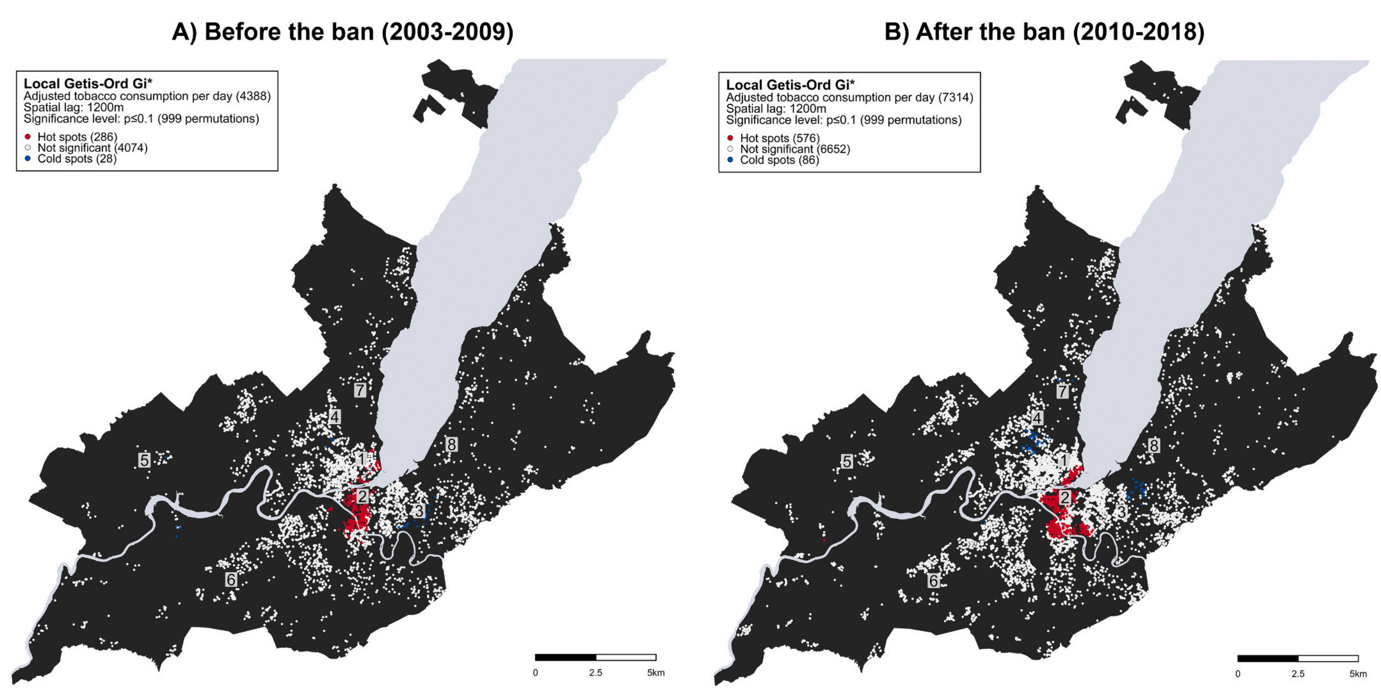

Fig. 2. Spatial distribution of daily tobacco consumption before (A) and after (B) the smoking ban implementation in Geneva adjusted for individual and neighborhood socioeconomic factors (Getis-Ord Gi*). Statistical significance is assessed at an α threshold of p ≤ 0.1 FDR correction included. Red dots (hot spots) indicate individuals in areas showing high values of daily tobacco consumption, blue dots (cold spots) indicate individuals in areas showing low values of daily tobacco consumption, white dots indicate individuals in areas where tobacco consumption is not spatially dependent. Numbers 1–8 in the maps represent landmarks to support the description of the results.

