A model of the impact of smoking bans on smoking with evidence from bans in England and Scotland

Andrew M Jones

Audrey Laporte

Nigel Rice

Eugenio Zucchelli

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Andrew M Jones[α], Audrey Laporte[β], Nigel Rice[γ], Eugenio Zucchelli[γ]

10 May 2011

This paper evaluates the impact of smoking bans on smoking using a policy change introduced by the UK government. We present a theoretical model of smoking that defines an individual's life-cycle addiction and cigarette consumption in the presence and in the absence of a public smoking ban. The model shows that the imposition of a public smoking ban should affect individuals differently according to their age, gender and previous level of cigarette consumption. We test the predictions of the model using data drawn from the British Household Panel Survey (BHPS). We assess the short-term impact of the UK smoking ban using differences-in-differences (DD) and changes-in-changes (CC) methods. We make use of the longitudinal nature of the data and implement a set of more flexible DD fixed effects panel data models. We find that the introduction of the smoking bans in Scotland and England had no impact on overall smoking prevalence. However, we do find some evidence on the effects of the ban on the level of cigarette consumption, especially among male heavy smokers, female moderate and heavy smokers and young people.

Key words: smoking, smoking bans, policy evaluation, BHPS

JEL Classification: C21, C23, D12, I10, I18

[α] Department of Economics and Related Studies (DERS), University of York, UK.
[β] Department of Health Policy, Management and Evaluation (HPME), University of Toronto.
[γ] Centre for Health Economics (CHE), University of York, UK.

1. Introduction

The introduction of a public smoking ban is one of the most high-profile public health interventions implemented in the UK in recent years. The Smoking Health and Social Care (Scotland) Act 2005 that prohibited smoking in enclosed public places was implemented in Scotland on 26th of March 2006. Although the primary aim of the Act was to protect non-smokers from the harmful effects of second-hand smoke, the reform was also intended to reduce the consumption of cigarettes and encourage greater quits amongst smokers. Similarly, England introduced legislation, implemented on 1st July 2007, to make virtually all enclosed public places, including workplaces, smoke free.

Despite steadily declining trends in tobacco consumption in most OECD countries, especially among men (OECD, 2010), smoking is still a major public health concern and one of the main causes of avoidable mortality and morbidity (Allender *et al.*, 2009; Peto *et al.*, 1994). In England, smoking remains a widespread phenomenon with, for example, 21 per cent of men and 20 per cent of women reporting smoking an average of 13 cigarettes per day (NHS, 2010). In 2009, 81,400 deaths of adults aged 35 or over were attributable to smoking (NHS, 2010); this corresponds to 18 per cent of all deaths for that age group. Medical and epidemiological evidence indicates that in addition to chronic pulmonary diseases and lung cancers, smoking is an important cause of a number of cardiovascular diseases and other types of cancers (Wald and Hackshaw, 1996; Kenfield *et al.*, 2008).

The potential policy relevance of a smoking ban goes beyond its immediate public health benefits and extends to impacts on health care costs (Barendregt *et al.* 1997; Hodgson, 1998) and inequalities in health. In 2006 smoking was estimated to cost the UK National Health Service (NHS) £5.2 billion, which accounts for approximately 5.5 per cent of the annual total health care costs for the year (Allender *et al.*, 2009). Further, both the economics and epidemiological literature have established the existence of a smoking gradient in developed countries with consumption of cigarettes concentrated among low educated and low income individuals (Muurinen and Le Grand 1985; Huisman *et al.*, 2005).

Accordingly, population-level tobacco control interventions are often concerned with reducing health inequalities (Thomas *et al.*, 2008).[1]

A substantial body of research suggests that anti-smoking policies such as imposing higher excise taxes and restricting smoking in public places can play an important role in reducing cigarette consumption (Chaloupka and Warner, 2000). Nonetheless, the literature on the effects of public smoking bans on smoking presents conflicting results. Callinan *et al.* (2010) review 50 studies on the impact of smoking bans in thirteen countries and conclude that while smoking bans lead to reductions in exposure to passive smoking, there is limited evidence on their impact on active smoking. Moreover, while the US literature is rich in empirical evaluations of different types of smoking bans (Abadie *et al.*, 2010; Adda and Cornaglia, 2006, 2010), evidence for the UK is very limited and has focused primarily on the indirect effects of a ban on passive smoking (Akhtar, 2007; Haw and Gruer, 2007; Jarvis *et al.*, 2009) and specific health outcomes such as respiratory and coronary diseases (Mackay *et al.*, 2010; Pell *et al.*, 2008). There is, however, sparse evidence from a UK perspective on the effects of the smoking ban on smoking. Moreover, few studies apply robust policy evaluation techniques and often lack theoretical support to guide empirical specifications.

The main objective of this paper is to evaluate the impact of smoking bans on smoking. We do this by developing a theoretical model of smoking behaviour that defines an individual's life-cycle addiction and cigarette consumption in the presence and absence of a public smoking ban. This framework allows us to predict the likely behavioural effects of the introduction of a public smoking ban on cigarette consumption. Employing a series of econometric methods common to the policy evaluation literature we test the predictions of our theoretical model using data drawn from the British Household Panel Survey (BHPS). In order to identify the effects of smoking bans on smoking we exploit the natural policy experiment that resulted from the differential timing of the introduction of the Scottish and English public smoking bans. We assess the short-term impact of the Scottish smoking ban using differences-in-differences (DD) and changes-in-changes (CC) methods (Athey and Imbens, 2006). We also make use of the longitudinal nature of the

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[1] However, Deaton (2002) argues that improving the health of the poor might be better achieved by targeting low incomes and low levels of education rather than health per se.

data and implement a set of more flexible DD fixed effects panel data models to assess the impact of the Scottish and English bans on both smoking prevalence and the number of cigarettes smoked.

Our theoretical framework shows that the imposition of a public smoking ban should impact individuals differently according to age, gender and level of consumption. Our empirical results broadly support these predictions. We find that the introduction of the UK smoking bans had no impact on overall smoking prevalence. However, we find some evidence that the ban affected levels of cigarette consumption, particularly among heavy smokers, female moderate smokers and younger people.

This paper offers three main contributions to the literature. First, it provides a theoretical framework that formulates and justifies heterogeneity in the impact of comprehensive smoking bans. This framework also sheds lights on the mechanics of the potential countervailing effects to this type of policy. Secondly, it offers a direct empirical assessment of these predictions employing rich longitudinal data on a recent policy experiment. Finally, this is, to the best of our knowledge, the first paper that evaluates the effects of the UK smoking bans on smoking using a series of robust methods of policy evaluation.

The remainder of the paper is organised as follows. Section 2 reviews the most recent literature on the effects of smoking bans. Section 3 describes our theoretical framework while Section 4 outlines the empirical models that we use to evaluate the impact of the UK smoking bans. Section 5 describes the data and Section 6 discusses the main results. Section 7 concludes.

2. Previous literature

While the UK introduced comprehensive public smoking bans only recently, the US has a long history of anti-smoking legislation (Dinan and Heckelman, 2005). As a result, the majority of the empirical literature on the effects of tobacco control policies is based on

US data and we focus attention on this literature.[2] Wasserman *et al.* (1991) employ a generalised linear model to analyse the demand for cigarettes among adults and teenagers. Combining a variety of data sources (The National Health Interview Survey (NHIS), Current Population Survey (CPS) and data from the Department of Health and Human Services and the Tobacco institute) they build a regulation index and find that regulations restricting smoking in public places significantly reduce the demand for cigarettes. Keeler *et al.* (1993) examine the effects of prices, taxes and anti-smoking regulation in California. After estimating alternative specifications that are robust to addictive behaviour and building a regulation index similar to Wasserman *et al.* (1991), they also find that regulations decrease cigarette consumption. Evans *et al.* (1999) investigate the impact of workplace smoking bans using a series of multivariate models on data from both the NHIS and the CPS. Their results indicate that workplace smoking bans reduce smoking prevalence and daily consumption of cigarettes among smokers.

More recently, Adda and Cornaglia (2006) analyse the compensatory behaviour of smokers and question the effectiveness of tax increases as a tool to regulate cigarette consumption. They develop a model that captures smoking intensity and, exploiting data on the levels of the biomarker cotinine from the National Health and Nutrition Examination Survey, they show that smokers increase the intensity of smoking in response to increases in excise taxes. The same authors also challenge the usefulness of smoking bans (Adda and Cornaglia, 2010). In particular, they evaluate the effects of smoking bans and excise taxes on smoking drawing on a theoretical framework for passive smoking and by using cotinine and time-use information in their empirical models. They find no clear evidence that smoking bans have an impact on either smoking prevalence, smoking cessation or attempted quits. However, the authors find that by displacing smokers from public to private locations, public smoking bans increase the exposure to cigarette smoke of non-smokers, especially among children living with smokers.

The literature on the effects of anti-smoking policies in other countries also presents mixed results. Buddelmeyer and Wilkins (2005) model the dynamics of smoking

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[2] Notable exceptions include Adda *et al.* (2006) and Adda *et al.* (2009) who study the economic impact of the Scottish smoking ban on public houses.

behaviour in Australia using multivariate probit models on data drawn from the Household, Income and Labour Dynamics in Australia (HILDA) survey. According to their findings, the impact of smoking restrictions in public places varies with age. Smoking bans decrease the probability of smoking initiation and increase the probability of smoking cessation only for teenagers while they enhance the likelihood of continued smoking for smokers aged between 18-24 years old. Employing logistic regressions on data from the Canadian Tobacco Use Monitoring Survey (CTUMS) and the National Population Health Survey (NPHS), Shields (2007) finds that smoking restrictions in Canada are associated with smoking cessation. De Chaisemartin and Geoffard (2010) evaluate the effects of workplace smoking bans in France using difference-in-differences models on a general population survey; the Health, Health Care and Insurance Survey (ESPS), and a dataset of patients utilising tobacco cessation services. They find that workplace smoking bans increase the demand for smoking cessation services but have no impact on overall smoking prevalence. Anger *et al.* (2011) examine the impact of public smoking bans on smoking behaviour using data from the German Socio-Economic Panel Study (SOEP). Their estimates, obtained using a series of difference-in-differences models, indicate that while smoking bans do not reduce smoking within the overall population, they significantly reduce both smoking propensity and intensity among individuals who frequently visit bars and restaurants.

