Impact of Smoke-Free Air Laws on Secondhand Smoking: Evidence From New York City

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Anti-smoking laws reduce exposure to secondhand smoke in areas that are targeted by such laws; however, the effects of these laws on displacing smokers to alternative locations where smoking is allowed remains unexplored due to limited data. This paper uses unique nonparticipant observational data on smoking frequency and location from New York City to estimate the impact of secondhand smoke exposure. Estimates indicate that nonsmokers are exposed to secondhand smoke once every 1.9 city blocks, and exposure is greater near smoking-restricted areas such as schools and hotels, which suggests anti-smoking laws displace smokers and increase exposure for others.

Keywords: secondhand smoke, anti-smoking laws

INTRODUCTION

Over past several decades, smoking rates in the USA have substantially declined, however, the public health dangers from smoking are still prevalent as approximately 30.8 million individuals continue to smoke daily according to the (Cornelius, et al., 2020). Smokers aren't the only individuals affected by smoking; nonsmokers face environmental tobacco smoke (ETS), also known as secondhand smoke, which affects approximately 58 million nonsmokers in the USA and is responsible for numerous deaths worldwide and is known to cause major health problems for adults and children (Tsai, et al., 2018). To combat the threat of secondhand smoke, many localities have enacted anti-smoking laws banning smoking in a variety of public and private places. These laws have little effect on decreasing smoking but have generally led to a reduction in exposure to secondhand smoke by nonsmokers in protected areas (Adda & Cornaglia, 2010; Carpenter, Postolek, & Warman, 2011). However, little is known regarding the effects of anti-smoking laws on secondhand smoking in locations that aren't protected by such laws. Large cities' main remaining smoking havens are sidewalks, private cars, and private residences. Evidence is mixed whether anti-smoking laws displaced smokers to private residences and cars (Adda & Cornaglia, 2010; Mons, et al., 2013; Callinan, et al., 2010). Evidence for smoking displacement onto city sidewalks is unknown due to lack of data. Survey data generally doesn't report precise smoking location and may suffer from underreporting by certain smoking populations (Nesson, 2017). Data on biomarkers such as serum cotinine levels provides accurate measurement of smoking, however it has a short half-life and cannot provide detail on where smokers actually smoke.

City sidewalks are important places of activity for city populations due to limited open spaces and lack of traditional suburban backyards. Understanding passive exposure to secondhand smoking on city sidewalks and crafting new policies to combat secondhand smoking will help to protect these populations and their children. Large cities such as New York City (NYC) have experienced population growth and have disproportionally attracted young working professionals who are in their prime childbearing years (Frey, 2017). Medical literature has identified that secondhand smoking can be harmful to individuals even if there is passive acute exposure (Flouris, et al., 2009). Recent medical studies suggest that a negative effect of outdoor secondhand smoking can be felt anywhere within 6.5 feet and even up to 30 feet (Howarth, 2013; Huffington Post 2012, October 22) . This would certainly affect all pedestrians on sidewalks walking in proximity to a smoker. Given the large population density in cities, understanding and preventing secondhand smoking exposure on sidewalks has potential to improve public health.

This study uses observational data collected over several months on NYC sidewalks to investigate smoking patterns and displacement on city sidewalks. The research documents frequency of nonsmokers' exposure to ETS and then shows how specific sidewalk locations are associated with the presence of businesses and organizations targeted by anti-smoking laws. The findings suggest that nonsmokers encounter ETS approximately once every 1.9 blocks, with areas near schools, health clinics, and hotels attracting higher concentrations of smokers.

