Impact of an acute health shock on lifestyles: evidence from French panel data*

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Abstract

This paper investigates the relationship between an acute health shock, namely the first onset of an accident requiring medical care, and lifestyles (i.e. cigarette consumption and the Body Mass Index, BMI) using a French panel data from 1989 to 2014. To identify the causal effect of such shock, we use a propensity score based on pre-accident covariates and pre-accident outcomes. Results suggest that there is a significant effect running from the shock to the number of cigarettes smoked with impact duration of eight years after the shock. Individuals subject to such a shock smoke 2.1 cigarettes less (per week) than those who do not face such a shock. There is no effect, however, of the shock on the BMI.

Keywords: health shock, panel data, France, lifestyles, Propensity score matching

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1 INTRODUCTION

By investigating the relationship between an acute health shock, namely the first onset of an accident requiring medical care, and lifestyles (i.e. cigarette consumption and the BMI), this paper contributes to a better understanding of smoking and eating patterns. Drawing on behavioral economics, the analysis considers the health shock experience as the provision of new and credible information, which can be used to update personal health risk beliefs and which may subsequently affect individuals' lifestyles.

Negative health shocks may both have beneficial and detrimental effects on lifestyle changes. Beneficial effects if individuals perceived such shock as a new source of health information that reveals their true health status. Detrimental effects (i.e. progress of the addiction, or a significant BMI change) if individuals do not want to prevent from shock that has already occurred. Understanding channels running from the shock to lifestyles is thus an empirical issue. Four channels may explain how health shocks influence lifestyles. First, health shocks could improve individuals willingness to stop smoking. Second, after such shocks, there may be an increase in social pressures to quit smoking from frequent interactions with the medical care system, and the urging of family members. Third, since health shocks are strongly associated with labor market inactivity and disability (Garcia Gomez and Lopez Nicolas (2006); Garcia Gomez et al. (2013); Jones, Rice and Zantomio (2016); Trevisan and Zantomio (2016)), with lower individual and household income (Riphahn (1999); Garcia Gomez and Lopez Nicolas (2006); Garcia Gomez et al. (2013)), individuals may reduce or quit smoking because of new financial constraints. Fourth, medical properties of nicotine may, however, become increasingly important as individuals cope with stress and/or fear due to reduced life expectancy that could lead to increase cigarette consumption. The same four channels are used to draw the impact of the health shock on individual BMI, and predict identical directions.

Several studies demonstrate that health shocks can induce healthy changes among British adults (Clark and Etile (2002)), on middle aged and retired Americans (Smith et al. (2001); Clark and Etile (2002); Falba (2005); Khwaja, Sloan and Chung (2006); Keenan (2009)), or on ageing Germans (Sundmacher (2012)). Some studies also offer theoretical guidance (Grossman (1972); Becker and Murphy (1988); Clark and Etile (2002)). Although these studies differ with respect to the explanation of why individuals change behavior patterns, they all predict a positive correlation between a decline in individuals' health and a decision to adopt healthier lifestyles. In addition, (Clark and Etile (2002))'s learning model assumes that individual can learn over time from non-personal experience (spouse or friends facing a shock). Very little, however, is known in France, either on the impact of such shocks on both cigarette consumption levels and on the BMI, or on the duration of this effect when it exists. This paper proposes to bridge this gap by contributing to the existing literature in three ways. First, by identifying some insights on changes in individual cigarette consumption and on BMI after an exogenous health shock. Second, by determining how long this effect lasts. Third, by providing empirical evidence on how people learn from such shocks about the risks associated with smoking and/or with a significant BMI change.

Chronic diseases due, in part, to lifestyle choices remain a societal challenge resulting in significant reductions in population health and increased medical care spending (Sturm (2002); Anderson, Frogner and Reinhardt (2007); Cawley and Meyerhoefer (2012); Danaei et al. (2012)). Despite anti-smoking measures[1], the smoking prevalence in France increases from 2005 and 2010. The number of habitual smokers increases from 28% to 30%[2]. In 2011, although 13.4 million French citizens smoke, the mean quantity of cigarettes smoked, however, has declined between 2005 and 2010[3], but has one of the highest in Western Europe[4]. In 2013, 50.7% of the adult population was overweight and 18.2% were obese. The prevalence of overweight was higher among men (56.4%) than women (45.4%). The same trend is observed for obesity prevalence: 19.1% for men and 17.4% for women[5]. In 2014, overweight and obesity rates in France are among the lowest in the OCED countries, but have been increasing steadily by 2-3% between 2004 and 2012[6].

