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UNIVERSITÄT DUISBURG ESSEN

#459

Imprint

Ruhr Economic Papers

Published by

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

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Hohenzollernstr. 1-3, 45128 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #459

Responsible Editor: Volker Clausen

ISSN 1864-4872 (online) – ISBN 978-3-86788-518-8

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Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

http://dx.doi.org/10.4419/86788518
ISSN 1864-4872 (online)
ISBN 978-3-86788-518-8

Christian Bünnings[1]

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The Effect of Health Events on Smoking Cessation

Abstract

This paper investigates whether new health information affects smoking behavior. Interpreting three distinct categories of health events as different information, the paper also tests whether behavioral change depends on the type of information received. Based on retrospectively reported data on smoking behavior from the Swiss Household Panel, a linear probability model is applied to estimate the effects of three different health events on the decision to quit smoking. The empirical results yield robust evidence that smokers respond differently to health events that are due to different causes. Suffering from physical health problems increases the inclination to stop smoking, the opposite holds true for mental disorders, while accidents do not affect health behavior at all. Analyses of effect heterogeneity further reveal that the same type of information affects various subgroups of the population differently.

JEL Classification: C23, I10

Keywords: Health events; behavioral change; smoking cessation; retrospective data

December 2013

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1 Introduction

Based on data from 2004, the World Health Organization (2009) estimates that tobacco consumption is the second most important risk factor for deaths worldwide, which translates to more than 5 million deaths each year. While smoking prevalence is slowly decreasing in high-income countries such as Switzerland, it is continuously increasing in low- and middle-income countries. This will lead to even more tobacco-related deaths in these countries in the future (World Health Organization, 2009).[1] How to prevent non-smokers from taking up smoking and how to motivate current smokers to quit smoking are important questions for public health policymakers. Existing anti-smoking measures operate through different channels. Smoking bans, for instance in public places or at work, aim at protecting non-smokers against secondhand smoke and at reducing the opportunities for smokers to smoke. Other campaigns, such as printing shocking images on cigarette packs, use emotional and fear-arousing messages to transmit information on the detrimental consequences of tobacco consumption. These campaigns are effective if they achieve changes in both the perception of the target group and their actual health behavior, i.e. quitting or at least reducing smoking.

The existing literature on this topic, however, provides mixed evidence on whether such information affects smoking behavior. Liu and Tan (2009) find that anti-smoking media campaigns significantly decreased the prevalence of smoking in California. In a controlled trial, McVey and Stapelton (2000) observe a reduction in smoking prevalence as a consequence of anti-smoking television campaigns in England. Using regional variation of per capita tobacco control expenditures in Switzerland, Marti (2013) estimates a discrete-time hazard model and finds a positive effect of tobacco control expenditures on the probability of quitting smoking. Bardsley and Olekalns (1999), however, find both health warnings on cigarette packs and workplace bans on tobacco consumption to have only minor effects in Australia. Moreover, Job (1988) argues that using emotional and fear-arousing messages in health-promoting campaigns may produce the opposite of the desired effects, which is also referred to as reactance (Brehm, 1966). Reactance reflects the tendency of individu-

[1] Even in Switzerland, tobacco use was still the most common cause of preventable deaths in 2007 (Federal Statistical Office, 2009).

als to respond counterproductively to restrictions on their freedom of choice (Wiium et al., 2009). Smokers with a high degree of reactance may even smoke more or downplay the risks of smoking if they feel constrained by these campaigns (Brehm, 1966; Harris et al., 2007). Ruiter and Kok (2005) conclude that those who are most at risk may react particularly defensively to such fear-arousing messages. In an experimental study, Erceg-Hurn and Steed (2011) observe a high degree of reactance among smokers who were exposed to graphic warnings, but little reactance among those who were subject to written warnings only. Hence, reactance, and thus the effectiveness of such anti-smoking campaigns, may also depend on how cautionary health information is delivered.

