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► **To cite this version:**

Jérôme Ronchetti, Anthony Terriau. Help me quit smoking but don't make me sick! The controversial effects of electronic cigarettes on tobacco smokers. *Social Science & Medicine*, 2021, 274, pp.113770. 10.1016/j.socscimed.2021.113770 . hal-03385340

**HAL Id: hal-03385340**

<https://univ-lyon3.hal.science/hal-03385340v1>

Submitted on 10 Mar 2023

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**Title:** Help me quit smoking but don't make me sick! The controversial effects of e-cigarettes on tobacco smokers

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# Help me quit smoking but don't make me sick!

## The controversial effects of electronic cigarettes on tobacco smokers

### Abstract

Despite its increasing use, little is known about the effect of electronic cigarette. This study estimates the impact of the use of electronic cigarettes on tobacco smoking and health among tobacco smokers, using French panel data derived from the Health, Health Care, and Insurance Survey for 2010–2014. We use a difference-in-differences propensity score matching approach to identify the effect of electronic cigarette use on a sample of 982 smokers. We show that the use of electronic cigarettes increases the probability of quitting smoking and reduces the number of regular cigarettes smoked per day. However, we also find evidence that electronic cigarette users have a higher probability of reporting poor health status and suffering from a chronic disease compared with those who only smoke regular cigarettes. Overall, our results do not support the use of electronic cigarettes for tobacco smokers.

**Keywords:** Electronic cigarette, Tobacco, Health, Difference-in-differences, Propensity score matching

# 1 Introduction

For decades, tobacco control has been a major public health concern, and a plethora of studies have highlighted the human cost of smoking. It is well known that smoking is linked to a higher prevalence of serious illnesses such as cancer, cardiovascular diseases, and lung diseases [Bartecchi et al., 1994; Bjartveit and Tverdal, 2005; Sturm, 2002; Teo et al., 2006; Turner et al., 1998]. In developed countries, 20% of deaths are attributable to tobacco, which makes it the leading cause of mortality [Danaei et al., 2009; Ma et al., 2018; Mokdad et al., 2004; Peto et al., 1992].

Smoking has also had a significant economic impact [John et al., 2009; Mcghee et al., 2006]. Goodchild et al. [2018], using the cost of illness approach, estimated the economic costs of smoking-attributable diseases in 2012 for 152 countries. The economic costs include direct costs such as hospital fees and indirect costs such as productivity losses due to morbidity and mortality [Batenburg and Reinken, 1990; Halpern et al., 2001]. They found that healthcare expenditure due to smoking-attributable diseases totaled purchasing power parity (PPP) \$467 billion, equivalent to 5.7% of global health expenditure. The total economic cost of smoking (from health expenditure and productivity losses) totaled PPP \$1852 billion in 2012, equivalent to 1.8% of the world's annual GDP. Smoking brings with it a heavy economic burden globally, but particularly in Europe and North America where the tobacco epidemic is most widespread. The majority of academic studies point out a need to implement stronger tobacco control measures to reduce these costs.

Several levers have been used to encourage people to stop smoking, including tax increases, information campaigns, and substitute products. In the latter case, therapeutic methods are usually adopted, and smokers begin by using nicotine products such as patches and gum. This approach is generally effective at progressively reducing the problem of addiction, while helping smokers avoid the toxic compounds associated with tobacco [Fiore et al., 1994b; Group, 1993; Tang et al., 1994]. However, these treatments require significant resources in terms of nursing, patient advice, follow-up, and relapse prevention [Fiore et al., 1992, 1994a; Hurt et al., 1994; Lemmens et al., 2008]. In addition, they do not compensate for social losses [Falomir and Invernizzi, 1999; Lindström et al., 2003]. In this context, it is easy to understand the rapid adoption of electronic cigarettes from the early 2010s among tobacco smokers [Farsalinos et al., 2016]. In France, electronic cigarettes began to be commercialized at the end of 2010/beginning of 2011. The wide-scale distribution of electronic cigarettes started in 2012 [Pasquereau et al., 2019]. This new mechanism

is a battery-operated device that provides a controlled dose of vaporized nicotine or non-nicotine solutions to the user. The objective is to provide a sensation that mimics inhaling tobacco smoke, but without the smoke. Using electronic cigarettes, which are thought to be less risky than regular cigarettes [Pepper et al., 2015], can preserve the social aspect of smoking. Consequently, they are often seen as a valuable theoretical tool to encourage people to reduce or stop tobacco consumption.

However, do electronic cigarettes really help users reduce or stop smoking? The evidence suggests that some tobacco smokers use electronic cigarettes as a therapeutic tool to help them reduce or quit smoking [Dawkins et al., 2013; Etter, 2010; Etter and Bullen, 2011; Farsalinos et al., 2013; Foulds and Veldheer, 2011]. Indeed, several studies suggest that nicotine addiction is as present as ever [Barbeau et al., 2013; Dawkins et al., 2013; Etter, 2010; Goniewicz et al., 2013]. Although tobacco smokers progressively replace regular cigarettes with electronic cigarettes, their nicotine consumption remains unchanged. On the one hand, the studies by Polosa et al. [2011, 2014] and Caponnetto et al. [2013] suggested that the use of electronic cigarettes can reduce the number of regular cigarettes smoked. On the other hand, Etter and Bullen [2014] highlighted that although electronic cigarettes may contribute to relapse prevention for former tobacco smokers and smoking cessation for current tobacco smokers, they are not significantly more effective than nicotine patch therapy [Bullen et al., 2013]. More recently, in a randomized trial of 886 participants, Hajek et al. [2019] found that electronic cigarettes may be more effective for smoking cessation than nicotine replacement therapy when both products are accompanied by behavioral support.