[1]Smoking in France was first restricted on public transport by the Loi Veil launched in 1976. Further restrictions were established in 1991 due to the Loi Evin. This law contains a variety of measures against alcoholism and tobacco consumption. On February 2007 smoking is ban from public places, such as offices, schools or restaurants.

[2]The 2014 INPES Health Barometer measures epidemiological monitoring indicators in the general population aged 15-75 years old living in metropolitan France. See more on: http://inpes.santepubliquefrance.fr/Barometres/barometre-sante-2014/index.asp.

[3]Tobacco in France: overview of 2004-2014. Observatoire Français des drogues et des toxicomanies, 2014. Aurélie Lermenier-Jeannet.

[4]See more on: http://ec.europa.eu/health/tobacco/docs/eurobaro_attitudes_towards_tobacco_2012_en.pdf.

[5]See more on: http://www.euro.who.int/__data/assets/pdf_file/0009/243297/France-WHO-Country-Profile.pdf.

[6]See more on: http://www.oecd.org/france/Obesity-Update-2014-FRANCE_EN.pdf.

To explore these issues, we use a French panel data (Gazel[7]), which covers 20.000 individuals (15.000 men and 5.000 women) working for the electricity board (EDF-GDF) over the period 1989 to 2014, with rich individual demographic, socio-economic and health-related information. It is collected routinely from first recruitment with EDF-GDF in all regions of France, individuals are between 35-50 at the inclusion and are then followed-up for 25 years. Attrition is very low as only 126 subjects (0.6%) were lost to follow-up during the first 17 years (1989-2005). Further, only 3.2% of the initial cohort never sent back any questionnaires during the 1989-2005 period. The use of longitudinal data allows benefiting from inter-individual differences and intra-individual dynamics that help for capturing part of the complexity of human behavior.

To identify the causal effect of the accident, a matching based on pre-accident covariates and pre-accident outcomes is performed. Specifically, we compute a propensity score for facing a shock one year before its occurrence with a Probit estimation including: demographic (age, age squared, gender, marital status, household size), and socioeconomic indicators (monthly household income, personal and father's educational attainment, professional status and self-reported health), along with pre-outcome variables (number of cigarettes smoked and BMI). We then associate a treated individual (i.e. facing a health shock) with a control individual (i.e. who do not face a health shock) based on this propensity score. Additionally, we restrict the analysis to observations within the common support range, and individuals with other types of shocks are dropped from sample and thus are not included in the control group. This leads to eliminate from our sample 184.606 observations, and then we obtain 301.891 complete observations for our analysis.

Results suggest that there is a significant effect running from the shock to the number of cigarettes smoked with impact duration of four years after the shock. Individuals subject to a shock smoke on average 2.1 cigarettes less (per week) than those who do not face such a shock. There is no effect, however, of the exogenous shock on the BMI. The findings are robust to a series of robustness checks.

The rest of the paper proceeds as follow. Section 2 describes the data. Section 3 presents our empirical strategy. Section 4 shows the results and reports the effectiveness of the identification strategy through the robustness check. The last section concludes the paper

[7]See more on: `:http://www.gazel.inserm.fr/en/`, and on Goldberg, Leclerc and Bonenfant (2007).

and highlights avenues for future research.

2 DATA

The Gazel dataset is an annual panel with approximately 20.000 individuals throughout France. It provides 25 waves (1989-2014) of microeconomics data on health status, lifestyles, socioeconomics and occupational factors collected via a standardized questionnaire. This questionnaire is sent to all participants every year by mail. Specifically, in January 1989, an invitation to participate was sent to all GDF-EDF male employees aged from 40 to 50, and to all 35-50 years old female. Invitation letters only mention a participation in a long-term health study to improve medical research. Less than 5% of the global cohort has died (861 men, and 155 women) by the end of 2005. We use this data to examine whether individuals stop, start or reduce their cigarette consumption and whether individuals lose or gain weight after a health shock