Analyzing the effects of anti-smoking campaigns on smoking prevalence usually raises the issue of how to measure exposure to and perception of such information. To circumvent this problem, another strand of the literature exploits the experience of a health event as specific type of new information. Using health events offers the advantage that the researcher knows individual exposure and perception, at least to a certain degree. Although self-perceived health events can be considered as extreme cases of new information, they are probably the most direct form of health information, as they instantaneously confront individuals with their own health behavior. Hsieh (1998) analyzes the decision to stop smoking based on increased health risks for the elderly in Taiwan. He observes that increases in health risks lead to significantly higher quitting rates. In a recent paper, Sundmacher (2012) analyzes the effect of health events on both smoking cessation and the probability of losing weight among obese individuals. Using the German Socioeconomic Panel, she observes that the experience of a general health event increases the likelihood of smoking cessation within the same year. Both Hsieh (1998) and Sundmacher (2012) interpret a drop in self-assessed health as the occurrence of a health event. Although self-assessed health has been shown to be a good predictor for both morbidity and mortality (Idler and Benyamini, 1997), it does not allow differentiating between what causes the health event. However, different health events may induce different reactions in terms of health behavior. Exploiting panel data from the Health and Retirement Study, Smith et al. (2001) observe that smokers downgrade their longevity expectations after a smoking-related health event more dramatically than after experiencing general health problems.

This paper is closely related to the study of Smith et al. (2001) and contributes to the understanding of how new information affects individual health behavior. Instead of analyzing induced changes in expectations (Smith et al., 2001), this paper aims at investigating how new information induces actual changes in health behavior, i.e. smoking cessation. To test whether behavioral change depends on the type of information received, this study interprets various health events as different types of new health information. In particular, it uses three distinct categories of health events: physical health problems, mental disorders and accidents, and forms the following hypotheses. First, and following the previous findings in the literature, physical health events, which could be related to smoking, increase the probability to stop smoking, as they confront individuals directly with the harmful consequences of their own health behavior. Second, mental illnesses decrease the probability of smoking cessation. The intuition behind this is that tobacco consumption may serve as self-medication, and that smokers may avoid the stress induced by smoking cessation, such as withdrawal symptoms. Lasser et al. (2000) and Ziedonis et al. (2008), for instance, observe that individuals who suffer from mental disorders have significantly lower quitting rates than smokers without mental problems. Third, accidents do not affect smoking behavior at all. The rationale here is that accidents can be assumed to be exogenous and thus unrelated to the affected person's smoking behavior. Hence, individuals are expected not to adjust their smoking behavior as a result of an accident. To test these hypotheses, the empirical analysis uses longitudinal individual-level data from the Swiss Household Panel. Individual smoking histories are constructed using contemporaneously and retrospectively reported data on smoking onset and on smoking cessation. The effects of the three types of health events discussed above on the decision to quit smoking are estimated in a linear probability model, taking into account the addictive nature of cigarette smoking as well as potential confounders. The estimation results yield robust evidence that individuals do react to new information in terms of health events. Furthermore, different types of information induce different behavioral changes. While suffering from physical health problems increases the probability of smoking cessation, the opposite holds for mental disorders. Accidents have no effect on smoking behavior. To investigate whether these effects are driven by certain subgroups, additional heterogeneity analyses are conducted. The results indicate that the same type of information leads to different reactions in various subgroups. Hence, designing effective anti-smoking campaigns requires taking into account not only that individuals react differently to various types of information, but also that different individuals respond differently to the same type of information. The effectiveness of anti-smoking campaigns might therefore be improved if these campaigns differentiated more clearly between target groups.

The rest of this paper is organized as follows. Section 2 outlines the empirical strategy and section 3 describes the data in more detail. Section 4 reports the main findings along with the results obtained from heterogeneity analyses and robustness checks. Section 5 concludes.