Another strand of literature investigates the influence of anti-smoking initiatives on a series of smoking-related childhood conditions. Lien and Evans (2005) use data from the Natality Details files for four states in the US to analyse the impact of tax increases on maternal smoking and infant birth weight. Estimating difference-in-differences and two-stage least squares models, they find that smoking during pregnancy doubles the chance of a low birth weight baby and that increases in cigarettes taxes decrease smoking participation of pregnant women. Markowitz (2007) examines the impact of smoking regulation on the incidence of sudden infant death syndrome (SIDS). Her findings using U.S. data from the Multiple Cause of Death Files suggest that higher cigarette prices and stricter indoor air policies reduce SIDS.

Economic models of behavioural responses and incentives to smoking bans have only recently been explored. Irvine and Nguyen (2009) propose a model of maximising

behaviour where individuals can choose the quantity, intensity and timing of their cigarette consumption. Their model predicts that heavy smokers and higher income smokers are most affected by workplace bans and, similarly to Adda and Cornaglia (2010), that in the presence of a ban, smokers have an incentive to smoke more intensively. The authors confirm these predictions using quantile regressions on data from the Canadian Community Health Survey (CCHS). De Bartolome and Irvine (2010) investigate the welfare impact of smoking bans in an economy where the government has two types of instruments to limit cigarette consumption: a price policy (i.e. levying a tax on cigarettes) and a quantity policy (i.e. banning smoking in workplaces or public places). Their model shows that the government's ability to reduce smoking through a price instrument (taxation) is limited by the black market where cigarettes are not taxed and that a quantity instrument (ban) is always welfare enhancing.

3. A model of smoking and smoking bans

3.1 Smoking in the absence of smoking restrictions

Probably the most obvious feature of a smoking ban is that it affects a particular place, whether the workplace, pubs, aircraft, or public areas more broadly defined. Smoking-cigarette consumption-can occur in a wide range of places, and a single cigarette can yield differing marginal utility depending on where it is smoked. For a commodity like cigarettes, the most important factor causing the marginal utility function to differ across places is the sociability of the activity. In this paper, then, we adopt the well-established convention in economics of defining a commodity not only in terms of its physical characteristics but also in terms of where it is consumed.[3] We consider the case of two basic goods, cigarettes, denoted by S and a second consumption good, denoted by B and we assume that both goods can be consumed in two settings, R and U, where setting R is the one on which a smoking restriction will eventually be imposed and setting U will remain unrestricted. Here R refers to smoking in public places and U to smoking at home.

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[3] Because our theoretical model is dynamic, we are in effect also indexing consumption by time - when the cigarette is smoked.

For simplicity it is helpful to think of smoking at home versus smoking in a pub and to think of the second consumption good as beer.

Assume that consumption of beer and cigarettes yields utility in each of the settings, according to $V^R(S_R, B_R)$ and $V^U(S_U, B_U)$. Here the super- and sub-scripts on V, S, and B reflect the assumption that where an individual consumes a good matters to the utility which they derive from that good. Assume that B and S are purchased at prices P_{SR}, P_{SU}, P_{BR}, and P_{BU}. The subscripts allow for the possibility that the price of the goods depends on where they are purchased. In addition, define a third good I, at price P_I, which represents all goods which are beneficial to health. Define health capital as H and assume the presence of a composite commodity C, which has a price of 1, and from which the individual derives utility V(C). For simplicity, assume that the individual's utility function is additively separable in the commodities. The individual's budget constraint, which is binding in any period t can be written as:

$$Y = C + P_{SR}S_R + P_{SU}S_U + P_{BR}B_R + P_{BU}B_U + P_I I \tag{1}$$

Assume that the individual is aware that smoking is bad for their health. Let A denote the stock of smoking-related health damage. Assume that A does not enter the individual's utility function directly, but that H, health capital, does and that A (rather than S) affects H. The stock of health damage evolves according to the equation of motion:

$$\dot{A} = g(S; H) - \delta A, \, g_S > 0, \, g_{SS} > 0 \tag{2}$$

where $S = S_R + S_U$. Note that the location where the individual smokes has no impact on the damage done by smoking. The function g(.) contains H. For simplicity assume that H affects only the marginal product of g and not its level, i.e. assume that $g_{SH} < 0$. This means that increases in health reduce the marginal productivity of smoking in producing addiction . Health capital enters the utility function separably, through the term $V^H(H)$ where $V^H_H(H) > 0$, $V^H_{HH}(H) < 0$. The equation of motion for H is:

$$\dot{H} = I - \propto A - \delta H \tag{3}$$

where, for simplicity, assume that A affects H linearly. S does not enter the equation of motion for H directly: this is to reflect the assumption that it is cumulative smoking-related damage which reduces the stock of health and that, even if the individual goes cold turkey and sets S = 0, their accumulated smoking capital will continue to harm health until that smoking capital has decayed away.

The Hamiltonian for the smoker's optimisation problem is:

$$\mathcal{H} = V(Y - P_{SR}S_R - P_{SU}S_U - P_{BR}B_R - P_{BU}B_U - P_I I) + V^R(S_R, B_R) + V^U(S_U, B_U) +$$
$$V^H(H) + \psi[I - \alpha A - \delta H] + \mu[g(S;H) - \gamma A] \tag{4}$$

At this stage no restriction has been imposed on smoking in public, S_R. The necessary conditions are:

$$\frac{\partial \mathcal{H}}{\partial S_R} = -P_{SR}\frac{\partial V}{\partial C} + \frac{\partial V^R}{\partial S_R} + \mu g_S = 0 \tag{5}$$

$$\frac{\partial \mathcal{H}}{\partial S_U} = -P_{SU}\frac{\partial V}{\partial C} + \frac{\partial V^U}{\partial S_U} + \mu g_S = 0 \tag{6}$$

$$\frac{\partial \mathcal{H}}{\partial B_R} = -P_{BR}\frac{\partial V}{\partial C} + \frac{\partial V^R}{\partial B_R} = 0 \tag{7}$$

$$\frac{\partial \mathcal{H}}{\partial B_U} = -P_{BU}\frac{\partial V}{\partial C} + \frac{\partial V^U}{\partial B_U} = 0 \tag{8}$$

$$\frac{\partial \mathcal{H}}{\partial I} = -P_I\frac{\partial V}{\partial C} + \psi = 0 \tag{9}$$

The equation of motion for the costate ψ is:

$$\dot{\psi} = [r + \delta]\psi - \frac{\partial V^H}{\partial H} \tag{10}$$

and the equation of motion for the costate μ is:

$$\dot{\mu} = [r + \gamma]\mu + \alpha\psi \tag{11}$$

μ is the shadow price of damage done by smoking and it is therefore negative and ψ, is positive as it represents the shadow price of health capital. While H appears in the

equation of motion for ψ, the equation of motion for μ depends on μ and ψ. This is a two state variable problem, albeit with a slight twist, in that one of the state variables A, appears in only the equation of motion for the other state variable, H. Looking at the equation of motion for μ, if we integrate it with respect to time, so that we are dealing with levels rather than changes, we can see that the value of the costate for A must, along an optimal trajectory, depend on the value of the costate for H, and that latter costate ψ is multiplied by α, which is the coefficient showing by how much health capital is reduced as a result of a one unit increase in smoking-related damage.

Interpretation

In our optimisation problem smoking is only one of the factors which might affect an individual's health. Rational smoking decisions also take account of how changes in H over time for non-smoking related reasons will affect the decision about whether, and how much, to smoke. In terms of the necessary conditions for the two S variables, if a reduction in H for non-smoking related reasons causes g_S to increase, as we have assumed, then the health cost term will become larger and the optimal level of smoking will decline, whether at home or at the pub. In particular, since H tends to decline with age, even when the individual is using health investment, I, to slow the rate of decline, the necessary conditions suggest that this will tend to cause the optimal level of smoking to decline with age.

In the absence of other health elements, as in a pure Becker-Murphy rational smoking model (Becker and Murphy, 1988), the optimal trajectory of cigarette consumption for a finite horizon problem is U-shaped: the individual starts at a relatively high level of cigarette consumption, reduces his consumption over time to slow the rate of accumulation of smoking damage, then, as the remaining horizon shortens (as the end of life approaches) tends to increase his cigarette consumption. Adding H to the problem means that reductions in H for other reasons can lead to the optimal smoking trajectory being negatively sloped throughout. Effectively, we are recognizing that S is a control variable in the individual's investment in health problem, and that under certain circumstances, reducing S might have a larger impact on H than would increases in I-type goods. Note, though, that by putting A rather than S in the equation of motion for H

means that we are incorporating a lag structure in the relation between changes in S and changes in H. Rewriting the various necessary conditions, we find:

$$P_{SR} \frac{\partial V}{\partial C} - \mu g_S = \frac{\partial V^R}{\partial s_R} \qquad (12)$$

This says that the marginal benefit derived from a cigarette smoked in a pub has to equal its marginal costs, which has two components- the utility of the other consumption given up when a cigarette is bought and the marginal impact of that cigarette on the smoker's lifetime utility through its impact on his health. The greater the weight the individual places on health damage, the larger the left hand side (since μ is negative) and the larger the marginal cost of smoking, meaning that the marginal benefit must be correspondingly larger and the level of smoking smaller. We also have:

$$P_{SU} \frac{\partial V}{\partial C} - \mu g_S = \frac{\partial V^U}{\partial s_U} \qquad (13)$$

And we can combine these to give:

$$P_{SR} \frac{\partial V}{\partial C} - \frac{\partial V^R}{\partial s_R} = P_{SU} \frac{\partial V}{\partial C} - \frac{\partial V^U}{\partial s_U} \qquad (14)$$

If we assume that people buy their own cigarettes and take them to the pub, we can assume that $P_{SR} = P_{SU}$ so that $\frac{\partial V^R}{\partial s_R} = \frac{\partial V^U}{\partial s^U}$. Smokers allocate their smoking between home and pub to equate the marginal utility in each setting. We are assuming that the differences in settings means that the two commodities are not identical - there may for example, be an extra social element to smoking in the pub which is not present at home, or it might be that concerns for the impact of second hand smoke on children in the house means that each cigarette smoked at home yields less marginal utility, and the marginal utility declines faster, than in the case of smoking in the pub. Also, women might take greater account of the impact of second hand smoke on children in the household and so they may attach greater marginal disutility to smoking at home compared to men with children. In this model, we assume the smoker internalizes at least to some degree, the externalities associated with smoking at home. Since we have assumed (for purposes

of setting out the basic model) that beer is not harmful, $\frac{\partial V^R}{\partial B_R} = P_{BR} \frac{\partial V}{\partial C}$ and $\frac{\partial V^U}{\partial B_U} = P_{BU} \frac{\partial V}{\partial C}$, where we would expect that beer bought at the pub has a different price than beer bought to take home. If we assume that there are no externalities associated with drinking beer either in the pub or at home, the individual will allocate their beer consumption so that the marginal rate of substitution between beer consumed at the pub and beer consumed at home equals the ratio of their prices. If there are externalities or other costs (e.g. strict blood alcohol rules for driving) the interpretation of the necessary condition would be modified as appropriate.