2.1 Health shock measurement

In the economics literature several alternatives exist to measure the experience of a health shock. Previous papers adopted the following measures: a serious decline in the self-assessed health status of individuals (Garcia Gomez (2011); Sundmacher (2012)), or with the level of satisfaction with one's health (Riphahn (1999)). Some others report the occurrence of an acute hospital admission (Garcia Gomez et al. (2013)), the onset of severe health conditions such as cancers (Smith et al. (2001); Sahm (2012)), a lost of grip strength (Decker and Schmitz (2016)), and other physical health problems, mental disorders and accidents (Bunnings (2017)). In the medical literature, other types of shocks are used. They are defined as any events disrupting daily routines: marriage, relative death, or retirement (Tamers et al. (2014), Tamers et al. (2015)). They are, thus, positive and negative shocks. In contrast with this previous literature, we suggest another measure of health shock. Specifically, we use the following question: "over the last twelve months, have you ever had an accident that led to medical care?" In other word, our measure of health shock is a dummy variable equals to one if individuals face such a shock, and zero otherwise. This measure improves upon the others in two ways. First, it is not a constructed measurement of shocks that lead to shortcomings regarding with different causes of the health event. Second, although cancers or hospitalizations are unanticipated, they suffer from endogeneity issues as individuals may know about their genetic factors that could conduct to hospitalizations, or because they adopt more risky behaviors. Put differently, cancers or hospitalizations are not random and could be thus the consequences of individual lifestyles.

2.2 Cigarette consumption, BMI, and covariates

The outcome variables are the number of cigarette smoked per day and the BMI. Each respondent was asked to answer the following question: "How many cigarettes are you smoking per day?" Individuals have to answer by a figure. In other words, our proxy of cigarette consumption is a continuous variable ranking from 0 to 57. To compute individuals' BMI, we use the body weight divided by the square of his or her height (Baum and Ruhm (2009)). Even thought this measure is less accurate than laboratory measures (i.e. that distinguish fat from fat-free (Burkhauser and Cawley (2008))), it is still a reference in obesity and overweight for the World Health Organization (WHO[8]). We exploit a broad set of covariates. Specifically we include age (linear and quadratic term), gender[9], income[10], father's socio-economic status[11], level of education[12], occupational status[13], family status[14], and self-reported health[15].

Overall, 3.470 individuals face a first-ever acute health shock. Individuals suffering from a health shock are more likely to be a male with low level of education (less or equal to

[8]See more on: http://www.who.int/topics/obesity/.

[9]Gender is a dummy that values one for women and zero for men.

[10]Income is an index ranging from one (the poorest) to 10 (the richest). More precisely: 1 stands for "earn less than 991 euros"; 2 for "earn more than 991 euros but less than 1144 euros"; 3 for "earn more than 1144 euros but less than 1372 euros"; 4 for "earn more than 1372 euros but less than 1601 euros"; 5 for "earn more than 1601 euros but less than 1982 euros"; 6 for "earn more than 1982 euros but less than 2592 euros"; 7 for "earn more than 2592 euros but less than 3811 euros"; 8 for "earn more than 3811 euros but less than 4574 euros"; 9 for "earn more than 4574 euros but less than 6098 euros"; 10 for "earn more than 6098 euros".

[11]Father's socio-economic status contains seven measures. Specifically, 1 stands for farmers; 2 for craftsman; 3 for chief executive officer; 4 for executive; 5 for intermediary profession; 6 for employee; 7 for worker.

[12]Individual level of education is coded as follow: 1 for "no education"; 2 for "incomplete primary education"; 3 for " complete primary"; 4 for "incomplete secondary", 5 for "complete secondary"; 6 for "higher education level".

[13]Occupation status equals to 1 if the individual is employed; 2 if the individual is in sick leave; 3 if the individual is retired; 4 if the individual is retired but still working.

[14]Family status is coded as follow: 1 stands for being single; 2 for being married; 3 for civil partnership; 4 for separated; 5 for divorced; 6 for being widowed.

[15]Individuals who identify them as is very good health are coded 1 and those in very bad health are coded 8. Answers could rank from 1 to 8.

a bachelor's degree) aged more than 55 years old (average of 56.5), and a low level of self-reported measure of health (an average of 3.24 on a 8 scale-points). This is in line with recent medical literature on the health shock semiology (Brandt et al. (1994); Moulin (2005); Bejot et al. (2007)). See more descriptive statistics on Table 1 and on Table 2.

3 EMPIRICAL STRATEGY

We aim at estimating the long-term impact of a health shock on cigarette consumption and on BMI. In other words, we want to compare the average cigarette consumption and the average BMI between treated (i.e. individuals experiencing a health shock) and control (i.e. individuals who did not) group. Yet, individuals in the treatment group should not be a specific group with respect to their characteristics. If these characteristics are also correlated with the outcome variables, the impact of the health shock yields to spurious results. It could be, for instance, that more risk-taking individuals exhibit unhealthier lifestyles, smoke more, eat fatter, or are less cautious car drivers. They are, therefore, more likely to face health shocks.