What exactly do electronic cigarettes contain? This is a controversial question. The huge number of liquids and high black market production make it difficult to generalize. A crucial distinction with regular cigarettes is that a variety of electronic cigarettes exist. The study by Pisinger and Døssing [2014] and survey by Palazzolo [2013] attempted to summarize all the detectable unsafe products that may be present during vaping. In general, these studies found a mixture of chemicals that included carrier liquids, flavors, and nicotine (some in high but most in low concentrations). In France, the regulation of electronic cigarettes was limited before 2014. Directive 2014/40/EU of the European Parliament adopted new rules in member states. To be marketed, the nicotine concentration should not exceed 20 mg/ml and refill containers should not exceed the maximum sizes set by the Directive. However, this Directive was only transposed into French law in May 2016. Consequently, this regulation was not effective during our study period. As shown

by Tierney et al. [2016], the concentrations of some flavors are sufficiently high to be unsafe when inhaled. More worryingly, some electronic cigarettes have been found to contain toxic chemicals, carcinogens, and substances potentially harmful to human health [Hadwiger et al., 2010; Khlystov and Samburova, 2016; Trehy et al., 2011; Vanderkam et al., 2016; Westenberger, 2009; Williams et al., 2013]. The latter are vaporized and potentially inhaled by both the electronic cigarette user and his or her entourage [Schripp et al., 2013]. It is thus clear that the hazards associated with this practice should be studied in detail.

The current literature is dominated by studies in the medical field, and it reports divergent results on health outcomes. An important factor in understanding these discrepancies is the significant presence of conflicts of interest comparable to those associated with the tobacco industry in the 1950s [Bero, 2005]. Pisinger and Døssing [2014] and Pisinger et al. [2018] showed that beyond any methodological problems, many of those studies conducted by authors with a conflict of interest claim that electronic cigarette use has no effect on health. By contrast, independent studies generally find that the use of both electronic and regular cigarettes has negative effects on health. Tobacco smoking and electronic cigarette use have been associated with higher cardiovascular risk [Benowitz and Fraiman, 2017; Münzel et al., 2020; Skotsimara et al., 2019], myocardial infarction [Alzahrani et al., 2018], airway inflammation/oxidative stress [Chaumont et al., 2019; Moheimani et al., 2017; Vardavas et al., 2012], and psychological distress [Park et al., 2017]. In the United States, the Wave 3 National Health Interview Survey (2014, 2016, and 2017) reports that electronic cigarette users have a higher risk of myocardial infarction, stroke, depression, and circulatory disorders, but a lower risk of hypertension and diabetes than non-users [Vindhyal et al., 2019a], [Vindhyal et al., 2019b]. Vlachopoulos et al. [2016] found that electronic cigarette use increases aortic stiffness and blood pressure in young smokers. Furthermore, the latter are more likely to smoke tobacco in the future if they have initially been exposed to electronic cigarettes [National Academies of Sciences, 2018]. The 2019 report published by the World Health Organization [2019] takes a similar line, arguing that electronic cigarette use is not without risks for young smokers and pregnant women. It notes a clear need to “minimize the content and emissions of toxic products.” While informative, however, these studies do not estimate the causal effect of electronic cigarettes on health.

These earlier studies, combined with the recent wave of deaths, have affected the dominant policy discourse on electronic cigarette use. Although electronic cigarettes have long been encouraged through television, online, and print advertising (partic-

ularly in the United States), the position has changed in many countries. Indeed, some governments such as those in Thailand, Argentina, Brazil, and Mexico have now banned electronic cigarettes. In Canada and Australia, electronic cigarettes cannot contain nicotine. More recently, India and the US states of Michigan and New York prohibited the marketing of electronic cigarettes. The European Union is seeking to further harmonize rules regarding their use. In 2014, it limited the amount of nicotine an electronic cigarette could contain and prohibited certain additives (See Directive 2014/40/EU of the European Parliament for more details). Furthermore, electronic cigarette users are generally subject to the same legislation as tobacco smokers, with a ban on sales to minors (under 18 years), prohibited use in public spaces (except for Romania and Bulgaria), and restrictions on advertising. Only the United Kingdom has taken a more lenient approach. The European Commission has committed to submitting a report by May 20, 2021 to potentially amend the current directive in light of the available scientific information.

In this study, we evaluate the causal impact of electronic cigarette use on both tobacco smoking and health among tobacco smokers. Our results are novel and important for at least two reasons. First, to the best of our knowledge, no study has thus far used longitudinal data to estimate this causal relation. As we show, cross-sectional methods are unsuitable for analyzing such an association because of the existence of confounding factors and selection bias. Most of the existing literature relies on correlation and does not provide evidence of a causal effect. Second, while the medical literature attempts to advance our knowledge, the economics literature suffers from a lack of evidence in this area of research.

The remainder of this paper is organized as follows. We first describe the database and variables used in Section 2. We then present the empirical strategy in Section 3 and robustness checks in Section 4. Section 5 highlights the main findings. Section 6 underlines the limitations of our study. Lastly, we discuss the implications of our results for both policymakers and researchers in Section 7.

## 2 Data and variables

Ethics approval is not required for this study. All data used in this study is available publicly from the National Archive of Data from Official Statistics (in French, « Archives de Données Issues de la Statistique Publique »). As a result, no data

was collected directly from human subjects.

## 2.1 Data description

Our study draws on a longitudinal French survey. The Health, Health Care, and Insurance Survey (Enquête Santé et Protection Sociale [ESPS]) is representative of the French metropolitan population. Conducted by the Institute for Research and Information in Health Economics (L’Institut de Recherche et Documentation en Economie de la Santé [IRDES]) since 1988, the same respondents are interviewed every four years and data are collected on their socioeconomic status, smoking behavior, and health. The survey database also contains health data drawn from the National Health Insurance database. The sample was entirely redesigned in 2010 to minimize attrition. As electronic cigarettes were commercialized in France in late 2010, survey questions on the use of electronic cigarette were first included in 2014. For these reasons, we use the 2010 and 2014 ESPS waves to investigate the effect of electronic cigarette use on tobacco smoking and health among tobacco smokers. The first interview (mid-2010) was undertaken before the arrival of electronic cigarettes on the French market, while the second interview (mid-2014) was performed after their introduction. Our sample is restricted to adults who daily or occasionally smoked tobacco cigarettes in 2010. Throughout this study, we distinguish between those who were electronic cigarette users in 2014 (e-users) and those who were not (non-e-users). Indeed, fewer than 1% of daily e-users have never smoked tobacco. In France, electronic cigarettes are mainly used by tobacco smokers to reduce tobacco consumption or quit smoking [Pasquereau et al., 2019]. We exploit the following question: "Do you currently use electronic cigarettes?" with three possible answers: "Yes, daily," "Yes, occasionally," and "No." We gather the first two modalities to identify electronic cigarette users in 2014. The next section describes the variables used in our study.

