Do Tobacco Taxes Influence Starting and Quitting Smoking? A Duration Analysis Approach Using Evidence from a Sample of Irish Women

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Abstract: This paper uses duration analysis to investigate factors influencing starting and quitting smoking, in particular the role of tobacco taxes. Applying a variety of parametric duration models, including a split population model, to a sample of Irish women, it finds mixed results regarding the effect of tobacco taxes. In general the coefficient on tobacco taxes is in the expected direction but in some cases statistical significance is low. The paper finds that among other factors education, health knowledge and marital status to be most important with no role for advertising bans. These results are not changed when account is taken of unobserved heterogeneity.

JEL Codes: I18, D12, C41.

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1. Introduction

There is ample medical evidence indicating the adverse effects of tobacco consumption upon health (see Madden, 2001a, for a recent summary). Recent Government publications in Ireland have suggested the long-term goal of a "tobacco-free society". As the accompanying letter to a recent Government report stated: "…there is a common objective of seeking the most effective measures possible to dramatically reduce the level of smoking in our society and above all to prevent our children from starting to smoke" (Mooney, 2000). It follows that identifying the factors behind the decision to smoke and the decision to quit is crucial in terms of formulating policy.

A recent paper examined the factors influencing participation in smoking, the amount smoked and factors influencing quitting for a sample of Irish women (Madden, 2001a). However, one factor absent from that work was the influence of a crucially important tool of government policy in its drive towards a tobacco-free society, the rate of taxation on tobacco and tobacco products. The data in Madden (2001a) was a single cross-section of Irish women and the absence of any variation in tax or price meant that it was impossible to infer the effect of these variables on smoking behaviour. The dataset however did include some retrospective data on the year of quitting smoking (for those women who quit) and also the number of years smoking (from which could be inferred the year of starting smoking). Using this data, and incorporating the relevant tax rate for the year in question, it is possible to construct a longitudinal data set with the tax rate as a time-varying covariate. Following this it is then possible to model the decision to start/quit smoking as either a binary choice or to model the duration before starting/quitting. We adopt the duration analysis approach in this paper. For duration modelling in the case of starting we use the split-population duration model of Schmidt and Witte (1989), Douglas and Harihan (1994) and Foster and Jones (2000) while for quitting we follow the approach of Tauras and Chaloupka (1999) and Foster and Jones (2000) in applying standard parametric models.

Note that we are not trying to estimate what the optimal tax on tobacco should be. For a comprehensive recent survey dealing with the US, see Evans et al (1999). The key issues in this literature appears to be (a) which external costs should be included in the social cost of tobacco consumption, in particular whether the costs of maternal smoking (in terms of the health costs of low-weight babies, sudden infant death syndrome etc) should be included and (b) assumptions regarding the time consistency of preferences. Gruber (2001), Gruber and Köszegi (2001) and Laux (2000) indicate that if preferences are *not* assumed to be time consistent then some of the internal cost of smoking should also be included in the social cost of smoking. This would imply huge tax increases over current levels. There is very little treatment of the optimal tobacco tax for Ireland but see Madden (1992) for an approach which attempts to infer the degree of consumption externality implicit in existing taxes.

The remainder of the paper is as follows: in section 2 we briefly discuss some of the existing literature and in section 3 we outline a simple model of starting and quitting smoking. In section 4 we discuss our data and describe and present results from our empirical model while section 5 provides concluding comments.

2. Review of Literature[1]

It was believed at one time that cigarette smoking and other addictive behaviour was not rational and so not suitable for conventional economic analysis (e.g. Schelling, 1984). There is now however a substantial body of literature to testify that the demand for cigarettes clearly responds to changes in prices and other factors. Early studies of cigarette demand employed aggregate time-series data and produced estimates of the price elasticity of demand in the region of –0.4. One disadvantage of these studies was that they were unable to distinguish between the elasticity of cigarette demand conditional upon smoking and the elasticity of participation. Later studies used the type of individual level data employed in this study. These studies are able to consider separately the effect of price on the probability of smoking and on average consumption of smokers. Furthermore, studies on the probability of smoking can be divided into those which view starting and quitting as binary events within a discrete choice framework and those which use duration analysis. For an example of an application of the former approach to the dataset used in this paper see Madden (2001a). However this paper only examined a single cross-section and so could not incorporate time series variation in price or tax data. As we will see below it is possible to expand this framework and extend the binary choice framework to include the effects of taxes/prices.[2]

Studies which have examined smoking initiation in a discrete choice framework have typically estimated elasticities of participation with respect to tax in the region of –0.5 to –1.0 with an apparent inverse relationship between age and smoking elasticity (for a summary see Chaloupka and Warner, 1999). There are fewer applications of duration analysis. Douglas and Harihan (1994) use a split population model to analyse starting smoking. They find no evidence of a statistically significant price effect. Douglas (1998) analysed the hazards of starting and quitting, once again using a split population model, but this time with an ordered probit, which distinguishes between those who never start smoking, those who start and quit and those who start but do not quit. The "delay" before starting and quitting are modelled using a log-logistic and Weibull specification

[1] The first part of this section draws upon the excellent survey by Chaloupka and Warner (1999).

respectively. The price of cigarettes is included as a time-varying covariate. The price of cigarettes has no significant effect upon the hazard of starting smoking but the number of years an individual smokes has an approximately unitary elasticity with respect to price. Forster and Jones (2000) analyse retrospective UK data with a split population model for starting smoking and a variety of parametric duration models for quitting. They find a tax elasticity of the age of starting smoking of +0.16 for men and +0.08 for women. The estimates of the tax elasticity of quitting are –0.6 for men and –0.46 for women. They also include a variety of specification tests and find their estimates to be quite robust.