In order to take into account for the non-randomness of the occurrence of such a shock, we use a quasi-experimental approach. Specifically, our empirical strategy relies on a balancing score matching approach. It entails matching treated and non-treated individuals based on only one variable called a balancing score. A balancing score is a function of $\mathbf{X}$, denoted by $f(\mathbf{X})$ that must satisfy the following balancing assumption:

$$T \perp\!\!\!\perp \mathbf{X} \mid f(\mathbf{X}) \tag{1}$$

This means that, conditional on the balancing score, the set of observables $\mathbf{X}$ are independent of assignment to the treatment (T). Put differently, for observations with the same balancing score, the distribution of observables is the same among the treatment and the control group. A possible balancing score is the propensity score (PS, hereafter) matching (Rosenbaum and Rubin (1983)). The PS is the probability for an individual to participate in the treatment given his or her observed characteristics $\mathbf{X}$.

Further, the outcome variables must be independent of treatment assignment conditional on observables. In other words, all the variables that influence both treatment assignment and the outcome variables should be included in the score. This ensures that the unconfoundedness assumption is not violated. To do so, we compute a propensity score with a Probit estimation including pre-outcomes and pre-covariate variables (Wooldridge (2000); Imbens and Wooldridge (2008); Lechner (2011)). Precisely, it contains pre-demographic (age, age squared, gender, marital status, household size) and pre-socioeconomic indicators (monthly household income, personal and father's educational attainment, professional status, self-reported health, drinking beer, wine or appetizer), along with pre-outcome variables (number of cigarettes smoked and BMI). We compute this propensity score one year before the occurrence of the shock. We then match an individual based on his or her PS the year before the treatment with individuals from the control group with similar PS the same year. The PS is ranked from 0 (low probability to have a health shock) to 1 (high probability to have such a shock). See more on Figure 1, and on Figure 2.

We apply a 3-nearest neighbors matching. This procedure selects, for each treated individual, the 3 closest controls (i.e. those that have the closest propensity score). The choice of the nearest neighbors is bounded to the common support range[16] (and thus respect the common support assumption) and the matching is performed with replacement[17]. Further, we calibrate the maximum difference in the propensity score between matched and control subjects to be at 0.001[18]. This ensures that the two matched individuals have similar propensity score. We plot the differences in the PS of the treated cases from the control cases in Figure 3. From this, we see that most of the treated cases were matched to controls with propensity score close to their own (most are less than a 0.001 difference).

To estimate the validity of our matching (verifying the three above assumptions), we display the following tables and figures. Figure 4 shows the distributions of the propensity scores for treated (continuous line) and control (dashed line) individuals before (left-hand side), and after (right-hand side) the matching procedure. While some overlap in distributions is visible before matching, post-matching distributions exhibit a better result. An overview of the different variables used is reported in Table 1. It provides further evidence

[16]Treatment observations whose pscore is higher than the maximum or less than the minimum pscore of the controls are discarded.

[17]The same potential control individual could serve as a nearest neighbor matched control for more than a single treated individual.

[18]This means, for example, that a treated individual with a propensity score of 0.6720 is matched with an individual in the control group with a propensity score of 0.6721 or 0.6719.

of the efficiency of the matching strategy. Before matching, substantial and statistically significant differences exist between the treatment and the control groups in the means of the variables. After matching, none of the differences in average characteristics are statistically significant at any conventional level, except for the maritas status. This table, thus, illustrates how matching ensures comparability between the treatment and the control group. Figure 1 and Figure 2 check the region of common support to be sure that the overlap between both groups is enough to make comparisons. Theses histograms display the propensity score for treatment and control cases. Control individuals span the full range of the propensity scores. All of these evidence gives strenght to our empirical strategy.

4 RESULTS

This section presents the main results, and performs some robustness checks.