3.2 Smoking in the presence of smoking restrictions

The easiest way to see the impact of a restriction on smoking at the pub on the allocation of cigarette consumption between R and U is to add the constraint: $\overline{S_R} - S_R \geq 0$, which says that S_R is subject to an upper limit. In the case of a complete ban, the upper limit will be zero, but in any case the restriction will impose a corner solution on some individuals in so far as their optimal level of smoking in the "R" setting is concerned. This constraint binds each period, and we assign the multiplier $\lambda \geq 0$. Then our necessary condition for S_R becomes:

$$-P_{SR} \frac{\partial V}{\partial C} + \frac{\partial V^R}{\partial S_R} + \mu g_S - \lambda = 0 \tag{15}$$

where $\lambda > 0$ when the constraint is binding. In terms of allocation of smoking, we now have:

$$-P_{SR} \frac{\partial V}{\partial C} + \frac{\partial V^R}{\partial S_R} - \lambda = -P_{SU} \frac{\partial V}{\partial C} + \frac{\partial V^U}{\partial S_U} \tag{16}$$

Since both the left and right hand sides are equal to μg_S, and we continue to assume that the money price of cigarettes is the same no matter where you smoke them, we have $\frac{\partial V^R}{\partial S_R} - \lambda = \frac{\partial V^U}{\partial S_U}$.

We are interested in analysing the impact of tightening smoking restrictions on overall cigarette consumption (both in public places and private dwellings). Smoking in public places will be reduced to the degree that the constraint is tightened. However, it is also important to account for the degree to which smoking at home is increased to compensate. In our model, λ represents how much the individual's utility in each period would increase if the constraint were eased by one unit. We would expect the value of λ to vary across different categories of smokers, and the degree of substitutability of smoking at home for smoking in public places to differ across these categories. In general, while complete substitution would be possible, we would not expect to observe it in every category of smoker.

The implication of this result for the effectiveness of a smoking ban is that people will tend to substitute away from the restricted environment toward the unrestricted environment but that the degree to which they substitute depends on their location-specific marginal utilities. Shifting smoking completely from public places to private premises will clearly reduce the marginal utility of smoking a cigarette, since smoking in pubs had yielded greater utility before the ban. Any substitution which is made must reduce the marginal utility of smoking a cigarette at home. It is possible that a light smoker might shift completely because the impact on marginal utility of smoking one more cigarette at home instead of at the pub would be quite small. A heavy smoker on the other hand might well be less inclined to shift completely because of the greater reduction in marginal utility associated with a large increase in the quantity of cigarettes consumed at home, so we hypothesize that heavier smokers should be more affected by the ban.

There might be other factors such as the presence of children in the home, which may cause the utility functions to differ significantly between the two settings. A light smoker, whose optimal smoking level at home had been at a corner solution (i.e. zero) because of concerns about external effects, might quit smoking altogether rather than start smoking in the home. A heavy smoker might not quit altogether but may not shift as much of his smoking as he otherwise would to a home environment in which there are children.[4] In any case, it becomes clear that there will be countervailing effects to the smoking ban, the

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[4] These effects may be small if those who were most concerned about the impact of smoking on dependent children have already quit (not part of the smoking population) or modified their smoking behaviour to take these externalities into account.

reduction in cigarettes smoked at the pub will to some extent be undone by an increase in cigarettes smoked in the home or unrestricted smoking environment. This adjustment process may take time as individuals find a new equilibrium so that short run and long run effects of the ban may well differ.

4. Data

The British Household Panel Survey

Information on smoking behaviour in the UK before and after the introduction of the public smoking ban (enforced on the 26th of March 2006 in Scotland and on the 1st July 2007 in England) is drawn from the British Household Panel Survey (BHPS). The BHPS is a household-based multi-purpose survey and we use 18 waves (1991-2009). Wave 1 (1991) consisted of 5,500 households and approximately 10,300 individuals sampled from England and Scotland.[5] Individuals are followed over time and interviews are conducted annually for all adult members (aged 16 years or over) in each household. Additional samples of 1,500 households in each of Scotland and Wales were added to the main sample in wave 9 (1999-2000); in 2001 a sample of 2000 households from Northern Ireland was also included. We make use of data solely from England and Scotland. The survey contains a wide range of variables on demographic and household characteristics; health, smoking habits and use of health services; labour market as well as income and wealth. A detailed BHPS quality profile can be found in Buck *et al.* (2006) while additional information on its sampling structure is contained in the user manual.[6]

Measures of smoking behaviour

We define smoking behaviour using two different indicators: smoking prevalence and the daily number of cigarettes smoked. Information on smoking prevalence is based on the question: "Do you smoke cigarettes?". [7] Accordingly, we create a dummy variable

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[5] Before 1999 (wave 9), Scottish individuals were only sampled if they resided at the south of the Caledonian Canal.

[6] Taylor, Marcia Freed (ed). with John Brice, Nick Buck and Elaine Prentice-Lane (2010) *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices. Colchester: University of Essex.*

[7] The question "Do you smoke cigarettes?" is not present in wave 9. Information on smoking prevalence for wave 9 is obtained using answers from two related questions "have you ever smoked a cigarette?" and the subsequent "do you smoke cigarettes at all now nowadays?".

assuming value 1 if the individual is a smoker and 0 otherwise. We perform our panel data analysis on the impact of the smoking ban on smoking prevalence by utilising data on smokers, ex-smokers or future smokers (i.e. individuals who self-report being a smoker at least once during the period of the survey). Accordingly, we exclude individuals who reported not smoking throughout the 18 waves of the BHPS. Concentrating on current smokers, ex- and future smokers allows us to isolate better the effects of the policy on our population of interest (smokers) and to better capture the effects of the ban on quits.[8]

We also consider the impact of the ban on the level of cigarette consumption. We derive information on the number of cigarettes smoked from the following question "Approximately how many cigarettes a day do you usually smoke?". Although this questions is only asked to smokers, "0" is a possible answer used to identify occasional or social smokers (i.e. individuals who defined themselves as smokers but declare an average daily consumption of 0 cigarettes). We convert to zero missing values for the number of cigarettes smoked reported by non smokers.[9] As for smoking prevalence, while we perform our short-run impact analysis on a sample of individuals who report smoking in wave 15 and follow them through wave 16 (corresponding to the years pre- and post-ban in Scotland, i.e. 2005 and 2006), we focus our panel data analysis on potential smokers and remove individuals who never report smoking a cigarette throughout the full survey period. Finally, due to the heaping of responses that are typical of self-reported information on the quantity of cigarettes smoked, we also recode consumption by considering multiples of five cigarettes (half packs).

While the BHPS has many strengths, particularly for considering dynamic behaviours over time, a potential limitation is a lack of biomarkers for tobacco intake such as cotinine concentration that could provide an objective assessment of cigarette consumption. Cotinine is a metabolite of nicotine whose concentration measured in body fluids (usually in saliva) has been used as a proxy for smoking consumption in recent studies on the effects of anti-smoking initiatives on both active and passive smoking (Adda and

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[8] However, the analysis was also performed on the full survey sample and produced very similar results. Estimates are available upon requests.

[9] Given the very limited amount of occasional smokers, the models presented in section 6 concerning the impact of the ban on the number of cigarettes smoked do not distinguish between zeros that define non smokers and zeros that identify occasional smokers. Nevertheless, the same analysis run dropping all occasional smokers produced very similar results.

Cornaglia, 2006, 2010; Irvine and Nguyen, 2009). This biomarker is an accurate measure of nicotine intake and other health-threatening substances that are present in cigarettes such as tar and carbone monoxide. Another reason for using biomarkers in evaluative studies of smoking behaviour is that self-reported measures of smoking consumption might be prone to measurement error that could bias the estimates of the effects of policies. However, a number of studies comparing biochemical measures, including cotinine concentration, with self-assessed measures of smoking status have suggested a generally high validity of the latter (Patrick et al., 1994; Vartiainen et al., 2002).[10] Further, in our panel data models, time-invariant reporting errors are captured by fixed effects and hence the presence of self-reporting bias is likely to be a concern only if it is correlated with the smoking ban (i.e. if after the introduction of the ban individuals systematically misreport smoking consumption).

Covariates and descriptive statistics

We condition our panel data models on age (age and age squared), a series of household related variables (being married or in a couple; household size; number of children living in the household) and labour market status (self-employed; unemployed; retired; being in maternity leave or family care; student; long-term sick/disability status; government training or in other jobs, all contrasted against being employed as an employee). In order to characterize an individual's health stock, we include a battery of health variables. In particular, we use a measure of self-assessed general health and create three dummy variables for health self-rated as excellent, fair and poor or very poor (contrasted against very good or good health).[11] We also control for two measures of psychological well-being: a widely used index of subjective well-being increasing in levels of distress, the GHQ (Goldberg and Williams, 1988), and a dummy variable identifying individuals who self-report being afflicted by anxiety or depression. Moreover, we include variables for the

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[10] Studies that examine the extent and sources of discrepancies between biomarkers and self-reported cigarette consumption suggest that self-reported measures of cigarette consumption are usually accurate (Patrick et al., 1994). These studies also underline that this is especially true for adult individuals while inconsistent reporting appear to be more concentrated among teenagers (Kandel et al., 2006; Patrick et al., 1994).