2 Empirical Strategy

To address the question whether different types of information induce different reactions with respect to health behavior, this paper exploits information on three different health events. In particular, the analysis distinguishes between health events caused by physical reasons, by mental problems, and by accidents. As outlined above, the hypotheses to be tested are: physical health events increase the probability of smoking cessation; mental disorders decrease the inclination to quit smoking; and accidents do not affect smoking behavior at all. To estimate the effects of these health events on the decision to quit smoking, a linear probability model is applied. Conditional on being a smoker, the probability of smoking cessation is expressed by the following equation:[2]

$$y_{it} = \beta HE_{it} + TaR'_{it}\delta + X'_{it}\gamma + \alpha_i + \varepsilon_{it}$$

where y_{it} is a binary variable representing smoking cessation between $t-1$ and t. The coefficient of interest is β, the effect of different health events (HE_{it}) on the decision to quit smoking. To account for both the survival characteristics of the data and the addictive

[2] Smokers are considered until they quit smoking or leave the sample for other reasons. Basically, this data setup could also be used to estimate as a hazard model in discrete time. However, analyzing the time to cessation, which is the purpose of a hazard model, may not be useful in this analysis, as individuals are expected to react instantaneously to new information in terms of health events.

nature of tobacco consumption, the vector TaR_{it} (*Time at Risk*) includes the cubic polynomial of the number of years an individual has smoked, a time-invariant indicator for heavy smokers, as well as the corresponding interaction terms.[3] The vector X_{it} contains potential confounding variables that may simultaneously affect both the probability of a health event and the decision to quit smoking. These potential confounders are discussed in more detail in section 3. One might argue that unobserved characteristics could simultaneously affect both the probability of smoking cessation and the likelihood of suffering from certain health events. Quaak et al. (2009), for example, find that smoking behavior is related to genetic factors which could also affect the probability of experiencing a health problem. To allow these time-invariant unobservables to be correlated with the explanatory variables, in particular with the probability of suffering from a health event, individual fixed effects also enter the model. All specifications are estimated using robust standard errors that are clustered at the individual level.

Identifying the effect of health events on smoking cessation requires the assumption that the health event is not a consequence of smoking cessation. Both smoking cessation and the health event occur in the same period of time, i.e. between two interview dates, which may raise concerns about reverse causality. Although the issue of potential reverse causality cannot be solved entirely, several arguments are provided below for why reverse causality, even if present, should not be a crucial issue in this application.

3 Data

The empirical analysis is based on data from the Swiss Household Panel (SHP), a representative longitudinal survey in Switzerland. The survey started in 1999 and collects information from all members aged 14 and older of more than 5,000 households. The SHP provides extensive information on socioeconomic characteristics, but also covers a broad range of health related topics such as mental and physical health as well as health behavior.[4]

[3] Sundmacher (2012) and Marti (2013) use similar approaches and include the cubic polynomial of time at risk.

[4] Detailed information on SHP can be obtained from Voorpostel et al. (2012).

3.1 Individual Smoking Histories

Individual smoking histories are constructed based on questions about current and past smoking behavior, which were introduced into the SHP in 2010. In particular, the age at smoking onset and the age at smoking cessation are used to classify an individual as a smoker at the time of his interview. As this analysis focuses on smoking cessation, only smokers enter the sample until they quit smoking or leave the study.[5] Furthermore, the estimation sample is restricted to cigarette smokers. Individuals who reported smoking only cigars or pipes are not considered, since it is not clear how to compare cigarette smokers to pipe or cigar smokers in terms of consumption levels and habits and with respect to addiction. The final sample thus consists of 1,681 individual smoking histories (10,742 person-year observations), of whom 468 individuals quit smoking during the observation period that covers the waves from 2000 to 2011.[6] Descriptive statistics of all variables used throughout the analysis are provided in Table 1.

3.2 Health Events

Survey participants state whether they have suffered from an illness, accident, or other serious health problem and report the month and year of its onset, which is used to match the health event with interview dates.[7] Moreover, participants report the type of health event they suffered from and select one of the following categories: physical reasons, mental reasons, four types of accidents, and other unspecified reasons.[8] This information is used to construct four binary health event indicators. The first simply indicates whether any type of health event has occurred since the last interview and might be comparable to an

[5] Only one period of smoking can be considered per individual (from the age of smoking onset to the age at potential cessation), as the data does not permit the observation of multiple periods of smoking and non-smoking. Similar approaches are adopted by Douglas and Hariharan (1994), who analyze the hazard of taking up smoking, Douglas (1998), who investigates the hazard rates for starting and quitting smoking, Forster and Jones (2001), who estimate tax elasticities for both taking up and quitting smoking, and Marti (2013), who estimates the impact of tobacco control expenditures on individual smoking behavior in Switzerland.