4.1 Main results

Table 3 and Table 4 present the main results of the effect of an acute health shock on cigarette consumption. We report the Average Treatment on Treated (ATT) from one year before the occurrence of the shock to 10 years after. For these two tables the ATT is the difference in mean between the treated and the control group once the matching procedure is complete. The coefficients explain, therefore, the evolution of the number of cigarette smoked between groups at each period. Specifically, table 3 shows that the year before the shock and the year of the shock do not affect the cigarette consumption. This means that before the occurrence of such a shock, there is no difference in the number of cigarette smoked between the treated and the control groups. This gives strength to our empirical strategy, as no pre-treatment trend was at stake before the shock. Table 4 exhibits the cigarette consumption after the shock. It explains that the ATT is significant and runs for eight years after the onset of the shock. This effect, however, is not significant the ninth and the tenth years. In other words, facing a health shock reduces the number of cigarette smoked during the eight years following this shock.

Table 5 and table 6 give the main results of the effect of the health shock on the body mass index. We proceed in the same way as for table 3 and table 4. Table 5 and table 6 show no significant difference among groups, whatever the period. Put differently, facing a health shock does not impact the body mass index.

We offer two possible explanations of why we find no effect of health shock on the individuals' BMI. First, unlike tobacco, food intake is not a substance that individual can abstain from. Many fattening foods that contribute to obesity, if consumed in adequate portions, are not unhealthy. This is in line with other papers on obesity (Sundmacher (2012)). Second, physicians may also less likely to advice patient about diet as they do for smoking cessation (Dolor et al. (2010)).

5 CONCLUSION

The paper offers informative evidence on how French workers have reacted to the onset of an acute health shock. The findings suggest that there is a significant effect running from the shock to the number of cigarettes smoked with impact duration of eight years after the shock. Individuals subject to a shock smoke on average 2.1 cigarettes less (per week) than those who do not face such a shock. There is no effect, however, of the exogenous shock on the body mass index.

Nonetheless, our results do face some limitations. First, because it only takes into account GDF-EDF's workers, and therefore is not representative of the French population. Second, data could suffer from selective mortality: individuals surviving to the health shock are a selective sample. Therefore, the finding is likely to suffer from a healthy bias because the unhealthier are died or drop out

Based on these findings, various prevention messages, mimicking the effect of a health shock could be defined and tested in order to establish whether or not they change cigarette consumption.