## 2.2 Sociodemographic variables

The set of sociodemographic variables includes age, sex, education, city size, marital status, household size, and household income. We add variables related to smoking behavior (years of smoking, attempts to quit smoking, and number of cigarettes smoked per day) and a measure of an individual’s health. Appendix A describes these variables.



## 2.3 Outcome variables

We use two sets of outcome variables. The first includes two variables related to smoking behavior: "Smokes cigarettes," which is a dummy that equals 1 if an individual smokes cigarettes and 0 otherwise, and "Number of cigarettes smoked," which measures the number of cigarettes smoked per day. The second set of outcomes includes two health-related variables. The first is self-rated health. This refers to the question "How would you describe your health at present?" with five possible answers: 1 ("excellent"), 2 ("very good"), 3 ("good"), 4 ("fair"), and 5 ("poor"). To measure individual health status, we introduce a variable "poor self-rated health" that equals 1 if an individual reports that his or her health is "fair" or "poor" and 0 otherwise. Although it is a subjective measure, a number of studies show that self-rated health is highly correlated with other objective measures and is a strong predictor of morbidity and mortality [Franks et al., 2003; Idler and Benyamini, 1997; McCallum et al., 1994; Van Doorslaer and Gerdtham, 2003]. As an alternative health indicator, we use the variable "chronic disease" that equals 1 if an individual has a chronic disease and 0 otherwise.

## 2.4 Descriptive statistics

Table 1 provides the descriptive statistics of e-users and non-e-users. These two groups differ in terms of age and employment status. On average, the population of e-users is younger and has a higher employment rate. Moreover, we observe statistical discrepancies in terms of initial smoking behavior. In particular, the number of years of smoking and cigarettes smoked per day are higher among e-users. In addition, more e-users have tried, at least once, to quit tobacco smoking. These important differences suggest that in the absence of randomized controlled experiments, longitudinal data are needed to fully assess the effect of electronic cigarettes on tobacco smoking and health. The next section presents our empirical approach.

[INSERT TABLE 1 HERE]

## 3 Empirical strategy

Our sample was composed of individuals who smoked regular cigarettes in 2010 ( $t = 0$ ). Let  $D$  be the treatment assignment, with  $D = 1$  if the individual was an e-user in

2014 ( $t = 1$ ) and  $D = 0$  otherwise. To evaluate the effect of electronic cigarette use, we would ideally compare the outcome  $Y_1$  of an e-user ( $D = 1$ ) with the outcome  $Y_0$  of a non-e-user ( $D = 0$ ). However, we cannot observe both sets of outcomes for the same individual. If the assignment to treatment was random, a simple difference in outcome means ( $Y_1 - Y_0$ ) could achieve consistent estimates of the treatment effect, but that is not possible here. For example, Table 2 shows that middle-aged people and individuals who have tried to quit smoking were more likely to smoke an electronic cigarette in 2014. To reduce selection bias, one solution is to match treated and non-treated samples with the same observed characteristics  $X$ . This strategy relies on the assumption that, conditional on  $X$ , the outcomes of the treated and non-treated samples are independent of the treatment assignment (the conditional independent assumption [CIA]). This requires that all the variables simultaneously affecting  $D$  and  $Y$  can be observed. However, if the sample is not sufficiently large or if certain variables are continuous, it is impossible to find comparable individuals. A solution proposed by [Rosenbaum and Rubin \[1983\]](#) is matching individuals on a propensity score  $p(X)$  that reflects the probability of treatment participation. The CIA, based on the propensity score, can be written as follows:

$$Y^0, Y^1 \perp D | p(X)$$

Matching on  $p(X)$  is equivalent to matching on  $X$  (propensity score theorem) if the common support assumption is satisfied:

$$0 < P(D = 1|X) < 1$$

This condition ensures that along with the set of observable characteristics  $X$ , there is a strictly positive probability of being either treated or untreated. First, we use nearest-neighbor matching (the most common method) to pair each treated individual to control for individuals with the closest propensity scores. We then test the robustness of our results to the use of alternative matching methods.

Our method combines propensity score matching (PSM) with the difference-in-differences (DiD) estimator (DiD-PSM); see [Böckerman and Ilmakunnas \[2009\]](#), [Ronchetti and Terriau \[2019\]](#), and [Stuart et al. \[2014\]](#) for a description of the DiD-PSM approach. Combining both methods, we minimize selection bias and remove unobserved fixed effects that are time-invariant. The DiD-PSM approach compares the change in the outcome of the treated and matched controls to estimate the

average treatment effect on the treated (ATT):

$$ATT^{DiD-PSM} = \frac{1}{N_{D_1}} \sum_{i \in D_1 \cap S} \left[ (Y_{i,t+1}^1 - Y_{i,t}^0) - \sum_{j \in D_0 \cap S} w_{ij} (Y_{j,t+1}^0 - Y_{j,t}^0) \right]$$

where  $D_1$  ( $D_0$ ) represents the treatment (control) group,  $w_{ij}$  is the nearest-neighbor matching weight, and  $S$  is the area of common support.

### 3.1 Propensity Score Matching

We first estimate the predicted propensity score from a probit model for using electronic cigarettes. The set of explanatory variables includes observable characteristics that simultaneously influence the treatment and outcomes. All the variables are measured in 2010 (pre-treatment) and are therefore not affected by the treatment. The covariates include demographics (age, age squared, sex, employment status, level of education, city size, marital status, and household income), smoking history (years of smoking, has ever tried to quit smoking, smokes fewer than 20 cigarettes per day), and health-related variables (poor self-rated health).

Table 2 presents the determinants of the use of electronic cigarettes. Age and variables related to pre-treatment smoking behavior appear to be the most significant factors. This underlines that in the case of a non-random treatment assignment, a longitudinal database containing information on smoking habits is needed to fully analyze the effect of electronic cigarette use.

[INSERT TABLE 2 HERE]

### 3.2 Common support condition

The common support condition requires that both treated and non-treated samples exist for any value of the propensity score. Figure 1 shows that, after matching, the distributions of propensity scores in the treatment and control groups overlap almost perfectly. There is almost no observations outside the region of common support. Consequently, the common support condition is satisfied. The final sample includes 982 observations (195 matched treated and 787 matched controls).