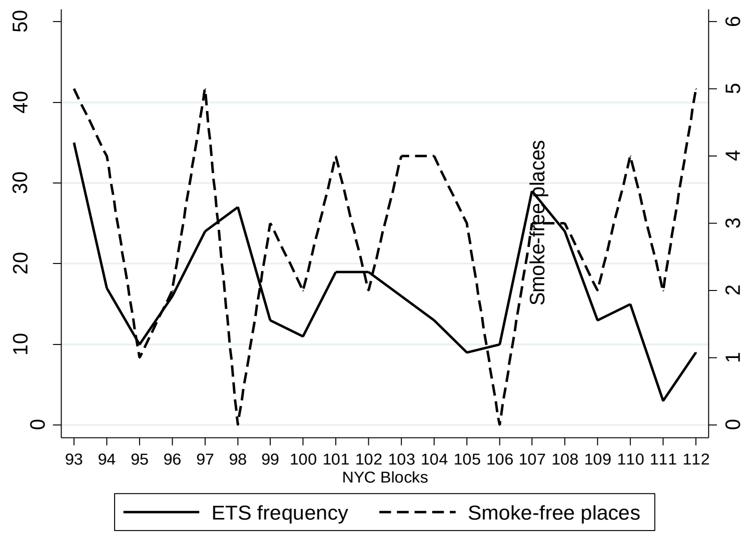
METHODS

The observational data collected on secondhand smoking consists of 332 observations collected over five months in New York City over a randomly selected 20 city blocks in Manhattan. Each observation in the data records the location of an individual smoking on city sidewalk. GPS technology was used to accurately observe the exact location of where individuals were observed smoking. In addition to randomly selecting city blocks, the days of the week were also randomly selected but only included weekdays. All data was collected between 8:00am and 4:30pm. Only the location of someone smoking was included in the data collection and no personal characteristics were collected. In addition, information on the characteristics of each city block was obtained, including the number of schools, restaurants/bars/pubs, health facilities, subway entrance, and hotels on or near a given city block. The data was verified using Google Maps to check the location of each of these establishments.

Analysis

Figure 1 provides the observed smoking frequency for each of the 20 blocks over sample observations. There is wide variation in exposure to ETS over the 20 city blocks. City blocks such as 111th street have very few encounters with ETS, whereas blocks such as 107/108 have high frequency of ETS exposure. There are several potential explanations for this pattern of ETS exposure. One possibility is that more smokers live near these city blocks; information on how many smokers live in each block is not available. However, information on income and education within four square blocks is available from NYC Population FactFinder data. There is substantial variation in education and income in these neighborhoods but no clear evidence that city blocks with more educated and wealthier individuals have fewer instances of ETS exposure.

FIGURE 1
ETS FREQUENCY AND SFP FREQUENCY



Furthermore, if number of smokers in each neighborhood was the main explanation for the variation in Figure 1, then there would be less variation in ETS exposure from block to block and more by neighborhood. For instance, the number of smokers in the neighborhood would not explain why the frequency of ETS exposure at 94^{th} and 96^{th} block is high and there are fewer instances on 95^{th}. If smokers selected certain neighborhoods, there should be less variation within a few blocks and higher variation from neighborhood to neighborhood, for example every 5 blocks. It is also possible that residents smoke on the sidewalk in front of their apartment building, but this again would not explain this high variation from block to block, especially that this street in Manhattan has few apartment building entrances and many more commercial establishments. Many of the residential entrances are on side streets where there is a lot less pedestrian traffic.

The other explanation for this variation is the possibility that the types of businesses/organizations located on the given city block influence where individuals smoke. Figure 1, in addition to the frequency of ETS for each city block, also includes the total frequency of places that prohibit smoking that were targeted by anti-smoking laws. Every city block includes predominantly commercial establishments that prohibit smoking. The only establishments that are excluded from anti-smoking laws are private residences and tobacco shops and bars.

Using the definitions of anti-smoking laws, I construct a Smoke-Free Places (SFP) variable, which is the total number of establishments on a given block that were targeted by anti-smoking laws, including all restaurants, bars, pubs, hotels, schools, subway station entrances, and health clinics. Anti-smoking laws were written to protect people from smoking in places where individuals spend long periods. Figure 1 compares SFP for each city block and to the observed ETS frequency. There is a positive correlation between the two variables; city blocks with higher number of SFP also have higher ETS frequency on sidewalks near the SFP. This provides evidence that there is an association between outdoor ETS and types of establishments that are present on a given block.

Model

I estimate the following reduce form model to further investigate the association between street/neighborhood characteristics and observed smoking frequency.

$$ln(S_{it}) = b_0 + b_1 ln(SFP_i) + b_2 \boldsymbol{X_i} + b_3 \boldsymbol{Z_t} + \boldsymbol{time_t} + e_{it} \quad (1)$$

This model does not attempt to explain why an individual decides to smoke, it only links smoking location choice to street characteristics. All results are conditional on individual deciding to smoke in the first place. The dependent variable S_{it} is the total number of times individual i is observed smoking on a given city block at survey time t. The main independent variable is the total number of smoke-free places (SFP_i) on a given block which does not vary over time. The vector $\boldsymbol{X_i}$ represents block specific demographic characteristics including proportion of females, racial make-up of the neighborhood, education, average age, income, and employment gathered from NYC Population FactFinder database. I control for these neighborhood characteristics as they affect individual's choice of residence and therefore, impact how many smokers are on the streets since individuals self-select to live in given neighborhoods. I also include vector $\boldsymbol{Z_t}$ which represents time-varying characteristics of when the observations were collected, including morning or afternoon, temperature at time of observation, and dummy for cloudy or sunny. The specification also includes time dummies ($\mathbf{time_t}$) for each time data was collected to account for any unobservable time characteristics. I estimate the equation using pooled OLS and random effects regression. Fixed effects regression cannot be utilized as SFP_i remains constant in each block over time.