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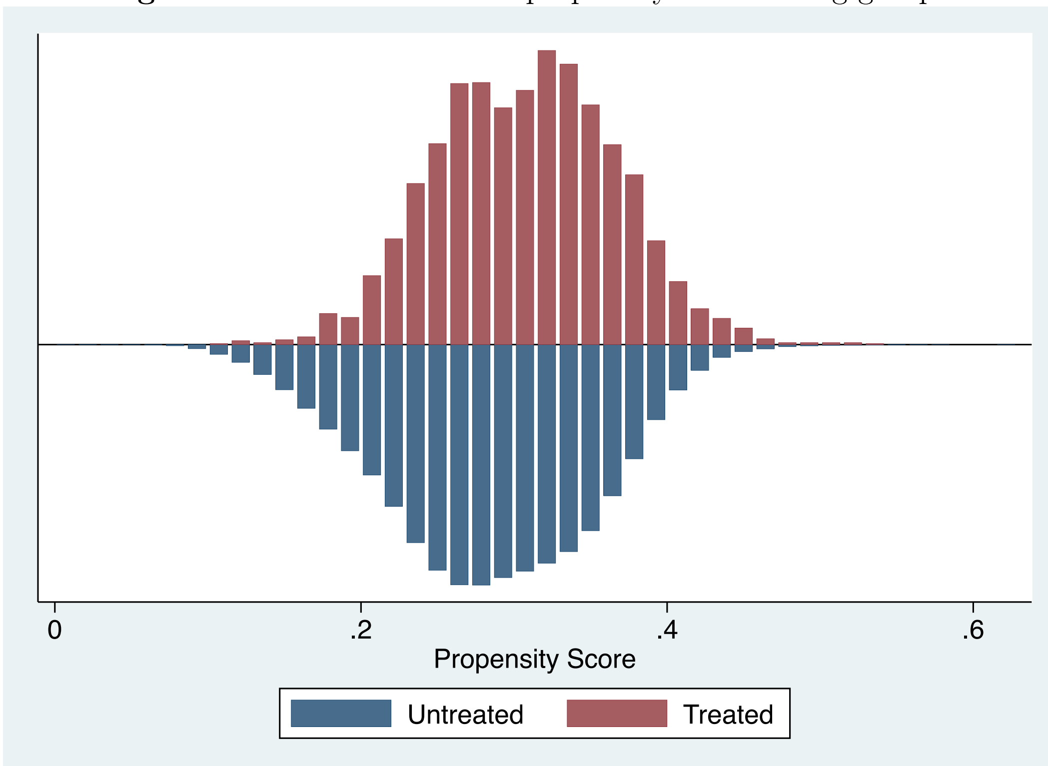
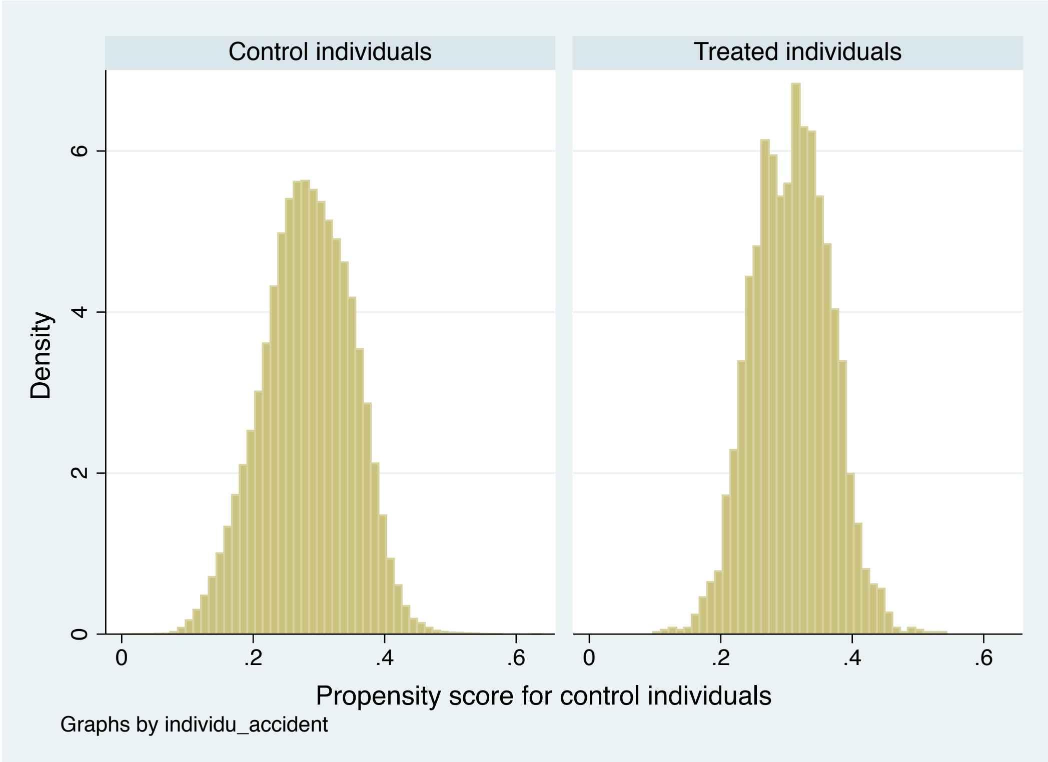
6 FIGURES & TABLES

Figure 1: Distribution of the propensity score among groups.



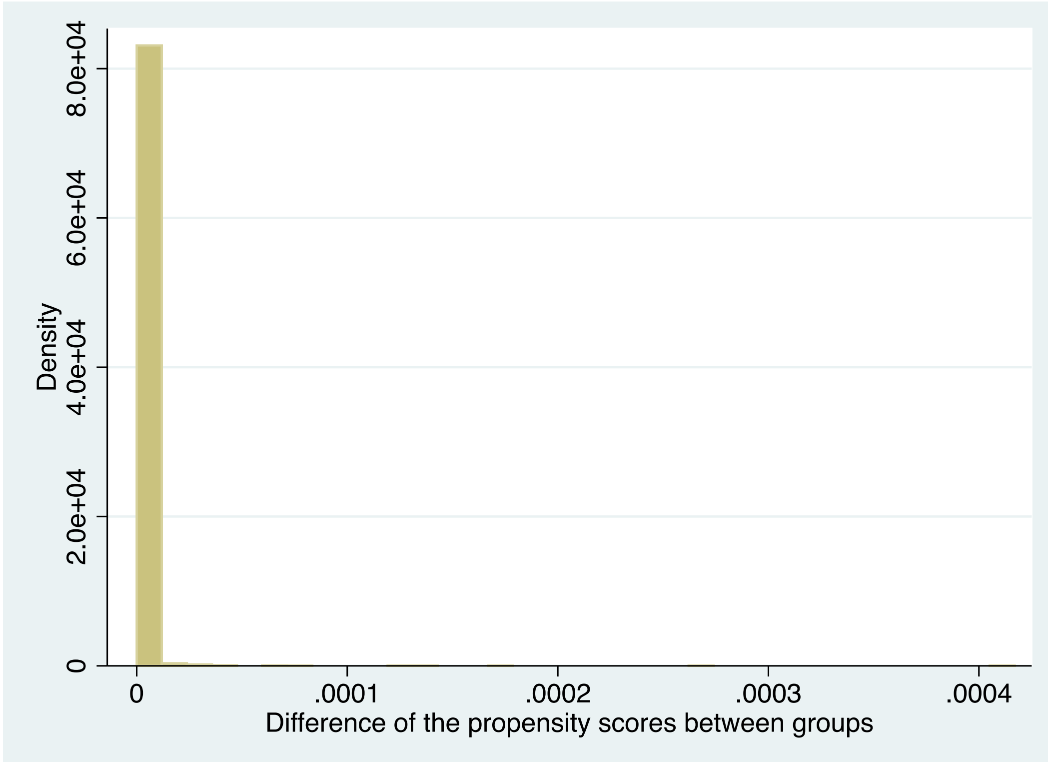
Note: This figure offers the propensity score distributions and its density among the treated and the control group. This shows the treated cases in red on top and the control cases in blue on bottom. Distribution of control and treatment cases appear to similar.