[6] Since questions concerning the key explanatory variable, i.e. the occurrence of a health event, were introduced in 2000, the first wave (1999) was not considered.

[7] An individual can report only one health event in the period between two interviews, but may experience more than one health event during the whole sample period.

[8] Physical and mental reasons are not specified in more detail. Accidents are subdivided into work accidents, road accidents, sport accidents, and accidents at home or in the garden.

Table 1: Descriptives

Variable	Mean	Std.	Min.	Max.
Quit smoking (dependent variable)	0.04	0.20	0	1
Health event (all reasons)	0.11	0.32	0	1
Health event (physical)	0.06	0.24	0	1
Health event (mental)	0.01	0.08	0	1
Health event (accident)	0.03	0.17	0	1
Health event (other)	0.02	0.14	0	1
Age	42.79	14.69	16	88
Female	0.55	0.50	0	1
Married / partner (base category)				
Single	0.25	0.43	0	1
Widowed	0.03	0.17	0	1
Divorced	0.09	0.29	0	1
Separated	0.02	0.13	0	1
Number of children	0.63	0.96	0	8
Income (CHF)	51,275	49,837	0	750,000
Years of education	12.73	2.70	9	21
Swiss citizenship	0.88	0.32	0	1
French-speaking (base category)				
German-speaking	0.66	0.47	0	1
Italian-speaking	0.04	0.20	0	1
Risk-averse	0.65	0.48	0	1
Unemployed	0.02	0.16	0	1
Pregnancy	0.01	0.08	0	1
Heavy smoker	0.44	0.50	0	1
Time at risk (in 10 years)	2.34	1.37	0	7.4

Note: Based on 10,742 observations.

overall measure of health events that is derived from a drop in self-assessed health.[9] This, however, does not allow the analysis of whether different information leads to different behavioral changes. Therefore, separate indicators for physical and mental health events are constructed. The four types of accidents are collapsed into another binary variable. Unspecified health events are not considered further, as they provide no basis for forming a hypothesis.[10]

3.3 Control Variables

Apart from a set of standard controls, such as age and its squared term, gender, the number of children, marital status, Swiss citizenship, years of education, and income, the model

[9] Several studies interpret a drop in self-assessed health between to interviews as a health event, e.g. Riphahn (1999) for the effect on labor market outcomes; Lindelow and Wagstaff (2005) for the effect on consumption, labor market outcomes and medical expenditures; Sundmacher (2012) for the effect on smoking cessation.

[10] The overall measure of health events does include these unclassified health events.

includes further controls which might affect both the decision to quit smoking and the probability of experiencing a health event. Pregnancy provides a strong motive to quit smoking, but may also lead to a higher vulnerability to negative health events. Since women are not explicitly asked whether they are pregnant, the model follows the approach of Sundmacher (2012) in assuming pregnancy in period t if a child under the age of one enters the household in $t+1$. Marcus (2012) finds that unemployment affects smoking initiation and observes a positive - though not significant - effect on smoking continuation. Given the large body of literature that highlights the negative effects of unemployment on health, a separate binary indicator for unemployment also enters the model. Smoking cessation might also be related to personality traits, in particular to extraversion or risk aversion (Van Loon et al., 2005; Ida et al., 2011). One may hypothesize that risk-loving individuals are more likely to experience a physical health event, which is why a time-invariant binary indicator for risk aversion is included. Self-stated willingness to take risks is reported on an 11-point scale ranging from 0 (*avoid taking risks*) to 10 (*fully prepared to take risks*). An individual is assumed to be risk-averse if she rates her willingness to take risks not greater than six. A growing body of literature considers the relationship between smoking behavior and both ethnicity and culture, though the results are inconclusive. Christopoulou and Lillard (2013), for instance, find that culture can predict smoking participation, while Hymowitz et al. (1997) observe no significant effect of ethnicity on smoking cessation. To allow culture to be related to the probability of reporting or experiencing a health event, I exploit the coexistence of four national languages in Switzerland as a proxy for cultural differences and include a set of language dummies.[11] As discussed in the previous section, the cubic polynomial of the number of years an individual has already been smoking, a binary time-invariant dummy variable for heavy smokers, as well as the corresponding interaction terms also enter the model. An individual is classified as a heavy smoker if he reports smoking more than 15 cigarettes per day.