[INSERT FIGURE 1 HERE]

### 3.3 Balance of the covariates

Rosenbaum and Rubin [1985] suggested using standardized bias as a measure of the covariate balance. Standardized bias indicates, for each covariate, the difference between the means of the treated and matched controls as a percentage of the square root of the average of the variance in the two groups. Figure 2 shows that standardized bias in the covariate means is considerably reduced after matching, falling from up to 32% (before matching) to below 20% (after matching) for all the variables. More importantly, t-tests confirm that the covariate means are not significantly different for the matched treated and matched control groups at the 5% level (see Appendix B). Hence, PSM can successfully balance the covariates in both groups.

[INSERT FIGURE 2 HERE]

## 4 Robustness checks

A number of matching algorithms can be employed to adjust for the observable pre-treatment differences between the treatment and control groups. There is no clear evidence in the literature that one matching method is superior to another in any context [Baser, 2006]. All algorithms trade off efficiency and bias. To test the robustness of our results to the choice of matching strategy, we estimate the ATT using three algorithms: nearest-neighbor, radius matching, and kernel weighting. All our estimates are performed with the *psmatch2* command of the Stata software (version 15), with nearest-neighbor matching. *Nearest-neighbor* implies that each treated individual is matched with the non-treated unit with the closest propensity score. Although the technique is widely used, there is a risk of imprecise matches if the closest neighbor is distant in terms of propensity score. To address this issue, each individual in the treatment group is matched with the control group member with the closest propensity score, subject to a certain maximum distance, called the "caliper." A potential drawback of this approach is the difficulty of defining the optimal caliper width. We follow Austin [2011] to determine the optimal caliper width. Lastly, under the *kernel approach*, all the treated subjects are matched with a weighted average of all the controls, with the weights inversely proportional to the distance between the propensity scores of the treated and controls. In this study, we use the Gaussian kernel estimator. The results converge in the same way when using epanechnikov kernel matching (results available upon request). In our study,

all the algorithms result in a similar balance of the covariates. Whichever method is used, the coefficients and bootstrapped ATT standard errors are close regardless of the empirical approach.

## 5 Results

This section outlines the ATT. We first present the effects on tobacco consumption and then on health.

### 5.1 Effects on cigarette smoking

Table 3 investigates the therapeutic value of electronic cigarettes; specifically, it shows the impact of electronic cigarette use on the probability of tobacco smoking and daily number of regular cigarettes smoked. Whichever the outcome and matching algorithm used, the estimated ATT is negative and significant at the 5% level. Our results show that electronic cigarette use reduces the probability of smoking tobacco by 12 percentage points and the number of cigarettes smoked per day by two units.

[INSERT TABLE 3 HERE]

### 5.2 Effects on health

Table 4 highlights the impact of electronic cigarette use on health. We first observe that the use of electronic cigarettes is associated with a greater probability (+12 percentage points) of reporting poor self-rated health, significant at the 5% level. We also find that e-users have a higher probability (+18 percentage points) of suffering from a chronic disease. This result clearly indicates that electronic cigarettes should not be seen as a therapeutic tool that has no adverse health effects.

[INSERT TABLE 4 HERE]

### 5.3 Sensitivity analysis

Our empirical strategy is based on the CIA that requires that all the variables that jointly affect the treatment assignment and outcomes are observable. We use the method presented by [Ichino et al. \[2008\]](#), based on Monte Carlo simulations, to test the robustness of our results to specific violations of the CIA. Here, we assume that

the CIA is not satisfied by the given observables (Equation 1), but would be satisfied if an additional binary variable  $U$  (Equation 2) could be observed:

$$Y^0, Y^1 \not\perp D | (X, U) \quad (1)$$

$$Y^0, Y^1 \perp D | (X, U) \quad (2)$$

The distribution of the unobserved binary confounding factor  $U$  can be characterized by the following four parameters:

$$p_{mn} = Pr(U = 1 | D = m, Y = n)$$

with  $m, n \in [0, 1]$ .

Ichino et al. [2008] defined the outcome effect  $\Gamma$  as the effect of  $U$  on the relative probability of a positive outcome in the absence of the treatment (Equation 3) and  $\Lambda$  as the effect of  $U$  on the relative probability of being assigned to the treatment (Equation 4):

$$\Gamma = \frac{\frac{Pr(Y=1|D=0,U=1,X)}{Pr(Y=0|D=0,U=1,X)}}{\frac{Pr(Y=1|D=0,U=0,X)}{Pr(Y=0|D=0,U=0,X)}} \quad (3)$$

$$\Lambda = \frac{\frac{Pr(D=1|U=1,X)}{Pr(D=0|U=1,X)}}{\frac{Pr(D=1|U=0,X)}{Pr(D=0|U=0,X)}} \quad (4)$$

In other words,  $\Gamma > 1$  ( $\Gamma < 1$ ) means that the unobserved binary confounding factor  $U$  positively (negatively) affects the outcome variable  $Y$  and  $\Lambda > 1$  ( $\Lambda < 1$ ) means that the unobserved binary confounding factor  $U$  increases (decreases) the probability of using electronic cigarettes.

In the first step, the ATT is estimated by nearest-neighbor matching. We also perform sensitivity analyses with alternative algorithms, with similar results. In the second step, a potential binary confounder  $U$  is simulated in the data, based on the four parameters  $p_{mn}$ . The latter parameters are selected to ensure that the distribution of  $U$  is similar to the empirical distribution of the important binary covariates.

Appendixes C, D, E, and F report the results of the sensitivity analyses. Overall, including  $U$  among the confounders in the PSM does not change the ATT estimates. The simulated ATTs are close to the baseline ATTs, indicating that our results are robust to specific deviations from the CIA.

## 6 Limitations

Our empirical approach has limitations that need to be discussed. First, our estimates may suffer from attrition bias if the probability of dropping out during follow-up depends on health status and smoking behavior. Several arguments can be put forward to support the validity of our results. First, the longitudinal survey used in our study was redesigned in 2010 to minimize non-response. The result is a low attrition rate. Second, the average age of daily e-users is 41.9 years and almost 85% are aged 55 or younger. Consequently, the mortality rate of e-users tends to 0 and is unlikely to significantly affect our results. Third, health and smoking behavior do not appear to be significant predictors of attrition and none of the variables used in our study are significantly associated with attrition at the 5% level. All these arguments suggest that attrition is unlikely to bias our estimates.