I also disaggregate the *SFP* variable and provide alternative specifications where I include dummies for each establishment that specifically prohibit smoking due to anti-smoking laws. I estimate the following equation.

$$ln(S_{it}) = b_0 + b_1 School_i + b_2 BRP_i + b_3 Health_i + b_4 Subway_i + b_5 Hotel_i + b_6 \boldsymbol{X_i} + b_7 \boldsymbol{Z_t} + \mathbf{time_t} + e_{it} \quad (2)$$

where *School* is a dummy equal to one if there is a school on a given block, *BRP* is dummy equal to one if there is a bar, restaurant, or pub on a given block, *Health* is a dummy equal to one if there is a health clinic on a given block, *Subway* is a dummy equal to one if there is a subway entrance on a given block, and finally *Hotel* is a dummy equal to one if there is a hotel on a given block.

RESULTS

Data was collected over 31 random days with 332 total observations on ETS, which provides an average of 10.7 observations per day; or the average exposure to ETS occurs once every 1.9 blocks. Literature on cigarette consumption indicates that it takes approximately 6.8 puffs to smoke a cigarette, depending upon the type of cigarette as higher-yield cigarettes take more puffs (Stitzer & Zacny, 1996). Therefore, a person walking 20 city blocks is exposed to approximately a total of 1.57 (10.7/6.8) cigarettes of outdoor ETS. This estimate assumes only one breath of ETS per exposure whereas in many situations a nonsmoker will inhale additional smoke. To put this estimate in a cumulative context, if a nonsmoker walks 20 blocks to and from work/school each day, she will be approximately exposed to 816.4 cigarettes of outdoor ETS per year, assuming 52 weeks and 5 days of work.

Table 1 provides the main estimation results from equation (1). I estimate six separate models, the first three using pooled OLS and the next three using random effects. All models include robust standard errors that were clustered at the block level. The main coefficient on the total number of smoke-free places (*SFP*) per given block is positive and significant indicating that an increase in one percent of smoke-free places (SFP) is associated with an increase of observable exposure to ETS by 0.136 to 0.247 percent. I conducted the Breusche and Pagan Lagrangian multiplier test, confirming the preferred estimation to be random effects. In the random effects estimation, the main coefficient of interests is positive and significant, with majority of the other variables lacking significant explanatory power for smoking location choice.

TABLE 1
RESULTS FOR MODEL

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) RE	(5) RE	(6) RE
ln SFP	0.136**	0.139*	0.247***	0.140**	0.143**	0.242*
	(0.0539)	(0.0662)	(0.0362)	(0.0589)	(0.0689)	(0.126)
Female percent		-0.00811	-0.0759***		-0.00622	-0.0561**
		(0.0301)	(0.0157)		(0.0326)	(0.0283)
White percent		0.0120	0.0209***		0.0100	0.0333
		(0.0241)	(0.00449)		(0.0258)	(0.0307)
Age		0.541			0.392	2.271
		(2.140)			(2.267)	(3.563)
Age squared		-0.00766	-0.000967*		-0.00570	-0.0303
		(0.0281)	(0.000474)		(0.0297)	(0.0466)
Education		0.00524	0.0281**		0.00348	0.0579
		(0.0447)	(0.0112)		(0.0473)	(0.0790)
Income		-2.12e-05	-5.09e-05**		-1.80e-05	-7.51e-05
		(5.28e-05)	(1.92e-05)		(5.60e-05)	(8.79e-05)
Employment		0.0484	0.0761*		0.0444	0.0777
		(0.0481)	(0.0399)		(0.0508)	(0.0827)
Morning Dummy		0.105	0.615**		0.100	0.439
		(0.0733)	(0.252)		(0.0725)	(0.319)
Temperature		-0.375**			-0.363**	-0.473
		(0.177)			(0.176)	(1.911)
Cloudy Dummy		0.0671	-0.196		0.0613	-0.458
		(0.0650)	(0.340)		(0.0639)	(0.426)
Constant	0.102*	-9.530	1.736**	0.103*	-6.638	-41.65
	(0.0578)	(41.95)	(0.695)	(0.0586)	(44.39)	(73.10)
Observations	209	209	209	209	209	209
R-squared	0.019	0.071	0.266			
Number of NYC blocks				18	18	18
Time FE			Yes			Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Breusche and Pagan Lagrangian multiplier test indicates that RE is the preferred method for all estimation.