[11] Roughly two-thirds of the Swiss population speak German. French is spoken by about 20 percent. About 7 percent speaks Italian, and a minority of 0.5 percent speaks Romansh.

4 Results

4.1 Main Results

Table 2 presents the results of the coefficient estimates of four different health event indicators using both a pooled OLS model, which disregards the panel structure of the data, and a fixed effects model, which accounts for time-invariant unobserved heterogeneity. Altogether, eight separate regressions were run. As outlined in section 3, the first health event dummy indicates whether any type of health event has occurred since the last interview (1.228 cases). The three remaining variables are mutually exclusive subsets of the first one. The second indicates a physical illness (642 cases), while the third and the fourth represent mental health events (70 cases) and accidents (308 cases), respectively.[12]

Beginning with the effect of having experienced any type of health event (HE_{all}) on the inclination to stop smoking, the point estimators exhibit positive signs and are highly significant in both specifications, in particular in the fixed effects model. This in line with the findings of Hsieh (1998) and Sundmacher (2012) to the extent that general self-perceived deterioration of health increases the probability of smoking cessation on average. Yet, looking at the different health events separately, it turns out that the overall effect is the product of two opposing effects. Physical health problems, which can be related to smoking behavior, significantly increase the likelihood of smoking cessation. In contrast, smokers are less likely to quit if they suffer from mental disorders. Accidents, which can be expected to be unrelated to smoking behavior, do not induce changes in smoking behavior at all.

To obtain a first idea of what the estimated coefficients imply in quantitative terms, the unconditional mean probability of quitting smoking in the sample, which corresponds to 0.044, serves as first benchmark. Against this measure, the estimated coefficients point towards an effect of substantive magnitude. Physical health events increase the unconditional mean probability of quitting by more than 80 percent, while mental problems lead to a reduction of almost 70 percent. However, when interpreting the coefficient estimates one must take into account that the unconditional mean probability of quitting is rather

[12] The remaining 208 cases are events without information on the health problem and are not considered further. Additional unreported regressions show no effect of these unspecified health events on the decision to quit smoking.

Table 2: Linear Probability Models

	Pooled OLS		Fixed Effects	
	β	$S.E.$	β	$S.E.$
HE_{all}	0.019^{***}	(0.007)	0.019^{***}	(0.007)
$HE_{physical}$	0.040^{***}	(0.011)	0.038^{***}	(0.011)
HE_{mental}	-0.039^{***}	(0.003)	-0.030^{***}	(0.008)
$HE_{accidents}$	-0.003	(0.012)	0.002	(0.012)
# observations		10,742		
# individuals		1,681		
# quitters		468		

The table shows the results of 8 separate regressions. All coefficients are regression-adjusted.
Robust standard errors are clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

low in this sample. To put the estimated coefficient into another perspective, the empirical standard deviation of the dependent variable, which amounts to 0.204, serves as a second benchmark. The coefficient estimates of physical and mental health events translate to roughly 20 percent and 15 percent of a standard deviation, respectively. This confirms the considerable impact that new information in terms of health events has on smoking behavior. However, the substantive size of the effect may also be explained by the fact that health events can be considered as an extreme case of new information (Smith et al., 2001).

Considering the research questions of interest here, i.e. whether new information induces behavioral changes, the empirical results have two implications: new information generally induces behavioral changes, but - probably more importantly - different kinds of information affect changes in health behavior in various ways. With respect to the impact of anti-smoking campaigns, which are based solely on emotional and fear-arousing messages, this means that this way of providing new information encourage some individuals to quit, but may produce counterproductive results among others. The latter can occur if emotional and fear-arousing messages negatively affect the recipient's mental wellbeing.