[11] We collapse the original 5 category self-assessed variable (SAH) to a four category measure due to a change of wording and response categories in the SAH question in wave 9. In waves 1-8 and 10-18, respondents are asked: "Compared to people of your own age, would you say your health over the last 12 months on the whole has been: excellent, good, fair, poor or very poor?" while in wave 9 question and possible answers are "In general, would you say your health is: excellent, very good, good, fair, poor". Creating a SAH variable with four health categories ("excellent, good or very good, fair, poor or very poor") ensures common support over the two versions of the question.

presence of chest or breathing problems and heart related problems. Descriptive statistics for smoking prevalence and consumption together with covariates and broken down by gender and country of residence can be found in Table 1.

[*Table 1 about here*]

5. Econometric methods

Our theoretical framework suggests that the introduction of smoking restrictions in public places will influence an individual's optimal smoking trajectory differently according to their age, gender, and level of cigarette consumption. We test these predictions by evaluating the impact of the UK public smoking ban using data drawn from the British Household Panel Survey (BHPS). Our empirical strategy exploits the timing of the implementation of the smoking bans in Scotland and England. First, we estimate the short-run impact of the smoking ban imposed in Scotland using England as a control group and employing simple difference-in-differences and changes-in-changes methods. Second, we exploit the longitudinal nature of the data and estimate a sequence of difference-in-differences style panel data models. These include a fixed effects difference-in-differences estimator again evaluating the impact of the ban in Scotland using England as a control group and a series of more flexible fixed effects models with regional time trends that allow the policy effect to vary by region (i.e. England and Scotland) and over time following the introduction of the ban.

As the Scottish ban pre-dates the ban in England by one year, this allows us to evaluate the short-run impact of the ban in Scotland using data from one year after its implementation and considering England as a control group. To evaluate the short-run impact we make use of two related methodologies: difference-in-differences (DD: Ashenfelter, 1978; Ashenfelter and Card, 1985; Heckman and Robb, 1985) and changes-in-changes (CC: Athey and Imbens, 2006).

5.1 Short-run impact: difference-in-differences and changes-in-changes

Difference-in-differences has been extensively used in the evaluative literature and measures the effect of an intervention (treatment) by comparing the difference in outcomes in treated subjects pre- and post-intervention to the difference in outcomes in controls subjects pre- and post-intervention. Estimates and their standard errors are often derived from a regression of the following form:

$$y_i = \alpha + \tau_s(S_i T_i) + \gamma S_i + \delta T_i + \epsilon_i \tag{17}$$

where y_i is the outcome of interest (cigarette consumption) for individual i $(i = 1, \dots, n)$, S_i represents a time-invariant indicator of group membership, here whether the individual resides in Scotland $(S_i = 1)$, or England $(S_i = 0)$ and T_i $(T_i = 0,1)$ is a time-effect common to both groups. The treatment effect is identified as the parameter, τ_s, on the interaction term between country of residence and time period. The identification assumption for DD estimation is that in the absence of treatment the trend over time in the treatment group is the same as the trend in the control group such that the outcome for an individual who is not subject to the treatment, y_i^N, can be represented by:

$$y_i^N = \alpha + \gamma S_i + \delta T_i + \epsilon_i \tag{18}$$

This provides the counterfactual for the treatment effect. Athey and Imbens (2006) relax the additivity assumption inherent in the DD approach in developing what they term the changes-in-changes estimator (CC). Their approach allows outcomes to be a general function of unobservables such that in the absence of treatment:

$$y_i{}^N = h_0(U_i, T_i) \tag{19}$$

where U_i represents unobservable characteristics of individual i. It is further assumed that $h_0(u, t)$ is strictly increasing in u for $t = 0, 1$. The model assumes that outcomes, y_{it}, do not depend on treatment assignment given unobservables, U_i, and time period, t and that unobservable characteristics may vary across groups but not across time within groups.

Let F_{st} denote the distribution function for y for group $s(0,1)$ at time t (0,1). The approach uses the distribution for the controls following treatment, F_{01}, to construct the counterfactual for an observed outcome for a treated individual as $F_{01}^{-1}(F_{00}(y))$, where $F_{00}(y)$ is the probability corresponding to y in the distribution of outcomes for the controls prior to treatment and $F_{01}^{-1}(.)$ gives the quantile of that probability in the post-treatment distribution for the controls. Accordingly the treatment effect can be estimated as:

$$\tau_{CIC} = E(y_{11}) - E\left[F_{01}^{-1}(F_{00}(y_{10}))\right] \tag{20}$$

Where $E(y_{11})$ can be estimated from the observed outcomes for the treated group at time, $t = 1$. Note that while the assumption that $h_0(u, t)$ is strictly increasing in u for $t = 0, 1$, requires continuous responses, Athey and Imbens (2006) provide bounds under weaker conditions applicable to the case where outcomes are discrete. We apply such bounds to our data in the number (half-packs) of cigarettes consumed.

5.2 Panel data difference-in-differences models

We further assess the impact of the UK smoking bans on smoking prevalence and the number of cigarettes smoked by estimating fixed effects difference-in-differences models. These models exploit differences in smoking behaviour over the full survey period (1991 – 2009), whilst conditioning on observed characteristics and time-invariant individual unobserved heterogeneity.

Simple panel data DD models
Our basic panel data DD estimator has the following form:

$$y_{it} = \alpha + \tau_S(S_i P_t) + X_{it}\phi + v_t + \mu_i + \varepsilon_{it} \tag{21}$$

where y_{it} is alternatively smoking prevalence or the number of cigarettes smoked by individual i at time t. P_t is an indicator for the post-treatment period and X_{it} is a vector containing individual observed characteristics in period t (age, marital status, household

characteristics and composition, job status and household income). X_{it} also contains a series of health variables (measures of general health status, psychological well-being and specific health conditions) lagged one period. We use lagged values of health variables to reflect the dynamics between changes in an individual's health capital and current smoking choices implicit in our theoretical model. μ_i defines an unobserved individual effect. While the observed regressors control for any observable differences between treated and controls, the individual effect captures any time-invariant unobservable attributes that might be correlated with the outcome and/or the allocation of the treatment. The time dummies ν_t account for time trends common to both the treatment and control groups and ε_{it} is an idiosyncratic error term. Once again τ_s is the treatment effect of interest.

We estimate model (21) for two different outcomes: smoking prevalence and the number of cigarettes smoked. We model the prevalence of smoking in two ways: linear probability models with fixed effects estimated by ordinary least squares (OLS) and fixed effects conditional logit models. The impact of the smoking ban on the number of cigarettes smoked is estimated using both linear fixed effects panel regression models and a fixed effects Poisson specification.

Regional time trends models

We also estimate the effects of the smoking bans using a more flexible fixed effects specification with regional time trends. This model identifies the impact of the ban by deconstructing the treatment effect for regions and different time periods. The empirical model can be written as:

$$y_{it} = \alpha + S_i \sum_{t=1}^{T} \tau_{St} \nu_t + E_i \sum_{t=2}^{T} \tau_{Et} \nu_t + X_{it} \phi + \mu_i + \varepsilon_{it} \tag{22}$$

Here, the effects of the bans on smoking are identified by the parameters τ_{St} and τ_{Et} on the interactions between being resident in Scotland, (S_i=1), or England, (E_i=1), and the set of time dummies, ν_t. Accordingly, changes in smoking behaviour due to the introduction of the ban are derived by comparing region-specific time trends with a baseline region-specific time period (in our case, England in wave 2, a period that

corresponds to 1992-93 when the smoking ban was not imposed). Again, these models are estimated using linear probability models and conditional fixed effects logit models to smoking prevalence and linear and Poisson fixed effects models for the number of cigarettes smoked.

6. Results

6.1 Short-run impact

Table 2 presents the results of the DD and CC estimates. These were computed for data on individuals in Scotland and England present in both 2005 and 2006 (waves 15 and 16 of the BHPS). The sample consists of all respondents who reported being smokers in the 15th wave, irrespective of smoking status in the following wave. Balanced samples of respondents were used and where respondents reported not to smoke in wave 16, consumption was set to zero. For these results we consider levels of smoking only and ignore possible effects on prevalence. Due to the results being highly sensitive to heaping of responses around multiples of 5 cigarettes, we recode the number of cigarettes consumed to the number of half-packs (packs of 5) per day. Results are presented for men and women separately.

[Table 2 about here]

The DD estimates of the treatment effects, estimated across all available data, indicate that the smoking ban reduced the consumption of cigarettes for both men and women. However, the effects are small and not statistically significant. In contrast point estimates for the CC estimates are negative, large and significant. However, given the discrete nature of the outcome variable, these results are likely to be unreliable and instead we focus on the upper and lower bounds of the estimated treatment effects. For both men and women the bounds straddle zero and the effect of the ban cannot be determined.

The theoretical model developed in Section 3 suggests that the response by individuals to a smoking ban is likely to vary by age. We test this hypothesis by considering the treatment effect by three broad age bands: 18 to 34; 35 to 54 and 55+ years. The CC

results show greater effects than the corresponding DD estimates, but when we consider the bounds then for all age groups and for both men and women the estimates straddle zero and no discernable pattern emerges when comparing across age groups.

For men, the results suggest that both light and heavy smokers are more responsive to the ban than medium smokers with both DD and CC estimates being larger for the former than the latter. However, the bounds of the CC estimates suggest again that a zero effect cannot be ruled out. For women, the results suggest that medium smokers have responded to the ban and the bounds on the treatment effect range from -0.468 to -0.024, however none of bounds are statistically significant from zero.

We further consider whether smokers with children respond different to the ban than smokers without children. Again, whilst on the whole the effects are negative, the bounds cross zero. However, the effects are more negative for smokers with children than for those without, and this is particularly so for women where the DD and CIC results suggest that the effects may be up to twice the size for the former compared to the latter (although again the bounds cross zero). This provides tentative empirical support for the predictions from the theoretical model that suggests that smokers facing a ban in public places are less likely to substitute smoking at home where there are children in the household, particularly women who may be more conscious of the harm caused by second hand smoke.

6.2 Panel data estimates

Prevalence of smoking

Estimates of the fixed effects DD models on the impact of the ban on smoking prevalence are presented in Table 3. These are provided for men and women separately as well as for two alternative models: linear fixed effects and conditional fixed effects logit models. All the corresponding treatment effects are small, positive and not statistically significant. This suggests that the smoking ban had little impact on overall smoking prevalence in Scotland.