To further investigate how individual street characteristics impact choice location of smokers and exposure to ETS, I estimate equation (2) where I use dummy variables for each place specifically targeted by anti-smoking laws. Table 2 reports six specifications with dummy variables for Bars, Restaurants, Pubs (BRP), Schools, Health facilities, Subway entrances, and Hotels. All specifications have robust standard errors clustered at the block level. In all six specifications, the coefficient on School is positive and significant, indicating that a block with a school is associated with an increase in incidence of observable ETS. The largest coefficient on School is in specification six where I estimate the full model using random effects with time dummies. The coefficient of 0.281 indicates that blocks with schools will have an increased ETS exposure of 28 percent relative to city blocks without establishments targeted by anti-smoking laws.

TABLE 2
RESULTS FROM MODEL

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) RE	(5) RE	(6) RE
School Dummy	0.193***	0.239***	0.222***	0.197***	0.239***	0.281***
	(0.0526)	(0.0578)	(0.0208)	(0.0545)	(0.0578)	(0.0412)
BRP Dummy	-0.0495	-0.0304	-0.191***	-0.0394	-0.0304	-0.117*
	(0.0850)	(0.0636)	(0.0422)	(0.0847)	(0.0636)	(0.0685)
Health Dummy	0.0424	-0.0302	-0.0450	0.0528	-0.0302	0.177**
	(0.0673)	(0.0833)	(0.0609)	(0.0626)	(0.0833)	(0.0869)
Subway Dummy	-0.0854*	-0.0946	-0.293***	-0.0889*	-0.0946	-0.234***
	(0.0484)	(0.0602)	(0.0300)	(0.0491)	(0.0602)	(0.0341)
Hotel Dummy	-0.0492	-0.0174	-0.110***	-0.0518	-0.0174	0.0969**
	(0.0469)	(0.0875)	(0.0303)	(0.0486)	(0.0875)	(0.0472)
Female percent		0.0922	0.0801***		0.0922	-0.00486
		(0.0570)	(0.0100)		(0.0570)	(0.0230)
White percent		-0.0218	0.0192***		-0.0218	0.0468**
		(0.0407)	(0.00342)		(0.0407)	(0.0198)
Age		-2.533			-2.533	1.975
		(3.642)			(3.642)	(1.779)
Age squared		0.0344	0.00209***		0.0344	-0.0253
		(0.0479)	(0.000263)		(0.0479)	(0.0236)
Education		-0.0948	-0.0475***		-0.0948	0.0232
		(0.0802)	(0.00537)		(0.0802)	(0.0429)
Income		0.000129	7.79e-05***		0.000129	-3.19e-05
		(9.93e-05)	(8.79e-06)		(9.93e-05)	(5.71e-05)
Employment		-0.181*	-0.185***		-0.181*	-0.0171
		(0.0989)	(0.0216)		(0.0989)	(0.0696)
Morning Dummy		0.0488	-0.166		0.0488	0.375
		(0.0690)	(0.333)		(0.0690)	(0.292)
ln Temperature		-0.0411			-0.0411	0.156
		(0.244)			(0.244)	(1.860)
Cloudy Dummy		0.0105	0.188		0.0105	-0.616
		(0.0629)	(0.327)		(0.0629)	(0.407)
Constant	0.223**	49.86	0.00381	0.212**	49.86	-39.07
	(0.101)	(71.20)	(0.514)	(0.0999)	(71.20)	(32.29)
Observations	233	233	233	233	233	233
R-squared	0.061	0.103	0.263			
Number of NYC blocks				20	20	20
Time FE			Yes			Yes

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Breusche and Pagan Lagrangian multiplier test indicates that random effects (RE) is the preferred method for all estimation.