Another issue to which particular attention needs to be paid is the limited information on electronic cigarette use in our database. The survey only allows us to know if an individual started using electronic cigarettes between 2010 and 2014. As previously noted, there is a plethora of products available to design an electronic cigarette and the mixing possibilities for the consumer are infinite. For example, electronic cigarette devices allow for liquids with concentrations of nicotine usually ranging from 0 to 15–18 mg/mL. This can change the health consequences of their use significantly. Our study only measures an average effect and more research is needed to analyze the differentiated effects of electronic cigarettes according to their frequency of use and types of products consumed. Moreover, as noted in the Introduction, the regulation has changed in recent years. Consequently, the effect of electronic cigarettes on tobacco consumption and health may have evolved since 2014.

Finally, our investigation is limited by the sample size. The literature, both economic and medical, underlines the differentiated health effects of tobacco consumption according to sociodemographic characteristics and the same could be true for electronic cigarettes. The limited dataset does not allow us to analyze the impact of electronic cigarettes on specific diseases or population subgroups. Further

research is thus needed to complement our recommendations and design targeted measures.

## 7 Conclusion

Tobacco smoking has a significant adverse impact on health. However, there has been relatively little research into the effects of electronic cigarettes. Moreover, most of this strand of the literature is based on simple correlations, and it investigates either the relation between electronic cigarette use and tobacco smoking or the link between electronic cigarette use and health. Our work sheds new light on the impact of electronic cigarettes on both tobacco smoking and health. We draw on a longitudinal French survey for 2010–2014. To the best of our knowledge, this is one of the few available longitudinal databases that investigates this question. We apply a DID-PSM approach to estimate the causal effect of electronic cigarette use on tobacco smoking and health. This strategy is robust to the selection of observables and time-invariant unobservables.

Our results suggest that baseline tobacco smokers who use electronic cigarettes are more likely to quit smoking or reduce their tobacco consumption. This first finding is in line with those of previous independent studies ([Etter \[2010\]](#), [Etter and Bullen \[2011\]](#), [Foulds and Veldheer \[2011\]](#), [Polosa et al. \[2011\]](#), [Caponnetto et al. \[2013\]](#), [Dawkins et al. \[2013\]](#), [Farsalinos et al. \[2013\]](#), [Polosa et al. \[2014\]](#)). However, we also find evidence of the damaging effects of electronic cigarette use on health. Among baseline tobacco smokers, those who start using electronic cigarettes have a greater probability of reporting poor health status and a higher risk of developing a chronic disease. These results are robust to the use of alternative matching algorithms and violation of the CIA.

Our study contributes to the debate on electronic cigarette use and health. To the best of our knowledge, it is the first to address electronic cigarettes and their effects on both tobacco smoking and health. The message of our study is that policymakers should not support the use of electronic cigarettes for tobacco smokers based on the argument that electronic cigarettes help stop smoking or reduce tobacco consumption. Our findings suggest that the use of electronic cigarettes does not improve the health of tobacco smokers over the period considered. Worse still, our results suggest that electronic cigarette use may increase the probability of having poor self-rated health status or suffering from a chronic disease. More research is needed to identify the components of electronic cigarettes that are damaging to



health and more regulation is required to regulate the market and ban products considered to be dangerous to consumers.

While regular and electronic cigarette legislation appears to be converging, medical studies tend to show a need for better controls of the products in the market. Recent deaths in the United States and Belgium are a reminder of the difficulty of keeping track of the products consumed. At the same time, some consumers will continue to adopt risky behaviors (e.g., alcohol and tobacco addiction). Nevertheless, public authorities must provide clear information, and a two-pronged approach seems appropriate. First, the various known risks associated with electronic cigarettes should be made clear through efforts to raise user awareness (e.g., prevention campaigns). Second, informed consumers should be encouraged to purchase substances that are both regulated and authorized. Without these clear messages, electronic cigarette use will become a major public health issue.

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## A Description of covariates and outcomes

Variables	Variables description
<b>Demographic variables</b>	
Age	Age (in years).
Age squared	Age squared (in years).
Female	Dummy that equals 1 if an individual is a woman, and 0 otherwise.
Employed	Dummy that equals 1 if an individual is employed (excluding students and retired), and 0 otherwise.
Level of education	Dummy that equals 1 if an individual has the corresponding level of education, and 0 otherwise.
City size	Dummy that equals 1 if an individual lives in the corresponding type of city, and 0 otherwise.
Couple	Dummy that equals 1 if an individual lives with a partner (married or not), and 0 otherwise.
Number of household residents	Dummy that equals 1 if an individual lives in a household with the corresponding number of members, and 0 otherwise.
Household income	Dummy that equals 1 if an individual lives in a household with the corresponding income, and 0 otherwise.
<b>Variables related to smoking behavior</b>	
Years of smoking	Number of years of smoking.
Has ever tried to quit smoking	Dummy that equals 1 if an individual has ever tried to quit smoking, and 0 otherwise.
Smokes fewer than 20 cigarettes per day	Dummy that equals 1 if an individual smokes fewer than 20 cigarettes per day, and 0 otherwise.
<b>Variables related to health</b>	
Poor self-rated health	Poor health (based on self-reported health). Dummy that equals 1 if an individual reports that his or her health is "Fair", "Bad" or "Very bad", and 0 otherwise.
<b>Outcomes</b>	
Smokes cigarettes	Dummy that equals 1 if an individual smokes cigarettes, and 0 otherwise.
Number of cigarettes smoked	Number of cigarettes smoked (per day).
Chronic disease	Dummy that equals 1 if an individual has a chronic disease, and 0 otherwise.