[Table 3 about here]

Results for the regional time trends models for smoking prevalence are presented in Figure 1. Including a full set of region-specific time dummies allows the effect of the policy to change over time and to vary across regions. The four graphs displayed in Figure 1 plot estimates for waves 2 - 18 of the survey (corresponding to the years 1992 – 2009) for England and Scotland. [12] Estimates are displayed for linear fixed effects and conditional fixed effects logit models and are broken down by gender. Apart from the conditional logit model for men, that reveals very small variation in smoking rates over time, all remaining models show declining trends in smoking prevalence. The graphs, however, also illustrate that the probability of smoking does not decrease more rapidly in the years corresponding to the imposition of the smoking ban (wave 16 onwards for Scotland and wave 17 onwards for England than before the ban). This indicates that the smoking ban had no significant impact on smoking prevalence in either Scotland or England.

[Figure 1 about here]

Intensity of smoking

Table 4 contains treatment effects for the fixed effects DD models for Scotland. Results are presented for the number of half packs for men and women separately. Estimates were obtained from two alternative models: linear and Poisson fixed effects models. The majority of the treatment effects reported display positive signs but none of these attain statistical significance. This implies that there is insufficient evidence to conclude that the imposition of a smoking ban in Scotland resulted in an overall decrease in cigarette consumption.

[Table 4 about here]

Figure 2 displays estimates of the regional time trends models on the effects of the ban on the level of cigarette consumption. Estimates are presented for the number of half packs obtained from both linear and Poisson fixed effects models and for men and women separately. For men, (upper part of Figure 2), the linear fixed effects model suggests an

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[12] As our panel data models include lagged values of the health variables, wave 1 is excluded from our analysis.

acceleration of the declining trend in cigarette consumption in the year of the introduction of the ban in England (wave 17). Compared to the baseline region and year (England wave 2), the ban decreased the level of cigarette consumption by approximately 1.5 half packs of cigarettes per day (around 7 cigarettes). This represents a further reduction of about 0.20 of a half a pack from the previous (no ban) wave and is the largest decrease observed along the trend line for England. Poisson fixed effects models also identify a sizeable reduction of cigarette consumption among men in the wave corresponding to the year of the introduction of the ban in England. However, the corresponding average marginal effects are not statistically significant. For women (lower part of Figure 2), both linear and Poisson models show sharper reductions in smoking levels in wave 17 in both regions. Accordingly, for women, the ban seems to have had a larger effect in the first year of introduction in England, while the dip in consumption in Scotland occurred only in the second year following the introduction of the ban.

[Figure 2 about here]

Heterogeneity in the impact of the smoking bans

Table 5 reports treatment effects estimated using linear fixed effects DD models for Scotland by age, gender and type of smoker.[13] The ban appears to have decreased cigarette consumption among older men. Our estimates also suggest that the ban increased cigarette consumption among male moderate smokers. For women, although treatment effects for most of the sub-groups exhibit a negative sign, suggesting a decrease in cigarette consumption, none of the coefficients are statistically significant.

[Table 5 about here]

The same heterogeneity analysis is provided for models with regional time trends in Figures 3a-b and Figures 4a-b. These graphs make it apparent that the trends in the level of cigarette consumption differ greatly according to gender and age, as predicted by the theoretical model. In particular, differences in smoking are concentrated in the younger

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[13] The heterogeneity analysis for all DD panel data models is only presented for linear fixed effects models. Poisson fixed effects models for the majority of the sub-groups failed to converge due to the limited number of observations.

age group. While men aged between 18 and 34 show an upward trend in the quantity of cigarettes smoked, women of the same age show a decreasing trend of cigarette consumption. The level of cigarette consumption decreased for both men and women aged between 18-34 in the years in which the reform became effective in Scotland and England. The bans do not appear to have had an effect for other age categories.

[Figure 3a-b and 4a-b about here]

The impact of the bans differs according to the pre-ban average daily consumption (Figures 4a-4b). For men (Figure 4a), the bans appear to have a small effect on light smokers and a larger effect appears to be larger for heavy smokers, breaking and reversing (for Scotland) the trend towards increasing smoking among this group of men and with an average pre-ban consumption between 10 and 19 cigarettes per day do not show sizeable decreases in consumption in the years following the bans. For both men and women light smokers seem to be less responsive to the introduction of the smoking bans. However, both moderate and heavy female smokers decrease their consumption of cigarettes with the imposition of the bans in both England and Scotland.

7. Conclusions

This paper develops a theoretical model of cigarette consumption to inform the likely behavioural effects on smoking following the introduction of a ban on smoking in certain (i.e. public) places. Our theoretical framework describes individuals' optimal smoking choices in the presence and absence of smoking restrictions and predicts heterogeneous effects of a public smoking ban on smoking according to age, gender, and type of smokers. We assess these predictions using UK data drawn from British Household Panel Survey (BHPS). Our identification strategy exploits differences in the timing of the introduction of comprehensive public smoking bans in Scotland and England.

Our empirical models provide evidence weakly consistent with the prediction of the theoretical model, that bans will tend to have a limited effect on smoking prevalence, at least in the short run, and a rather limited impact on the total level of smoking. We

hypothesize, based on the model that this is because individuals can to varying degrees substitute to other settings. We found that reductions in cigarette consumption appear to be mainly concentrated among male and female heavy smokers as well as female moderate smokers. This is consistent with the hypothesis that heavy smokers can substitute some but not all of their smoking to the alternate setting as the cost to them of doing so in marginal utility terms, is higher than for light smokers. For both genders, we also found that older individuals and light smokers are less affected by the policy change. Again, this is consistent with the model predictions as these groups tend to smoke fewer cigarettes; the older people because as health deteriorates with age, this is offset by declining smoking intensity and the young, all else being equal, will tend to have smoked for shorter periods of time and will therefore have not accumulated as high a stock of addiction.

While these results challenge the ones found in the public health literature (Fowkes *et al.*, 2008), they are in line with the most recent economic literature indicating that there is no firm evidence on the effects of smoking bans on smoking prevalence (Adda and Cornaglia, 2010). Our model and results provide more details about who will and will not tend to be affected by smoking bans. In terms of assessing policy effectiveness, a further implication of the results is the idea that the effect on smoking behaviour of smoking bans will to some extent be undermined by the ability of individuals to shift their smoking to unrestricted settings. It still seems to be the case however, that heavy smokers (male and female) are the least able to substitute fully and to the extent that these people are the most likely to experience serious negative health consequences of smoking, bans are not an entirely blunt instrument for health promotion.

References

Abadie, A., Diamond, A. and Hainmueller, J. (2010) 'Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program', *Journal of the American Statistical Association* 105**,** 493–505.

Adda, J., Berlinski, S., Bhaskar, V. and Machin, S. (2009) 'Market regulation and firm performance: the case of smoking bans in the UK', *IFS Working Papers,* Institute for Fiscal Studies, W09-13.

Adda, J., Berlinski, S. and Machin, S. (2007) 'Short-run economic effects of the Scottish smoking ban', *International Journal of Epidemiology,* 36**,** 149-154.

Adda, J. and Cornaglia, F. (2006) 'Taxes, Cigarette Consumption, and Smoking Intensity', *American Economic Review,* 96**,** 1013-1028.

Adda, J. and Cornaglia, F. (2010) 'The Effect of Bans and Taxes on Passive Smoking', *American Economic Journal: Applied Economics.,* 2**,** 1-32.

Akhtar, P. C., Currie, D. B., Currie, C. E. and Haw, S. J. (2007) 'Changes in child exposure to environmental tobacco smoke (CHETS) study after implementation of smoke-free legislation in Scotland: national cross sectional survey', *British Medical Journal,* 335**,** 545-549.

Allender, S., Balakrishnan, R., Scarborough, P., Webster, P. and Rayner, M. (2009) 'The burden of smoking-related ill health in the UK', *Tobacco Control,* 18**,** 262-267.

Anger, S., Kvasnicka, M. and Siedler, T. (2011) 'One Last Puff? Public Smoking Bans and Smoking Behavior', *Journal of Health Economics,* In Press, Accepted Manuscript.

Ashenfelter, O. and Card, D. (1985) 'Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs', *The Review of Economics and Statistics,* 67**,** 648-660.

Ashenfelter, O. C. (1978) 'Estimating the Effect of Training Programs on Earnings', *The Review of Economics and Statistics,* 60**,** 47-57.

Athey, S. and Imbens, G. W. (2006) 'Identification and Inference in Nonlinear Difference-in-Differences Models', *Econometrica,* 74**,** 431-497.

Barendregt, J. J., Bonneux, L. and Maas, P. J. V. D. (1997) 'The Health Care Costs of Smoking', *The New England Journal of Medicine* 337**,** 1052-1057.

Bartolome, C. A. M. D. and Irvine, I. J. (2010) 'The Economics of Smoking Bans', *UCD Geary Institute Working Paper series,* University College of Dublin, 2010-27.

Becker, G. S. and Murphy, K. M. (1988) 'A Theory of Rational Addiction', *The Journal of Political Economy,* 96**,** 675-700.

Buck, N., Burton, J., Laurie, H., Lynn, P. and Uhrig, S. C. N. (2006) 'Quality Profile: British Household Panel Survey', In Lynn, P. (Ed.). Institute for Social and Economic Research (ISIER), University of Essex.

Buddelmeyer, H. and Wilkins, R. (2005) 'The Effects of Smoking Ban Regulations on Individual Smoking Rates', *IZA Discussion Papers,* Institute for the Study of Labor (IZA), 1737.

Callinan, J. E., Clarke, A., Doherty, K. and Kelleher, C. (2010) 'Legislative smoking bans for reducing secondhand smoke exposure, smoking prevalence and tobacco consumption'. The cochrane collaboration.

Chaisemartin, C. D. and Geoffard, P.-Y. (2010) 'Workplace smoking ban effects in an heterogeneous smoking population', *PSE Working Papers,* PSE (Ecole normale supérieure), 2010-21.

Chaloupka, F. J. and Warner, K. E. (2000) 'The economics of smoking', In Newhouse, J. P. and Culyer, A. J. (Eds.) *Handbook of Health Economics.* New York, North Holland,

Elsevier Science B.V. .

Deaton, A. (2002) 'Policy Implications Of The Gradient Of Health And Wealth ', *Health Affairs,* 21**,** 13-30.