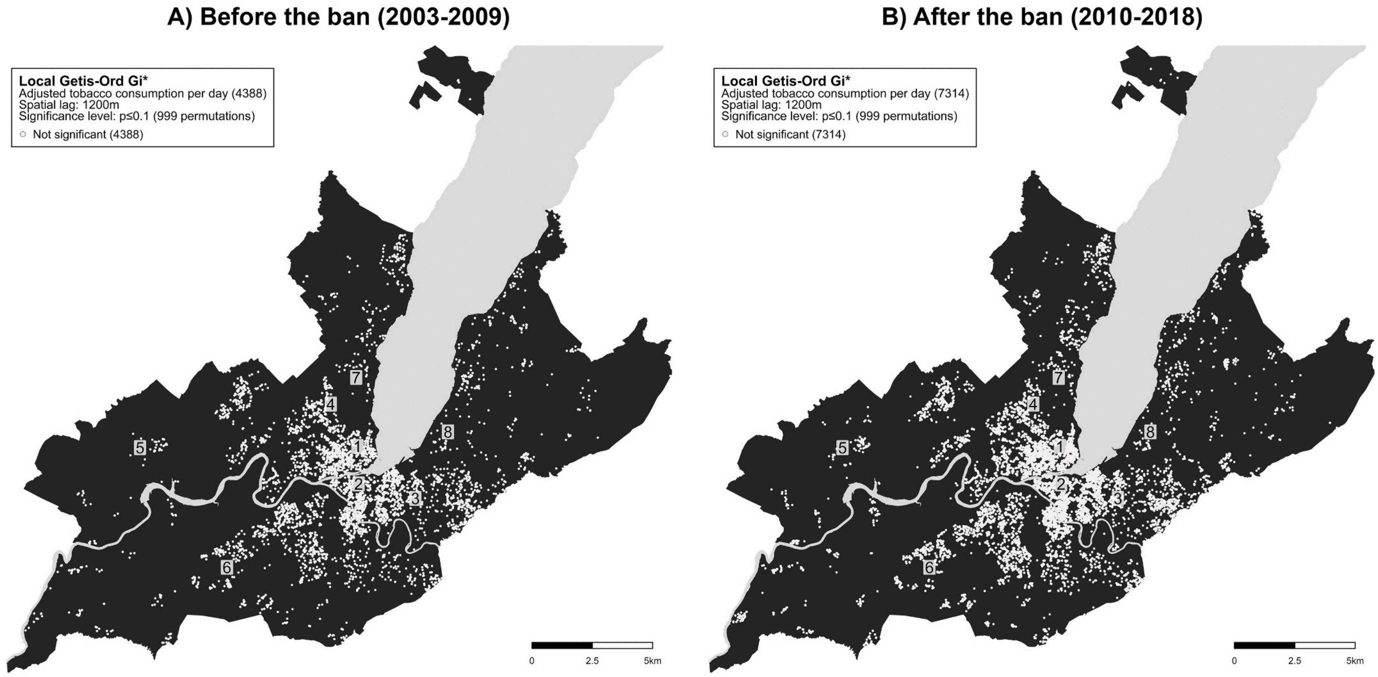

Fig. 3. Spatial distribution of daily tobacco consumption before (A) and after (B) the smoking ban implementation in Geneva adjusted for individual and neighborhood socioeconomic factors and the density of tobacco consumption facilities (Getis-Ord Gi*). Statistical significance is assessed at an α threshold of $p \leq 0.1$ FDR correction included. Red dots (hot spots) indicate individuals in areas showing high values of daily tobacco consumption, blue dots (cold spots) indicate individuals in areas showing low values of daily tobacco consumption, white dots indicate individuals in areas where tobacco consumption is not spatially dependent. Numbers 1–8 in the maps represent landmarks to support the description of the results.

distributions of smoking behaviors using a spatial methodology (Brooks et al., 2021; Caraballo et al., 2019; Galiatsatos et al., 2020; Généreux et al., 2012; Kane and Farshchi, 2019; Xie et al., 2020). Since socioeconomic factors are closely related to smoking outcomes, it is not surprising that we observed a substantial reduction in the cluster sizes after adjusting for such variables. Indeed, individuals with lower education and income are less likely to quit smoking (Hiscock et al., 2012; Reid et al., 2010) and married individuals present a lower smoking prevalence (Ramsey et al., 2019). Those socioeconomic differences in the spatial clusters of daily tobacco consumption were observed before and after the implementation of a smoking ban. Other authors have also observed persistent socioeconomic inequalities in smoking after the introduction of smoke-free policies (Gagné et al., 2020; Tchicaya et al., 2016). Such findings should be paid significant attention as they suggest that smoke-free legislations are not achieving a pro-equity effect as desired (Smith et al., 2020).