## B Balance of covariates

Variables	Unmatched		Control	%bias	% reduc bias.	t-test
	Matched	Treated				
Age	U	42.82	44.11	-10.3		-1.21
	M	42.82	42.51	2.5	75.7	0.29
Age squared	U	1954	2135	-15.6		-1.81
	M	1954	1913	3.5	77.6	0.42
Female	U	0.446	0.471	-5.1		-0.63
	M	0.446	0.503	-11.3	-123.3	-1.11
Employed	U	0.774	0.679	21.6		2.61
	M	0.774	0.779	-1.2	94.6	-0.12
Level of education:						
<i>Middle school</i>	U	0.492	0.476	3.2		0.40
	M	0.492	0.554	-12.3	-289.1	-1.22
<i>High school</i>	U	0.215	0.219	-0.8		-0.10
	M	0.215	0.190	6.2	-709.7	0.63
<i>Higher education</i>	U	0.226	0.227	-0.4		-0.05
	M	0.226	0.205	4.9	-1036.5	0.49
City size:						
<i>Less than 20 000 inhab.</i>	U	0.256	0.238	4.4		0.55
	M	0.256	0.333	-17.8	-309.2	-1.67
<i>Between 20 000 and 200 000 inhab.</i>	U	0.169	0.188	-4.9		-0.61
	M	0.169	0.174	-1.3	72.8	-0.13
<i>Between 200 000 and 2 000 000 inhab.</i>	U	0.272	0.215	13.3		1.71
	M	0.272	0.190	19.1	-43.8	1.93
<i>More than 2 000 000 inhab.</i>	U	0.036	0.072	-16.2		-1.85
	M	0.036	0.036	0.0	100.0	0.00
Couple	U	0.841	0.785	14.3		1.73
	M	0.841	0.877	-9.2	35.6	-1.02
Number of household residents:						
2	U	0.241	0.300	-13.3		-1.62
	M	0.241	0.256	-3.5	73.9	-0.35
3	U	0.195	0.203	-2.1		-0.26
	M	0.195	0.180	3.8	-82.5	0.39
4	U	0.287	0.243	10.1		1.28
	M	0.287	0.354	-15.1	-49.9	-1.41
5	U	0.133	0.094	12.4		1.63
	M	0.133	0.128	1.6	87.0	0.15
$\geq 6$	U	0.041	0.039	0.8		0.10
	M	0.041	0.021	10.4	-1154.2	1.17
Household income (minimum wage):						
<i>Between 1 and 2</i>	U	0.292	0.306	-3.0		-0.38
	M	0.292	0.272	4.5	-47.4	0.45
<i>Between 2 and 3</i>	U	0.431	0.366	13.2		1.67
	M	0.431	0.503	-14.7	-10.8	-1.42
<i>More than 3</i>	U	0.221	0.228	-1.7		-0.21
	M	0.221	0.185	8.6	-417.8	0.88
Years of smoking	U	18.81	16.07	19.9		2.3
	M	18.81	17.84	7.0	64.6	0.73
Has ever tried to quit smoking	U	0.615	0.469	29.7		3.68
	M	0.615	0.615	0.0	100.0	0.00
Smokes fewer than 20 cigarettes per day	U	0.651	0.792	-31.6		-4.16
	M	0.651	0.667	-3.5	89.0	-0.32
Poor self-rated health	U	0.313	0.290	5.0		0.63
	M	0.313	0.354	-8.9	-77.5	-0.86

## C Sensitivity analysis (Smokes cigarettes)

	ATT	SE	Outcome effect $\Gamma$	Selection effect $\Lambda$
Female	-0.124	0.054	1.085	0.935
Employed	-0.124	0.054	1.131	1.675
Level of education:				
<i>Middle school</i>	-0.124	0.054	1.231	1.079
<i>High school</i>	-0.124	0.054	0.985	1.013
<i>Higher education</i>	-0.124	0.054	0.936	0.971
City size:				
<i>Less than 20 000 inhab.</i>	-0.124	0.054	0.673	1.137
<i>Between 20 000 and 200 000 inhab.</i>	-0.124	0.054	0.933	0.862
<i>Between 200 000 and 2 000 000 inhab.</i>	-0.124	0.054	0.850	1.394
<i>More than 2 000 000 inhab.</i>	-0.124	0.054	2.360	0.470
Couple	-0.124	0.054	1.152	1.535
Number of household residents:				
2	-0.124	0.054	1.148	0.756
3	-0.124	0.054	0.903	0.950
4	-0.124	0.054	1.243	1.257
5	-0.124	0.054	0.731	1.551
$\geq 6$	-0.124	0.054	3.612	1.049
Household income (minimum wage):				
<i>Between 1 and 2</i>	-0.124	0.054	1.370	0.954
<i>Between 2 and 3</i>	-0.124	0.054	0.781	1.332
<i>More than 3</i>	-0.124	0.054	1.036	0.955
Has ever tried to quit smoking	-0.124	0.054	0.522	1.832
Smokes fewer than 20 cigarettes per day	-0.124	0.054	1.049	0.494
Poor self-rated health	-0.124	0.054	1.087	1.180

Note: 1000 replications have been performed for the sensitivity analysis.  
All covariates are binary variables. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*)

## D Sensitivity analysis (Number of cigarettes smoked)

	ATT	SE	Outcome effect $\Gamma$	Selection effect $\Lambda$
Female	-2.010	0.979	1.222	0.935
Employed	-2.010	0.979	1.012	1.663
Level of education:				
<i>Middle school</i>	-2.010	0.979	0.796	1.065
<i>High school</i>	-2.010	0.979	1.048	1.004
<i>Higher education</i>	-2.010	0.979	1.423	0.985
City size:				
<i>Less than 20 000 inhab.</i>	-2.010	0.979	0.753	1.151
<i>Between 20 000 and 200 000 inhab.</i>	-2.010	0.979	0.895	0.871
<i>Between 200 000 and 2 000 000 inhab.</i>	-2.010	0.979	1.012	1.392
<i>More than 2 000 000 inhab.</i>	-2.010	0.979	1.281	0.474
Couple	-2.010	0.979	1.209	1.521
Number of household residents:				
2	-2.010	0.979	1.215	0.745
3	-2.010	0.979	0.913	0.948
4	-2.010	0.979	1.063	1.259
5	-2.010	0.979	0.677	1.560
$\geq 6$	-2.010	0.979	1.038	1.052
Household income (minimum wage):				
<i>Between 1 and 2</i>	-2.010	0.979	1.327	0.951
<i>Between 2 and 3</i>	-2.010	0.979	0.980	1.331
<i>More than 3</i>	-2.010	0.979	1.024	0.949
Has ever tried to quit smoking	-2.010	0.979	0.412	1.815
Smokes fewer than 20 cigarettes per day	-2.010	0.979	3.858	0.491
Poor self-rated health	-2.010	0.979	0.471	1.185

Note: 1000 replications have been performed for the sensitivity analysis.  
All covariates are binary variables. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*)