In Table 2, other coefficients on street characteristics are also significant. I focus on specification six with all control and random effects estimation as per the Breusche and Pegan Lagrangian multiplier test. The coefficient on bars, restaurants, and pubs is negative indicating that blocks with these establishments have a decreased smoking presence by 11.7 percent relative to blocks without bars, restaurants, and pubs. Blocks that have health facilities are associated with a 17.7 percent higher incidence of smoking and exposure to ETS. Hotel dummy is positive and significant, indicating an increase in smoking incidence by 9.7 percent relative to blocks without hotels. The last coefficient of interest is the dummy on subway entrances, where this coefficient is negative and significant across all specifications, indicating blocks with subway entrances have a lower incidence of smoking.

DISCUSSION

There is little known about the effects on passive ETS experienced by individuals in places that legally allow smoking. City sidewalks are one of the main public places left that allow smoking in the presence of large numbers of nonsmokers. There is anecdotal evidence that this is a problematic issue for residents of cities (Saletan, 2012). This study has used observational data gathered in New York City to examine smoking frequency and exposure to secondhand smoke on city sidewalks. Anti-smoking legislation enacted over the past several decades has improved health outcomes for entire populations (Callinan, et al., 2010; Hahn, 2010; International Agency for Research on Cancer, 2009). However, recent study on multiple states passing anti-smoking laws found no association between these laws and hospital admittance rates for heart failure but did reduce pneumonia hospitalization (Ho, et al., 2016; Grier, 2017). A potential reason for these laws not having the desired effect could be displacement of smokers from restricted areas to homes and allowed public places. Displacement to home isn't clear as research found no displacement among Canadian smokers, but other studies did find higher presence of smoking at home (Carpenter, Postolek, & Warman, 2011; Adda & Cornaglia, 2010). Effects of smoking displacement to city sidewalks has previously been undocumented due to lack of data. This research provides the first evidence for positive association between establishments that were targeted by anti-smoking laws and frequency of ETS on city blocks with those establishments.

The largest positive effect is found on blocks with a school in the vicinity. New York law dictates that individuals are not allowed to smoke within 100 feet of the school, which would propel smokers to gather within close distance before entering or leaving school areas. Data used in the research doesn't identify individuals, however, it is logical that parents light up a cigarette after dropping off their child for school or finish smoking just before they pick up their child. This idea would support previous literature that found no smoking displacement to homes, as parents smoke outside of home to avoiding exposing children (Carpenter, Postolek, & Warman, 2011). Further data collection with the ability to identify individuals is needed to prove this.

Results show that there is a negative effect for blocks with bars, restaurants, and pubs (BRP). Aim of many anti-smoking laws was to specifically ban smoking in BRP which would potentially lead to individuals smoking outside before they enter one of these establishments. The observation data used in this study was collected during working hours where fewer individuals are likely to visit these establishments.

City blocks that have health facilities are associated with higher incidence smoking and exposure to ETS. Anti-smoking laws prohibit smoking within 15 feet of the entrance to health clinics, which would indicate that individuals will smoke on the block away from the entrance, regardless of whether they will go into the clinic or not. The coefficient on hotels is positive as smoking inside most of the hotel space is prohibited forcing individuals to smoke outside the hotel on the sidewalk. The negative coefficient on subway entrances is harder to explain since smoking inside the subway stations is prohibited. One potential explanation is that individuals smoke on their way to the subway instead of getting to it and then lighting up a cigarette. Individuals who exit the subway will start smoking but will walk away and not linger next to the subway entrance.

Weaknesses

It is possible that due to the nature of the data used in this research, the findings are more generalizable to large cities like New York City and results could potentially be weaker for cities with lower population density and less applicable to rural areas where population density is much lower and anti-smoking laws are less applicable in outdoor settings. However, this research is still important as in sheds light on the potential health effects to large population and hopefully will encourage further investigation to which populations are affected by ETS, how much they are affected, and what policy needs to be implemented to further limit negative impacts of ETS on population health.

CONCLUSION

This research aims to shed light on frequency of exposure to ETS individuals face on city sidewalks and to provide evidence that this exposure to ETS is linked to two decades of anti-smoking laws that have effectively displaced smokers to sidewalks. To understand patterns of sidewalk smoking, nonparticipant observation data was collected over several months on New York City sidewalks. The findings indicate that nonsmokers are exposed to ETS once per 1.9 blocks, and locations such as schools, health clinics, and hotels attract a greater number of smokers in their vicinity. If anti-smoking laws are contributing to sidewalk smoking through the displacement of smokers, then a new policy should be drafted that will further address this unintended consequence.

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