4.2 Heterogeneity Analysis

The previous subsection addresses the question whether various types of information have different effects on health behavior. This subsection goes one step further and tests whether the same type of information is equally effective for different subgroups of the population.

Table 3: Heterogeneity Analysis

FE-Estimation	Physical HE β	S.E.	Mental HE β	S.E.
Gender				
HE	0.047^{***}	(0.019)	-0.046^{**}	(0.020)
$HE \times female$	-0.016	(0.023)	0.025	(0.021)
Age				
HE	0.010	(0.013)	-0.029^{**}	(0.012)
$HE \times 50$ *and older*	0.059^{***}	(0.022)	-0.001	(0.015)
Education				
HE	0.033^{***}	(0.011)	-0.022^{***}	(0.006)
$HE \times 18$ *years and more*	0.050	(0.042)	-0.068	(0.055)

The table shows the results of 6 separate regressions. All coefficients are regression-adjusted.
Robust standard errors are clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

This insight can help to further improve the effectiveness of anti-smoking campaigns. If a segmentation of anti-smoking measures is to be feasible, the targeted subgroups must be easily identifiable to policymakers. This analysis therefore considers gender, age, and education as sources of potential effect heterogeneity. To analyze the effect for these subgroups separately, the models are re-estimated with additional interaction terms for the main independent variables ($HE_{physical}$ and HE_{mental}) and the corresponding subgroup identifiers. The latter are binary indicators for women, individuals aged 50 and older, and persons with more than 17 years of formal education. Table 3 presents the results of six different regressions using the fixed effects model. The left and right parts respectively report the estimated coefficients of the interaction terms with physical and mental health events. The corresponding main effects are also included.

Beginning with gender, the estimated interaction effects reveal moderate, though not significant heterogeneity for both physical and mental health problems. The interaction effects carry the opposite signs than the corresponding main effects. This can be interpreted such that women are less sensitive to both types of health events, which might explain why women were found to be generally less successful at giving up smoking than men (e.g. Wetter et al., 1999).

The positive and highly significant estimated interaction effect with respect to age suggests that the overall impact of physical health events on behavioral change is driven mainly by individuals aged 50 and older. Older persons, who are presumably long time smokers, might be more likely to relate physical problems to their smoking behavior than younger individuals. Moreover, older people may allocate more weight to end-of-life utility (Suranovic et al., 1999), and hence react more sensitively to such information. With respect to mental disorders, the corresponding point estimator is close to zero and statistically insignificant, suggesting similar reactions for both younger and older individuals.

Finally, more highly educated individuals who might be more aware about the harmful consequences of smoking appear more likely to quit smoking after a physical health event. However, the opposite holds for mental health problems, suggesting that better educated individuals are even less likely to stop smoking as a consequence of mental problems. Again, although the point estimators are of considerable magnitude, the estimated coefficients are not significant at conventional levels. However, this is likely to be the result of too few cases in the single cells, especially regarding mental disorders (70 cases).

4.3 Robustness Checks

This subsection discusses the potential problem of reverse causality and presents the results of additional robustness checks. As mentioned in section 2, both the health event and the decision to quit smoking take place between two interview dates. Although exact information exists on the onset of the health event, the exact timing, i.e. the month of smoking cessation is not available from the survey. This may raise concerns about reverse causality. Apart from an instrumental variable, which is not available from the survey, a natural approach would be to use the lagged health event variable to ensure that the health event occurred before individuals quit smoking. However, smokers are expected to adjust their behavior immediately after the health event occurs, when awareness of this new information is likely to be highest. This is also observed by Sundmacher (2012), who finds no effect for the lagged health event variable. For the present sample, Appendix A.1 shows smoking cessation by year of the health event. The heap at zero clearly suggests that individuals respond rather directly to new information in terms of health events. Additionally, Appendix A.2 presents the results of regressions using different lags of the health event variable. All estimated coefficients are close to zero and statistically not significant. Hence, using the lagged health event does not seem feasible in this application.