## E Sensitivity analysis (Poor self-rated health)

	ATT	SE	Outcome effect $\Gamma$	Selection effect $\Lambda$
Female	0.117	0.056	0.625	0.938
Employed	0.117	0.056	0.705	1.672
Level of education:				
<i>Middle school</i>	0.117	0.056	1.294	1.078
<i>High school</i>	0.117	0.056	0.591	1.024
<i>Higher education</i>	0.117	0.056	1.146	0.984
City size:				
<i>Less than 20 000 inhab.</i>	0.117	0.056	1.033	1.122
<i>Between 20 000 and 200 000 inhab.</i>	0.117	0.056	1.133	0.860
<i>Between 200 000 and 2 000 000 inhab.</i>	0.117	0.056	0.774	1.408
<i>More than 2 000 000 inhab.</i>	0.117	0.056	1.644	0.463
Couple	0.117	0.056	0.900	1.531
Number of household residents:				
2	0.117	0.056	1.357	0.747
3	0.117	0.056	0.928	0.956
4	0.117	0.056	0.641	1.260
5	0.117	0.056	0.607	1.554
$\geq 6$	0.117	0.056	1.628	1.080
Household income (minimum wage):				
<i>Between 1 and 2</i>	0.117	0.056	1.391	0.948
<i>Between 2 and 3</i>	0.117	0.056	0.709	1.336
<i>More than 3</i>	0.117	0.056	1.131	0.953
Has ever tried to quit smoking	0.117	0.056	0.860	1.822
Smokes fewer than 20 cigarettes per day	0.117	0.056	0.624	0.500
Poor self-rated health	0.117	0.056	0.001	1.183

Note: 1000 replications have been performed for the sensitivity analysis.  
All covariates are binary variables. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*)

## F Sensitivity analysis (Chronic disease)

	ATT	SE	Outcome effect $\Gamma$	Selection effect $\Lambda$
Female	0.179	0.054	0.888	0.938
Employed	0.179	0.054	0.951	1.686
Level of education:				
<i>Middle school</i>	0.179	0.054	1.232	1.078
<i>High school</i>	0.179	0.054	0.285	1.024
<i>Higher education</i>	0.179	0.054	1.294	0.989
City size:				
<i>Less than 20 000 inhab.</i>	0.179	0.054	1.030	1.132
<i>Between 20 000 and 200 000 inhab.</i>	0.179	0.054	1.611	0.869
<i>Between 200 000 and 2 000 000 inhab.</i>	0.179	0.054	0.790	1.413
<i>More than 2 000 000 inhab.</i>	0.179	0.054	1.783	0.472
Couple	0.179	0.054	0.880	1.512
Number of household residents:				
2	0.179	0.054	1.395	0.751
3	0.179	0.054	1.094	0.958
4	0.179	0.054	0.610	1.263
5	0.179	0.054	0.654	1.544
$\geq 6$	0.179	0.054	1.534	1.080
Household income (minimum wage):				
<i>Between 1 and 2</i>	0.179	0.054	1.276	0.953
<i>Between 2 and 3</i>	0.179	0.054	0.726	1.334
<i>More than 3</i>	0.179	0.054	1.132	0.953
Has ever tried to quit smoking	0.179	0.054	0.852	1.809
Smokes fewer than 20 cigarettes per day	0.179	0.054	1.119	0.499
Poor self-rated health	0.179	0.054	0.624	1.181

Note: 1000 replications have been performed for the sensitivity analysis.  
All covariates are binary variables. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*)

# Figures

Figure 1: Kernel density estimates

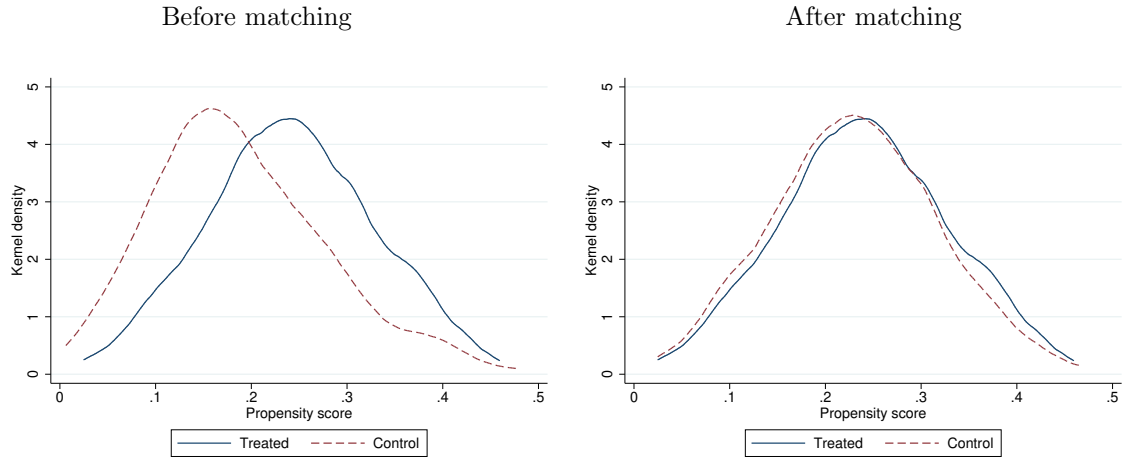
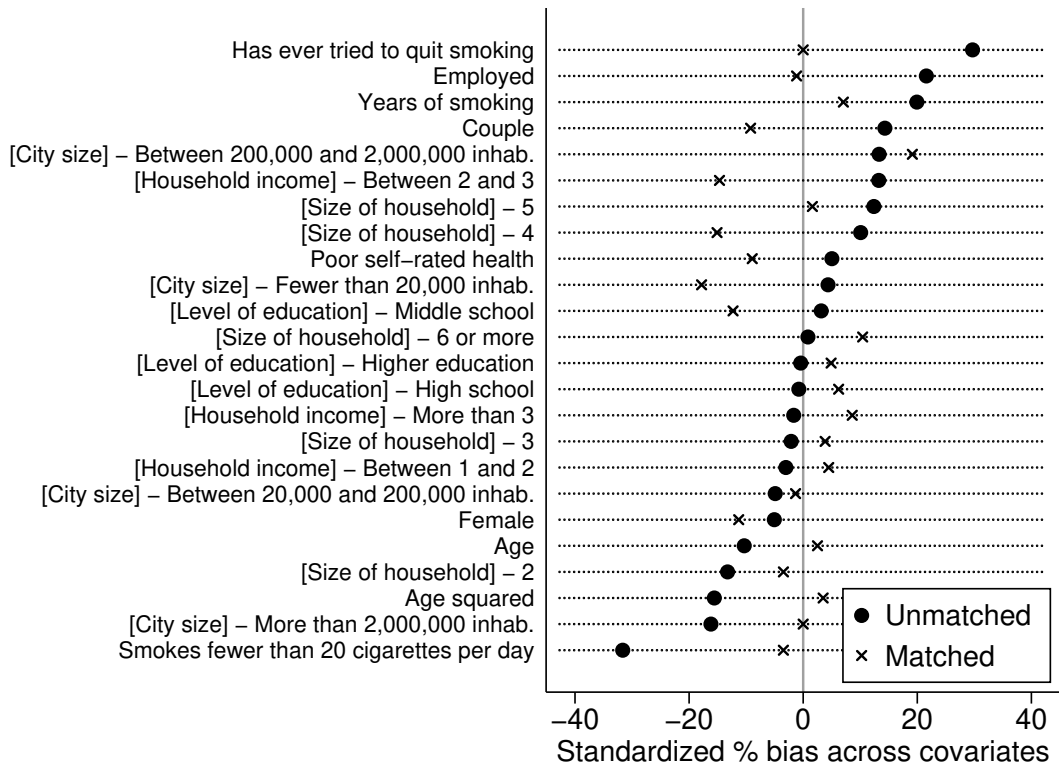