Figure 2: Histogram of the distribution of the propensity score for both groups.



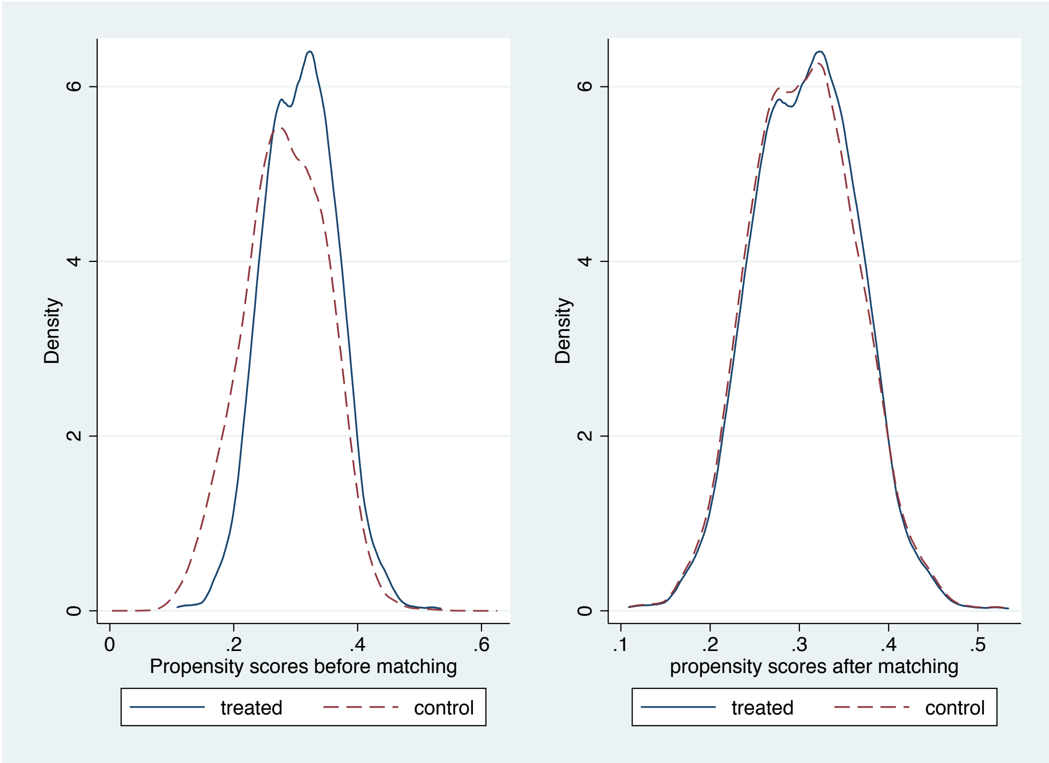
Note: It shows that control group span the full range of propensity scores.

Figure 3: Difference in the propensity score between treated and control group.



Note: This figure displays that most of the treated cases were matched to controls with propensity score close to their own (most are less than a 0.0001 difference).