Furthermore, reverse causality should not be a substantial problem in the present case. As discussed above, health events are expected to lead to an immediate adjustment of smoking behavior. The reverse effects of smoking cessation on the probability of suffering from a health event, however, are likely to appear much later. The positive impact of smoking cessation on physical health, for instance, comes into effect only after a certain period of abstinence. Furthermore, even if there are simultaneous effects in both directions, this is likely to result in conservative estimates, as they are expected to carry opposite signs. To be more specific, on the one hand the hypothesis is that experiencing a physical health event, which might be related to smoking, increases the probability of quitting smoking. On the other hand, the reverse effect of improved health behavior, or smoking cessation, on the probability of experiencing a physical problem can be assumed to be negative. The opposite is expected to hold for the relationship between mental disorders and smoking cessation in the short run. Mental problems affect the likelihood of smoking cessation negatively, for instance as continued smoking could be used to self-medicate symptoms of mental disorders, such as depression. The reverse effect of smoking cessation on the probability of suffering from mental problems is expected to be positive. Withdrawal symptoms associated with smoking cessation induce stress and may affect mental balance, which in turn leads to a higher vulnerability to mental problems. Since the estimated coefficient actually suggest that $\beta_{physical\ HE} > 0$ and $\beta_{mental\ HE} < 0$, potential reverse causality would result in conservative estimates.

Table 4 provides the results of additional robustness checks using the fixed effects model.[13] To add further credibility to the direction of causality, two placebo regressions are conducted. The first one pretends that the health events ($HE_{physical}$ and HE_{mental}) occur one period earlier (column (1)), while the second one pretends they happened two periods earlier (column (2)). The estimated coefficients are close to zero and insignificant across all specifications. This can be interpreted as further evidence that there are no unobservable time-invariant factors which simultaneously affect both the experience of a health event and the inclination to stop smoking.

One may also hypothesize that retrospectively collected data - though found to be a useful

[13] I also use the pooled OLS model, which does not affect the results in qualitative terms.

Table 4: Robustness Checks

FE-Estimation	(1)	(2)	(3)	(4)	(5)
$HE_{physical}$	0.003	−0.010	0.032**	0.034***	0.060***
	(0.008)	(0.008)	(0.014)	(0.010)	(0.023)
HE_{mental}	−0.011	0.007	−0.017	−0.024***	−0.044**
	(0.017)	(0.023)	(0.012)	(0.008)	(0.020)
# observations	9,628	8,276	5,656	10,193	7,698
# individuals	1,622	1,544	1,424	1,571	1,290
# quitters	375	321	267	358	344

The table shows the results of 10 separate regressions. All coefficients are regression-adjusted. Column (1) shows the results where the health events are pretended to have happened one period earlier. Column (2) presents the results where the health events are pretended to have happened two periods earlier. Column (3) restricts the sample to 2007 - 2011. Column (4) drops all individuals who reported to quit at one of the prominent ages. Column (5) excludes individuals with more than one health event in the observation period. Robust standard errors are clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

source for research on cigarette addiction - bias the results here due to measurement error in the dependent variable (Kenkel et al., 2003, 2004). Individuals may not remember correctly when they took up and quit smoking and may round their answers to multiples of 5 (Lopez Nicolas, 2002). Therefore, column (3) reports the results of restricting the sample to the period from 2007 to 2011. The idea behind this approach is to reduce potential misclassification, as only individuals are considered who quit smoking during the last five years. Additionally, column (4) presents the results excluding individuals who reported to have quit smoking at ages that are multiples of 5, as suggested by Kenkel et al. (2011). The results of both are close to those obtained from the unrestricted sample, indicating that they are not affected by recall bias.

The sample also contains some individuals who report more than one serious health event during the observation period. To ensure that the results are not driven by this subgroup, the models are re-estimated excluding all individuals who state having experienced more than one health event. The estimated coefficients, shown in column (5), are even larger than the coefficient estimates drawn from the basis specification. This is reasonable, as several health events that have not induced smoking cessation are now excluded from the sample. The overall conclusion, however, remains unchanged.