The significant reduction in the size of the spatial clusters after including the density tobacco consumption facilities in the regression model was not surprising for the period before the ban, as these locations may promote smoking through high accessibility to tobacco products and tobacco advertising (2National Center for Chronic Disease Prevention and Health Promotion (US) Office on Smoking and Health, 2012). However, this strong association with the density of tobacco consumption facilities was unexpected after the ban as smoking was no longer allowed in such facilities. Some other factors may explain why we found a reduction in the size of the spatial clusters when including tobacco consumption facilities in the model after the smoking ban. For instance, some smoke-free policies (Geneva included) are limited by allowing smoking in amenities that have dedicated or ventilated areas (van Beek et al., 2019; WHO, 2019), and evidence shows that some individuals may move smoking from indoors to outdoors in public spaces after a smoke-free policy (Kennedy et al., 2012; Rooke et al., 2013), Moreover, it is likely that in areas with a high density of tobacco consumption facilities also exists a higher exposition to other factors that may influence smoking, such as promotion of tobacco products (Giovenco et al., 2020) and tobacco retailers (Finan et al., 2019; Marsh et al., 2020). Indeed, in a complementary analysis, we observed that a high density of tobacco consumption facilities was positively correlated with a high density of tobacco retailers. Sensitivity analysis also showed that tobacco consumption facilities explained a higher proportion of the spatial clusters of tobacco consumption than tobacco consumption retailers (i.e. the size of the spatial clusters is greater reduced when adjusting for tobacco consumption facilities).

As in studies assessing the spatiotemporal trends of smoking behaviors (Lee and Lawson, 2016; Meng et al., 2015) that found a decrease in the smoking prevalence and incidence over time, we also observed a reduction in the amount of tobacco smoked after the ban. The health effects of a reduction in the number of cigarettes smoked are still controversial (Lindson-Hawley et al., 2016; Tverdal and Bjartveit, 2006), but evidence suggests that this reduction (three daily cigarettes in our study) may impact the success of smoking cessation (Begh et al., 2015). Nevertheless, better individual and environment life conditions - in line with demographic developments in Geneva - (OCSTAT, 2018) were observed after the ban. Thus, we cannot conclude this reduction in daily tobacco consumption was an exclusive effect of the smoke-free policy, as it is very likely that these individual and environment differences also accounted for the lower amounts of tobacco consumed after the ban implementation.

Despite a lower tobacco consumption after the ban, we observed a persistent geographic pattern of tobacco consumption. Over time, geographic persistence in tobacco use has been suggested to reflect an interplay between tobacco price, the income of individuals, and smuggling across adjacent borders (Almeida et al, 2020, 2021; Ciccarelli and Elhorst, 2018; Hoffer et al., 2019). However, due to the fact tobacco is cheaper in Switzerland than in France (pack of 20 cigarettes: 6.83 vs 10.08 US dollars, adjusted for purchasing power parity) (WHO, 2019), we should not expect cross-border smuggling to be a key determinant of the persistence of the spatial tobacco footprint in the particular case of Geneva. In fact, French smokers reported a high proportion of cross-border purchases in the Swiss border due to lower cigarette prices

(Nagelhout et al., 2014). Since the individual and neighborhood socioeconomic status and built environment characteristics (density of tobacco smoking facilities) of the spatial clusters of tobacco consumption were similar between the two studied periods, the geographical persistence of tobacco consumption in Geneva seems to be explained by these socioeconomic and built neighborhood factors. Nevertheless, we cannot exclude completely the role that tobacco price might play either, indeed, the increment of tobacco taxes in Switzerland over time (FCA, 2020) could also account for the lower consumption of tobacco we observed after the smoking ban (Almeida et al., 2020; Hoffer et al., 2019; Nargis et al., 2020). We also observed an increment in the size of the hot spots after the ban (3% and 1% for the raw and adjusted models, respectively), however, this could be a product of random variability in the analysis as we used random permutations to assess significance.

The spatial analyses using Local Moran's I showed similar patterns as Getis-Ord Gi*. Nevertheless, the former approach allowed us to identify clusters of intertwined subjects (i.e. individuals with high daily tobacco consumption surrounded by individuals with low daily tobacco consumption and vice versa), which is partially expected because we included the non-smoker population. However, the fact that there were several clusters showing individuals with opposite smoking behaviors is indeed worrying, as it suggests that low tobacco consumers may be at risk of becoming high tobacco consumers, either influenced by high tobacco users or by the environment where they live. Moreover, it may also indicate a high concentration of potential passive smokers, a population at risk of lung cancer, and cardiovascular and respiratory diseases (National Center for Chronic Disease Prevention and Health Promotion (US) Office on Smoking and Health, 2014).