Figure 4: Estimated propensity score distributions by groups before and after the matching procedure.



Note: This figure shows the propensity score distributions and its density among the treated and the control group. It displays that before the matching strategy, there is some difference between these two groups. After the matching, however, the two groups seem to be comparable.

Table 1: Achieved balancing on conditioning variables.

	Before matching		After matching			
Variables	Pseudo-treated	Pseudo-matched	Treated	Matched	% bias	P-value
Age	56.590	56.058	55.895	55.841	1.1	0.826
Age squared	3269.742	3210.078	3139.8	3136.5	0.6	0.904
Educational attainment	4.238	4.156	4.4081	4.1792	13.2	0.024
Educational attainment squared	21.072	20.349	22.32	20.44	12.1	0.033
Marital status	2.346	2.315	2.2697	2.4372	-18.2	0.007
Number of individuals in the household	2.571	2.743	2.3993	2.4664	-6.7	0.252
Household income	5.920	5.769	6.007	5.8033	13.9	0.501
Professional status	2.068	1.837	2.1751	2.1349	4.0	0.660
Gender	1.258	1.288	1.2347	1.2382	-0.8	0.889
Number of cigarette smoked	1.831	2.754	0.92469	1.1804	-5.8	0.276
Self-reported health status	3.239	3.196	3.1471	3.1623	-1.3	0.832
Body mass index	25.915	25.616	25.684	25.625	1.7	0.770

Note: This table reports the balancing between the two groups. There is still some statistical differences between the control and the treated group, but this is not for important variables (i.e. number of cigarette smoked or the BMi). The standardised % bias is measured as the difference of the means in the treated and non-treated as a percentage of the square root of the average of the sample variances in the treated and controls groups.

Table 2: Sample description for time invariant variables at the individual level

	Number of obs.	Percentage
Individual facing a health shock		
Yes	3,465	28.25%
No	8,802	71.75%
Educational attainment		
Less or equal to a bachelor's degree	6319	51.40%
Bachelor's degree to complete secondary education	4352	35.40%
Higher than secondary education	1623	13.20%
Father profession		
Farmers	1158	9.42%
Crafts-man	1295	10.53%
Chief executive officer	105	0.85%
Executive	1334	10.85%
Intermediary profession	2600	21.15%
Employee	800	6.51%
Worker	3886	31.61%
Other	1116	9.08%
Sexe		
Women	8,895	72.35%
Men	3,399	27.65%
Total	12294	100%

Standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Difference in cigarette consumption before the health shock

	Difference in cigarette smoked between groups	
ATT_{t-1}	-0.195	
	(0.170)	
ATT_{t_0}		-0.240
		(0.160)
Observations	97433	97486

Standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Difference in cigarette consumption after the health shock

	Difference in cigarette smoked between groups									
ATT_{t+1}	-0.284*									
	(0.151)									
ATT_{t+2}		-0.439***								
		(0.159)								
ATT_{t+3}			-0.398**							
			(0.161)							
ATT_{t+4}				-0.457***						
				(0.170)						
ATT_{t+5}					-0.509***					
					(0.175)					
ATT_{t+6}						-0.409**				
						(0.181)				
ATT_{t+7}							-0.402**			
							(0.185)			
ATT_{t+8}								-0.358*		
								(0.194)		
ATT_{t+9}									-0.347	
									(0.217)	
ATT_{t+10}										-0.186
										(0.217)
Observations	92747	87665	82471	77309	72037	66798	61620	56478	51316	46182

Standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Difference in body mass index before the health shock

	Difference in body mass index between groups	
ATT_{t-1}	-0.003	
	(0.141)	
ATT_{t_0}		-0.031
		(0.137)
Observations	77797	97486

Standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Difference in body mass index after the health shock

	Difference in body mass index between groups									
ATT_{t+1}	-.051									
	(0.139)									
ATT_{t+2}		0.105								
		(0.146)								
ATT_{t+3}			0.080							
			(0.155)							
ATT_{t+4}				0.027						
				(0.162)						
ATT_{t+5}					0.157					
					(0.201)					
ATT_{t+6}						-0.291				
						(0.242)				
ATT_{t+7}							0.016			
							(0.190)			
ATT_{t+8}								0.008		
								(0.202)		
ATT_{t+9}									-0.062	
									(0.225)	
ATT_{t+10}										0.045
										(0.243)
Observations	78003	72485	67066	61970	56810	51911	51918	46973	42239	37567

Standard deviations in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$