Dinan, J. and Heckelman, J. C. (2005) 'The anti-tobacco movement in the Progressive Era: A case study of direct democracy in Oregon', *Explorations in Economic History,* 42**,** 529-546.

Evans, W., Farrelly, M. and Montgomery, E. (1999) 'Do Workplace Smoking Bans Reduce Smoking? ', *American Economic Review,* 89**,** 728-747.

Fowkes, F. J. I., Stewart, M. C. W., Fowkes, F. G. R., Amos, A. and Price, J. F. (2008) 'Scottish smoke-free legislation and trends in smoking cessation', *Addiction,* 103**,** 1888-1895.

Goldberg, D. and Williams, P. (1988) *A User's Guide to the General Health Questionnaire,* Windsor, NFER-Nelson.

Haw, S. J. and Gruer, L. (2007) 'Changes in exposure of adult non-smokers to secondhand smoke after implementation of smoke-free legislation in Scotland: national cross sectional survey ', *British Medical Journal,* 335**,** 549-552.

Hodgson, A. (1998) 'The Health Care Costs of Smoking', *New England Journal of Medicine,* 338**,** 470-472.

Huisman, M., Kunst, A. E. and Mackenbach, J. P. (2005) 'Inequalities in the prevalence of smoking in the European Union: comparing education and income', *Preventive Medicine,* 40**,** 756-764.

Irvine, I. J. and Nguyen, V. H. (2009) 'Toxic Choices: The Theory and Impact of Smoking Bans', *UCD Geary Institute Working Paper series,* University College of Dublin, 2009-51.

Jarvis, M. J., Mindell, J., Gilmore, A., Feyerabend, C. and West, R. (2009) 'Smoke-free homes in England: prevalence, trends and validation by cotinine in children', *Tobacco Control,* 18**,** 491-495

Kandel, D., Schaffran, C., Griesler, P., Hu, M.-C., Davies, M. and Benowitz, N. (2006) 'Salivary cotinine concentration versus selfreported cigarette smoking: Three patterns of inconsistency in adolescence', *Nicotine and Tobacco Research,* 8**,** 525-537.

Keeler, T. E., Hu, T.-W., Barnett, P. G. and Manning, W. G. (1993) 'Taxation, regulation and addiction: A demand function for cigarettes based on time-series evidence', *Journal of Health Economics* 12**,** pp. 1–18.

Kenfield, S. A., Stampfer, M. J., Rosner, B. A. and Colditz, G. A. (2008) 'Smoking and Smoking Cessation in Relation to Mortality in Women', *The Journal of the American Medical Association,* 299**,** 2037-2047.

Lien, D. S. and Evans, W. N. (2005) 'Estimating the Impact of Large Cigarette Tax Hikes: The Case of Maternal Smoking and Infant Birth Weight ', *Journal of Human Resources,* 40**,** 373-392.

Mackay, D., Haw, S., Ayres, J. G., Fischbacher, C. and Pell, J. P. (2010) 'Smoke-free Legislation and Hospitalizations for Childhood Asthma', *New England Journal of Medicine,* 363**,** 1139-1145.

Markowitz, S. (2008) 'The effectiveness of cigarette regulations in reducing cases of Sudden Infant Death Syndrome', *Journal of Health Economics,* 27**,** 106-133.

Muurinen, J.-M. and Le Grand, J. (1985) 'The economic analysis of inequalities in health', *Social Science & Medicine,* 20**,** 1029-1035.

NHS (2010) 'Statistics on smoking: England 2010'. National Health Service (NHS).

OECD (2010) 'OECD Health Data 2010'. Paris.

Patrick Dl, Cheadle A, Thompson Dc, Diehr P, Koepsell T and S., K. (1994) 'The validity

of self-reported smoking: a review and meta-analysis', *American Journal of Public Health,* 84**,** 1086-1093.

Pell, J. P., Haw, S., Cobbe, S., Newby, D. E., Pell, A. C. H., Fischbacher, C., Mcconnachie, A., Pringle, S., Murdoch, D., Dunn, F., Oldroyd, K., Macintyre, P., O'rourke, B. and Borland, W. (2008) 'Smoke-free Legislation and Hospitalizations for Acute Coronary Syndrome', *New England Journal of Medicine,* 359**,** 482-491.

Peto, R., Lopez, A. D., Boreham, J. and Thun, M. (1994) *Mortality from smoking in developed countries,* Oxford, Oxford University Press.

Scottish Government (2005) 'The Smoking Health and Social Care (Scotland) Act 2005'.

Shields, M. (2007) 'Smoking bans: influence on smoking prevalence', *Health Reports.* Statistics Canada.

Thomas, S., Fayter, D., Misso, K., Ogilvie, D., Petticrew, M., Sowden, A., Whitehead, M. and Worthy, G. (2008) 'Population tobacco control interventions and their effects on social inequalities in smoking: systematic review ', *Tobacco Control,* 17**,** 230-237.

Wald, N. J. and Hackshaw, A. K. (1996) 'Cigarette smoking: an epidemiological overview', *British Medical Bulletin,* 52**,** 3-11.

Wasserman, J., Manning, W. G., Newhouse, J. P. and Winkler, J. D. (1991) 'The effects of excise taxes and regulations on cigarette smoking', *Journal of Health Economics* 10**,** 43–64.

Table 1: Descriptive statistics

Variables	Scotland			England		
	Pooled	**Men**	**Women**	**Pooled**	**Men**	**Women**
Smoker	0.285	0.287	0.284	0.255	0.263	0.249
# cigarettes	16.372	17.253	15.71	14.712	15.633	13.887
Age	46.435	45.744	46.934	45.916	45.183	46.563
Married/couple	0.641	0.688	0.604	0.676	0.707	0.650
Household size	2.693	2.741	2.660	2.822	2.872	2.781
Number of children	0.510	0.481	0.538	0.525	0.501	0.547
Employed	0.520	0.549	0.496	0.529	0.564	0.496
Self-employed	0.065	0.104	0.034	0.076	0.119	0.038
Unemployed	0.039	0.053	0.028	0.037	0.051	0.025
Retired	0.215	0.188	0.236	0.198	0.182	0.212
Maternity leave/family care	0.640	0.006	0.113	0.088	0.005	0.21
Student	0.040	0.037	0.041	0.035	0.036	0.034
Long term sick	0.052	0.057	0.047	0.033	0.037	0.029
Government training	0.001	0.002	0.001	0.001	0.002	0.001
Other jobs	0.004	0.003	0.004	0.004	0.004	0.004
SAH excellent	0.233	0.255	0.215	0.226	0.252	0.203
SAH good/very good	0.472	0.475	0.470	0.483	0.481	0.485
SAH fair	0.200	0.193	0.206	0.204	0.192	0.215
SAH poor/very poor	0.095	0.077	0.109	0.087	0.076	0.097
GHQ	11.135	10.382	11.742	11.151	10.428	11.771
Anxiety	0.086	0.056	0.111	0.072	0.048	0.093
Chest problems	0.134	0.134	0.133	0.128	0.121	0.135
Heart problems	0.173	0.16	0.184	0.155	0.146	0.162
Log household Income	2.731	2.897	2.595	2.758	2.899	2.635

Notes: the Table contains mean values for all variables computed for waves 1-18 for pooled samples of men and women as well as for men and women separately, all broken down by country of residence.

Table 2: Short-run impact of the smoking ban on smoking

|	Men				Women			
	DD	CIC	Lower bound	Upper bound	DD	CIC	Lower bound	Upper bound
All data	-.053	-.886	-.886	.467	-.038	-.720	-.720	.643
(M: 1851; W: 2066)	(.195)	(.332)	(.332)	(.223)	(.154)	(.286)	(.286)	(.231)
Heterogeneity in effect:								
Age	-.179	-.690	-.690	.494	-.093	-.878	-.878	.459
18yrs – 34yrs	(.272)	(.391)	(.391)	(.343)	(.264)	(.328)	(.328)	(.258)
(M: 651; W: 654)								
35yrs – 54yrs	.014	-.658	-.658	.514	-.181	-1.336	-1.336	.115
(M: 767; W: 752)	(.337)	(.482)	(.482)	(.391)	(.270)	(.517)	(.517)	(.425)
55yrs –	-.047	-1.239	-1.239	.582	.092	-.167	-.167	.951
(M: 361; W: 553)	(.419)	(.727)	(.727)	(.502)	(.283)	(.460)	(.460)	(.403)
Level of consumption								
Light (2 packs or less)	-.149	-.424	-.424	.576	.111	-.223	-.223	.777
(M: 554; W: 720)	(.129)	(.133)	(.133)	(.152)	(.110)	(.086)	(.086)	(.086)
Medium (greater than 2 packs to 4 packs)	-.005	-.023	-.023	.568	-.063	-.468	-.468	-.024
(M: 634; W: 710)	(.087)	(.196)	(.196)	(.272)	(.078)	(.197)	(.197)	(.247)
High (greater than 4 packs)	-.220	-.915	-.915	.016	.192	-1.280	-1.280	.240
(M: 195; W: 129)	(.469)	(.891)	(.891)	(.441)	(.475)	(.644)	(.644)	(.302)
Children								
Without	.004	-.659	-.659	.566	.026	-.621	-.621	.682
(M: 1259; W: 1342)	(.228)	(.354)	(.354)	(.239)	(.188)	(.341)	(.341)	(.267)
With	-.150	-.783	-.783	.493	-.231	-1.263	-1.263	.379
(M: 520; W: 662)	(.396)	(.564)	(.564)	(.489)	(.283)	(.561)	(.561)	(.416)

Notes: the Table shows analytical standard errors for DD estimates and bootstrapped standard errors for CIC estimates. Balanced samples of individuals present in both pre- and post- period waves used throughout. Sample sizes for men and Women are provided in the first column.

Table 3: DID estimator for Scotland – smoking prevalence

	Men	Men
	Linear fixed effects	Conditional logit
ATET Scotland	0.00925	-0.00005
	(0.43)	(0.0002)
N	22210	11958

	Women	Women
	Linear fixed effects	Conditional logit
ATET Scotland	0.0197	0.0032
	(1.05)	(0.0152)
N	24752	13277

Notes: the Table displays coefficient estimates of linear fixed effects models and average marginal effects of conditional fixed effects logit models; standard errors in parentheses.