4.1. Strengths

To the best of our knowledge, this is the first study to evaluate the spatial dependence of tobacco consumption at the individual level and to assess the impact of tobacco consumption facilities on daily tobacco consumption before and after a smoke-free policy from a geographic perspective. Moreover, using individuals georeferenced at the place of residence, instead of populations aggregated at the level of administrative units, allowed us to analyze a large population sample over a continuum space which is better translating the way people interact in their daily life.

4.2. Limitations

The use of a single indicator - neighborhood household income - to represent a complex dimension such as the deprivation status of the neighborhood may limit our inferences from this environment. Similarly, we did not include data related to tobacco products' costs and taxes, such information associated with tobacco affordability and smuggling, is recognized to influence tobacco consumption (Nargis et al., 2020) and would have allowed a better characterization of tobacco consumption's geographic distribution and evolution. Additionally, the REG lists only data from active facilities, which may not be entirely representative of all tobacco consumption facilities during the studied period (2003–2018). Due to the nature of cross-sectional studies, our results may suffer from reverse causation (i.e. areas of high tobacco users may increase the presence of tobacco consumption facilities), and we were limited by not being able to evaluate other environments in addition to the place of residence, such as the work or study environments. Likewise, the limited size of our yearly sample did not allow performing a spatiotemporal analysis to identify possible yearly differences in the geographic distribution of tobacco consumption. Moreover, the comparison before and after the ban could be biased since the data are cross-sectional and not longitudinal. Finally, smokers may be misrepresented (Jakob et al., 2017), and our results may not be representative of individuals below 35 years as they were not consistently included in the selection criteria of the Bus Santé survey.

4.3. Policy implications

Our findings show that spatial analysis can highlight the impact of smoke-free policies from a geographic perspective and delimit local areas of populations at risk. Such tools can guide decision-makers to reinforce public health policies and better allocate resources in small areas.

Furthermore, our results may encourage policymakers to reinforce comprehensive smoke-free legislations (WHO, 2019) as policies that allow smoking in ventilated or dedicated areas may be ineffective on impacting the spatial distribution of tobacco consumption. The lack of effectiveness of smoke-free policies can also be motivated by other factors that should be considered when implementing smoking preventive policies such as restricting the proximity and density of tobacco retailers per neighborhood (Finan et al., 2019; Marsh et al., 2020), banning tobacco consumption at institutional settings (Fichtenberg and Glantz, 2002; Frazer et al., 2016b), and controlling the exposure to pro-tobacco campaigns (Giovenco et al., 2020). Particular attention should be paid to increasing tobacco taxes since such interventions were proven to lower tobacco consumption (Almeida et al., 2020; Hoffer et al., 2019; Nargis et al., 2020) without a negative equity impact on socioeconomic inequalities (Smith et al., 2020). Furthermore, the implementation of such policies demands cooperation among adjacent regions or nations. The lack of a coordinated strategy could increase tobacco smuggling (Almeida et al., 2020) and lack of impact on smoking outcomes.

5. Conclusions

Spatial analysis revealed geographic patterns of daily tobacco consumption in Geneva before and after a smoke-free policy implementation. The smoking ban did not modify the geographic patterns of daily tobacco consumption. Tobacco consumption facilities were spatially associated with daily tobacco consumption independently of individual and neighborhood socioeconomic factors. Spatial analysis should be considered to highlight the role of the living environment, assess the impact of public policies, and strength public health interventions.

Statements

Contributors JRV-R, JLS, IG, SJ, J-PH, JC, PM-V, and NP-H designed the research. JRV-R, JLS, IG, and SJ analyzed and wrote the paper. JRV-R, IG, SJ, DDR, and AL collected and prepare the data. All the authors reviewed the paper, contributed intellectually to the development of this paper, and approved the final manuscript. IG is the guarantor.

Funding

This paper is part of a major project supported by the Tobacco Control Fund from the Federal Office of Public Health in Switzerland, grant number: 240.0007–16/3/5390186. The Bus Santé study is funded by the General Directorate of Health, State of Geneva, Switzerland, and the Geneva University Hospitals. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Data availability statement

Data are not publicly available due to the sensitive nature of individual geolocated information. Data requests to the GIRAPH group (giraphlab@giraph.org) may be possible upon agreement of the data provider and signature of a data transfer agreement.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2021.102616.

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