Figure 2: Balance of the covariates





# Tables

Table 1: Descriptive statistics

Variables	Non		Difference	
	All	E-users		
<b>Sociodemographic variables</b>				
Age	43.85	44.11	42.82	1.2888
Age squared	2099	2135	1954	181.08*
Female	0.47	0.47	0.45	0.0253
Employed	0.70	0.68	0.77	-0.0958***
Level of education:				
<i>Middle school</i>	0.48	0.48	0.49	-0.0158
<i>High school</i>	0.22	0.22	0.22	0.0032
<i>Higher education</i>	0.23	0.23	0.23	0.0018
City size:				
<i>Less than 20 000 inhab.</i>	0.24	0.24	0.26	-0.0188
<i>Between 20 000 and 200 000 inhab.</i>	0.18	0.19	0.17	0.0188
<i>Between 200 000 and 2 000 000 inhab.</i>	0.23	0.21	0.27	-0.0571*
<i>More than 2 000 000 inhab.</i>	0.07	0.07	0.04	0.0365*
Couple	0.80	0.79	0.84	-0.0558*
Number of household residents:				
2	0.29	0.30	0.24	0.0589
3	0.20	0.20	0.19	0.0084
4	0.25	0.24	0.29	-0.0445
5	0.10	0.09	0.13	-0.0390
≥ 6	0.04	0.04	0.04	-0.0016
Household incomes (minimum wage):				
<i>Between 1 and 2</i>	0.30	0.31	0.29	0.0139
<i>Between 2 and 3</i>	0.38	0.37	0.43	-0.0648*
<i>More than 3</i>	0.23	0.23	0.22	0.0069
Years of smoking	16.61	16.07	18.81	-2.7404**
Has ever tried to quit smoking	0.50	0.47	0.62	-0.1465***
Smokes less than 20 cigarettes per day	0.76	0.79	0.65	0.1403***
<b>Outcome variables</b>				
Number of cigarettes smoked	10.94	10.15	14.11	-3.9603***
Poor self-rated health	0.29	0.29	0.31	-0.0231
Chronic disease	0.30	0.31	0.26	0.0511
Observations	982	787	195	

Note: We distinguish between those who smoked were electronic cigarette users in 2014 from those who did not (non-e-users). All variables refer to 2010 data. Household income is converted into minimum net monthly salary.

Table 2: Determinants of electronic cigarette use (probit model)

Variables	Coefficient	SE
Age	0.0526*	0.0273
Age squared	-0.0007**	0.0003
Female	-0.0247	0.0981
Employed	0.0702	0.1308
Level of education:		
<i>Middle school</i>	-0.1753	0.2097
<i>High school</i>	-0.2341	0.2298
<i>Higher education</i>	-0.1808	0.2336
City size:		
<i>Less than 20 000 inhab.</i>	0.0551	0.1303
<i>Between 20 000 and 200 000 inhab.</i>	-0.0247	0.1445
<i>Between 200 000 and 2 000 000 inhab.</i>	0.2079	0.1316
<i>More than 2 000 000 inhab.</i>	-0.3058	0.2344
Couple	0.2735	0.2016
Size of household:		
2	-0.2949	0.2372
3	-0.3555	0.2536
4	-0.2848	0.2626
5	-0.2500	0.2863
$\geq 6$	-0.4351	0.3505
Household income (minimum wage):		
<i>Between 1 and 2</i>	0.2473	0.2075
<i>Between 2 and 3</i>	0.3222	0.2222
<i>More than 3</i>	0.1993	0.2432
Years of smoking	0.0077*	0.0042
Has ever tried to quit smoking	0.2161**	0.1008
Smokes fewer than 20 cigarettes per day	-0.2926***	0.1114
Poor self-rated health	0.0470	0.1089
Constant	-1.8429***	0.6096
Observations	982	

Note: All variables relate to 2010, before treatment.

Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*).

Table 3: Average treatment effect on the treated (cigarette smoking)

Matching method	Outcome	
	Smokes cigarettes	Number of cigarettes smoked
Nearest-neighbor	-0.123** (0.0548)	-2.010** (1.0256)
Caliper	-0.124** (0.0553)	-1.995** (1.0350)
Kernel	-0.123** (0.0559)	-2.010** (1.0359)

Note: Bootstrapped standard errors (10,000 replications) in parenthesis. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*).

Table 4: Average treatment effect on the treated (health outcomes).

Matching method	Outcome	
	Poor self-rated health	Chronic disease
Nearest-neighbor	0.118** (0.0561)	0.179*** (0.0510)
Caliper	0.124** (0.0562)	0.175*** (0.0524)
Kernel	0.118** (0.0554)	0.179*** (0.0519)

Note: Bootstrapped standard errors (10,000 replications) in parenthesis. Significance: 10% (\*), 5% (\*\*), 1% (\*\*\*).