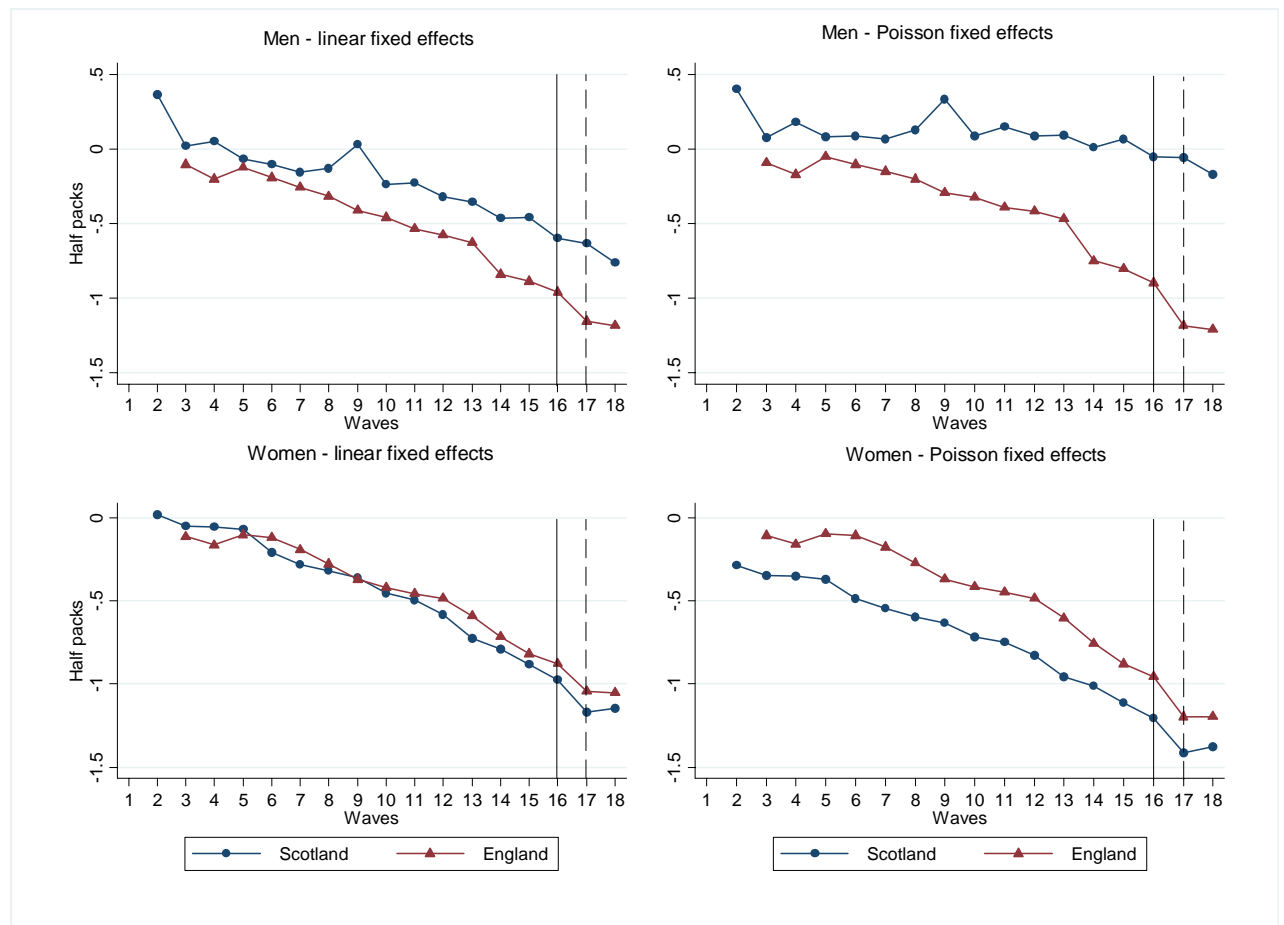**Figure 1: Regional time trends models – smoking prevalence**
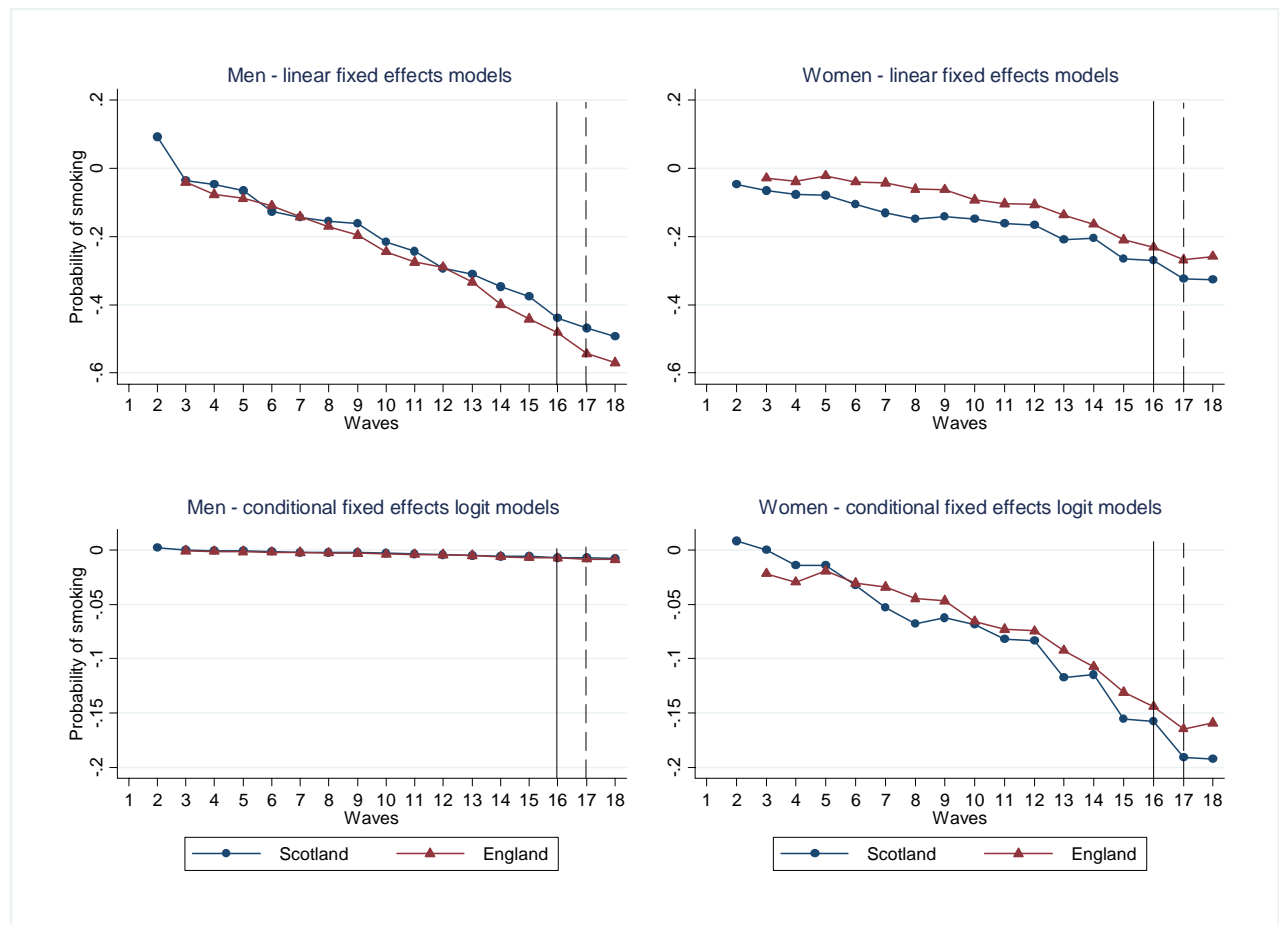
Notes: the continuous vertical lines indicate the Scottish smoking ban while the dashed lines represent the English ban.

Table 4: DID estimator for Scotland – smoking intensity (half packs)

	Men	Men
	Linear fixed effects	Poisson fixed effects
ATET Scotland	0.0724	0.2204
	(0.0814)	(0.1595)
N	21798	19974
	Women	Women
	Linear fixed effects	Poisson fixed effects
ATET Scotland	-0.0272	0.0643
	(0.0629)	(0.1039)
N	24329	22497

Notes: the Table displays coefficient estimates of linear fixed effects models and average marginal effects of Poisson fixed effects models; standard errors in parentheses.

Figure 2: Regional time trends models – number of cigarettes smoked

Notes: the continuous vertical lines indicate the Scottish smoking ban while the dashed lines represent the English ban.

Table 5: DID models for Scotland – heterogeneity: age profiles and type of smokers (half packs)

	Men - age profiles			Men – type of smokers		
	age 18-34	age 35-54	age 55 over	cigs 0-9	cigs 10-19	cigs 20 over
ATET Scotland	0.159	0.0881	-0.280*	-0.0672	0.304**	0.158
	(0.144)	(0.131)	(0.156)	(0.104)	(0.147)	(0.211)
N	8152	8578	5068	10589	7745	3955
	Women – age profiles			Women – type of smokers		
	age 18-34	age 35-54	age 55 over	cigs 0-9	cigs 10-19	cigs 20 over
ATET Scotland	-0.101	-0.0741	-0.0638	0.0326	-0.0845	-0.106
	(0.123)	(0.101)	(0.110)	(0.0807)	(0.106)	(0.189)
N	8847	9557	5925	12143	9689	3096

Notes: the Table displays coefficient estimates of linear fixed effects models; standard errors in parentheses.