5 Conclusion

The present paper investigates whether new health information can induce changes in health behavior. On the basis of retrospective data from the Swiss Household Panel the empirical results yield robust evidence that new information in terms of self-perceived health events affects health behavior. More importantly, the results provide clear evidence that different types of information affect health behavior differently. Physical health events, which could be related to smoking, increase the probability of instantaneous smoking cessation. In contrast, individuals who suffer from mental health problems are less likely to quit smoking. Accidents have no effect on smoking behavior, as was expected. Moreover, the paper provides some evidence that the same sort of information leads to different reactions in various subgroups. Men and better educated individuals are generally more sensitive to new information, while older people react particularly sensitively to physical health problems.

These findings might explain to some extent the ambiguous results on the effectiveness of anti-smoking campaigns. Apart from the desired impact, i.e. to motivate smokers to quit, campaigns that are based solely on emotional and fear-arousing messages might even have counterproductive effects. The latter is conceivable if such information also affects the mental balance of certain subgroups or even evokes reactance. Therefore, designing effective anti-smoking campaigns needs to take potential adverse reactions into account. Moreover, the effectiveness of anti-smoking campaigns might be further improved if these campaigns differentiated more between target groups.

Although the paper provides relevant findings on how new information affects individuals' health behavior, several aspects motivate further research. First, the present analysis cannot ultimately rule out potential reverse causality. However, the paper argues and provides some evidence indicating that reverse causality - though problematic in theory - does not seem to be an issue in this application. Second, little is known about the long-term effectiveness of such information on smoking cessation. Individuals who quit smoking due to a health event may relapse after a certain period of time. The present results should therefore be interpreted as short-term rather than long-term effects. Finally, it would be desirable to differentiate further between the various possible causes of health events, especially between health problems that are related to smoking, such as stroke or lung cancer, and those that are presumably not attributable to smoking behavior.

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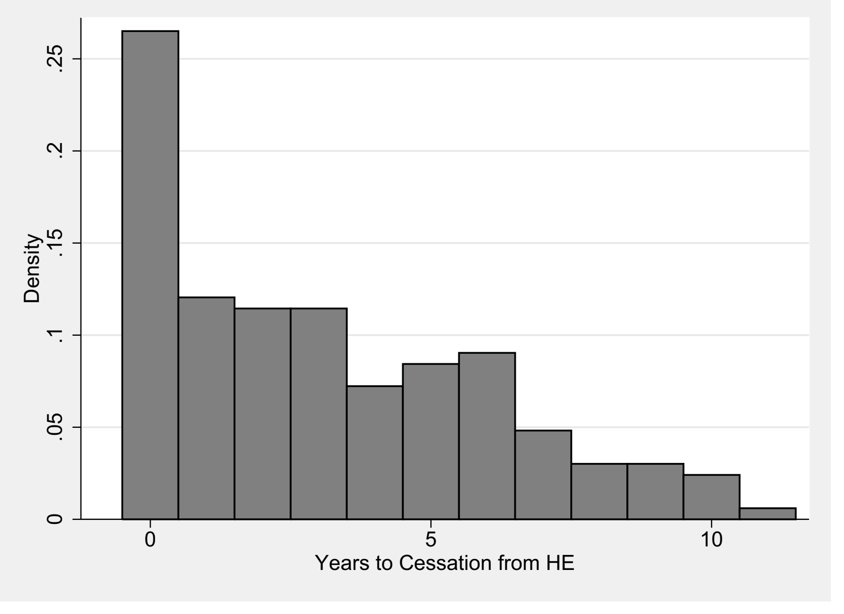
A Appendix

A.1 Quit smoking by year from health event



A.2 Coefficient estimates of lagged health events

HS_{all}	Pooled OLS β	Pooled OLS $S.E.$	Fixed Effects β	Fixed Effects $S.E.$	# Observations
no lag	0.019***	(0.007)	0.019***	(0.007)	10,742
1 lag	−0.001	(0.007)	0.000	(0.006)	8,815
2 lags	0.000	(0.008)	0.002	(0.008)	7,406
3 lags	0.005	(0.009)	0.007	(0.010)	6,079
4 lags	−0.005	(0.010)	−0.003	(0.010)	4,973

The table shows the results of 10 separate regressions. All coefficients are regression-adjusted. Robust standard errors are clustered at the individual level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$