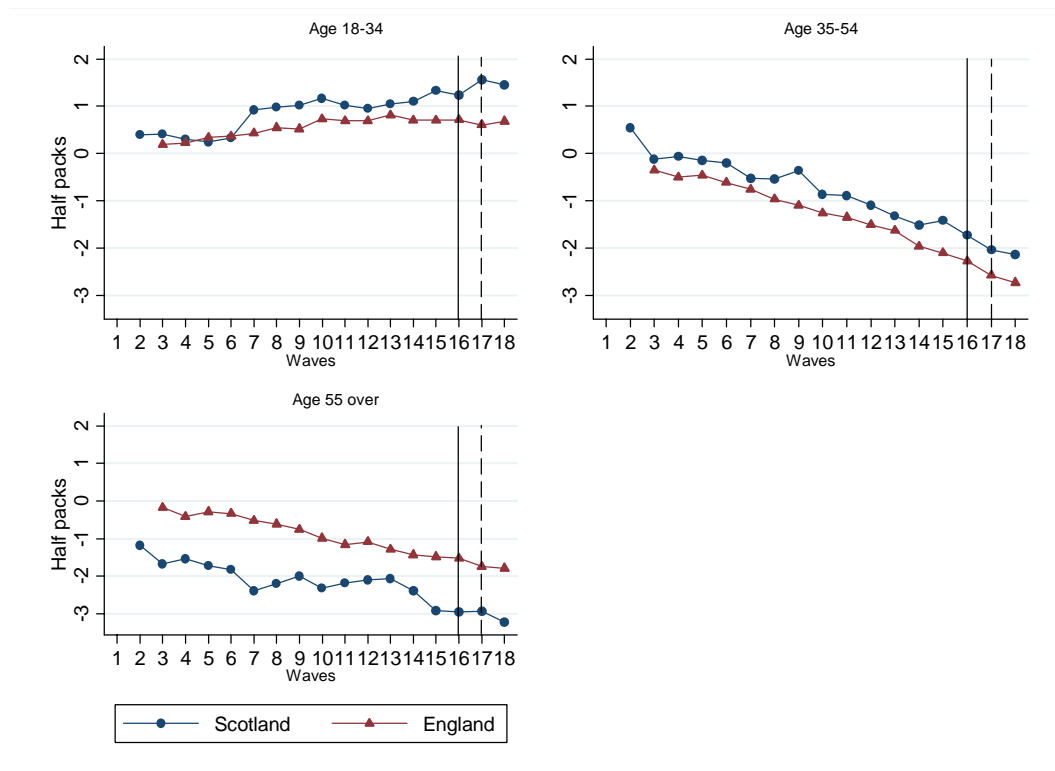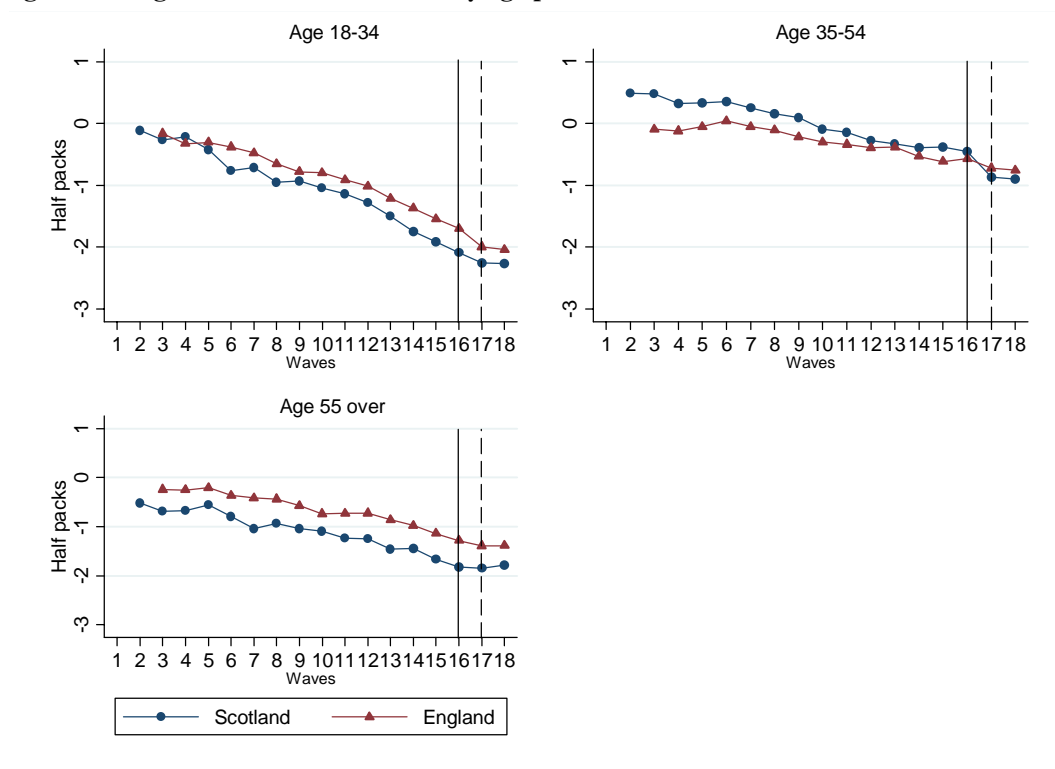**Figure 3a: Regional time trends – heterogeneity: age profiles for men**

Figure 3b: Regional time trends models by age profiles - women

Notes: the continuous vertical lines indicate the Scottish smoking ban while the dashed lines represent the English ban.

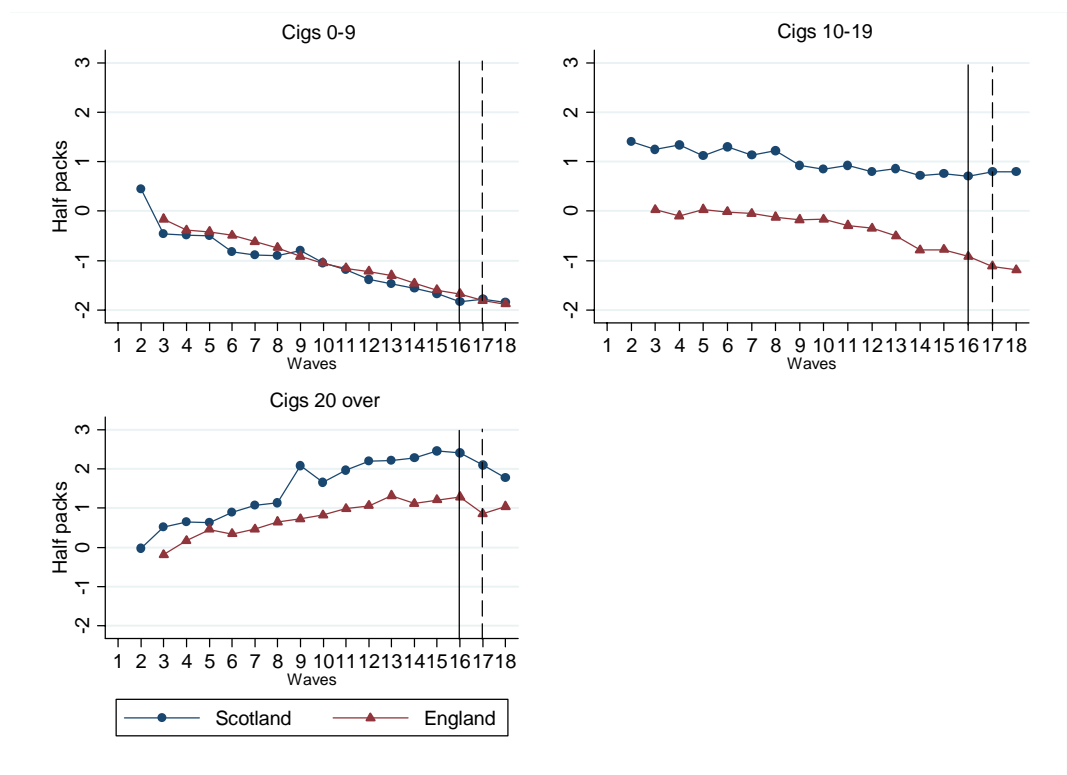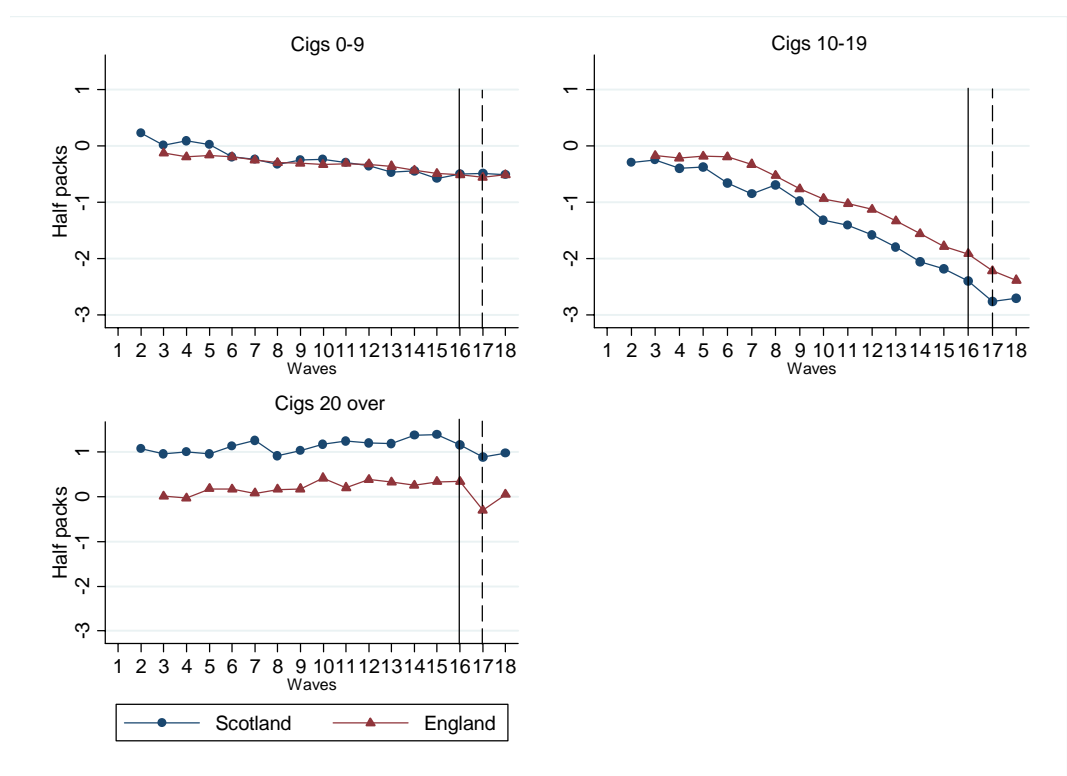**Figure 4a: Regional time trends models by type of smokers – Men**

Figure 4b: Regional time trends models by types of smokers - Women

Notes: the continuous vertical lines indicate the Scottish smoking ban while the dashed lines represent the English ban.