We complete this section by briefly reviewing the existing Irish studies on tobacco consumption. A variety of models of tobacco consumption have been estimated mostly using aggregate time-series data for Ireland dating from O'Riordan (1969) to Madden (1993).[3] These studies have produced broadly comparable results with a median estimate for the price elasticity of tobacco in the region of –0.5, which is in line with results from elsewhere in the world. The use of aggregate time-series data precludes distinguishing between the effect of price on the probability of smoking and on the demand for cigarettes conditional on smoking. Conniffe (1995) remedies this to some extent by combining analysis of aggregate time-series data with data on the proportion of the total population who are smokers. He found that the proportion of the population smoking is unaffected by price (or income) but exhibits a downward trend related to health concerns. Consumption by smokers does not exhibit such a downward trend but appears to have a significant price elasticity of around –0.3.

We now turn to outline the simple model of starting and quitting smoking which underlies our analysis.

3. A Model of Starting and Quitting Smoking

In this section we outline a simple theoretical model which underlies our empirical approach. The model draws on the exposition of Douglas and Harihan (1994). Suppose each individual has a concave utility function at time t

$$U_t = U(C_t, Y_t, S_t, L_t)$$

where C_t is the level of consumption of the addictive good whose price is P_t, Y_t is consumption of a non-addictive numeraire good whose price is unity, S_t is the stock of accumulated addiction capital and L_t represents other demographic/life cycle variables which may affect utility.

[2] In a companion paper to the current one, Madden (2001b) estimates the effect of taxes using a discrete choice approach.
[3] The exception was O'Riordan (1969) who used data from the Tobacco Research Council.

The stock of addictive capital S_t depreciates at rate γ but it is replenished by current consumption of the addictive good C_t so that

$$S_{t+1} = (1-\gamma)S_t + C_t .$$

Since the individual starts off with zero units of consumption $S_0 = 0$.

Assume that each individual is infinitely lived, then discounted remaining lifetime utility at time t, V_t is given by

$$V_t = \sum_{i=t}^{\infty} \frac{1}{(1+\rho)^{i-t}} U_i$$

where ρ is the rate of time preference.

The lifetime budget constraint is determined by the present value of lifetime wealth A_t, the present value of lifetime expenditure on the numeraire good Y and the present value of lifetime expenditure on the addictive good C at prices P_t. We make the simplifying assumption that lifetime earnings are not affected by the stock of addiction.[4] The budget constraint for the individual at time t is

$$\sum_{i=t}^{\infty} \frac{1}{(1+r)^{i-t}} (Y_i + P_i C_i) = \sum_{i=t}^{\infty} \frac{I_i}{(1+r)^{i-t}} \equiv A_t$$

where I_i is income at time i and r is the rate of interest. We can now look at the decisions to start and quit smoking. Dealing with starting first, a rational individual will begin smoking if the marginal benefit of the first cigarette exceeds its marginal cost i.e.

$$MB_C(C_t, Y_t, L_t \mid S_t = 0) > MC_C(C_t, Y_t, L_t \mid S_t = 0)$$

where MB_C is the marginal discounted remaining lifetime benefit of cigarette consumption while MC_C is the marginal discounted remaining lifetime cost. It seems likely that some of the variables affecting marginal cost and benefit will have a stochastic component. For example, they could both be affected by the occurrence of respiratory illnesses which would reduce the appeal of smoking or they could be influenced by the number of smokers in the potential smoker's peer group. So the above condition could be re-specified along the lines:

$$MB_t^* + \varepsilon_t > MC_t^* + \mu_t$$

where $MB_t^* \equiv E\{MB_C(C_t, Y_t, L_t \mid S_t = 0)\}$ and $MC_t^* = E\{MC_C(C_t, Y_t, L_t \mid S_t = 0)\}$.

Thus the probability of staring smoking at time *t* given that an individual has not started smoking in a previous period is

[4] There is some controversy as to the effect of the consumption of addictive goods on wages. Clearly ill-health (arising from smoking) could affect earnings via lost hours and there is also evidence that moderate alcohol consumption has a positive effect upon wages but that tobacco use reduces wages. See Auld (2000) for a recent discussion.

$$\Pr\{C_t > 0 \mid S_t = 0\} = \Pr\{MB_C(C_t, Y_t, L_t \mid S_t = 0) > MC_C((C_t, Y_t, L_t \mid S_t = 0)\}$$

$$= \Pr\{\varepsilon_t - \mu_t > MC_t^* - MB_t^*\}.$$

$$= H(MC_t^* - MB_t^*) = H(t)$$

where $H(t)$ is a hazard function based on the distribution $F(T) = \Pr\{\text{Start Smoking at } t \leq T\}$. $H(t)$ will be decreasing in $MC_t^* - MB_t^*$. In this case the hazard function is the *conditional* probability that a person will smoke in period *t* given that he has not smoked up to and including period *t-1*.

The analysis of quitting is very similar, except of course that marginal cost and benefit are now conditional upon a stock of accumulated addictive capital. A person will quit in period *T* if the following condition holds:

$$MC_C(C_t, Y_t, L_t \mid \sum_{t=\tau}^{T-1} S_t > 0) > MB_C(C_t, Y_t, L_t \mid \sum_{t=\tau}^{T-1} S_t > 0)$$

where $\sum_{t=\tau}^{T-1} S_t > 0$ reflects the stock of accumulated addictive capital up to period *T* and the person started smoking in period τ. Note that this assumes a single spell of smoking – we do not allow for multiple spells of smoking, not smoking, smoking again etc. Then, following the analysis above, the probability that someone will quit smoking in period T, given that they were smoking in period T-1 is

$$\Pr\{C_T = 0 \mid C_{T-1} > 0, \sum_{t=\tau}^{T-1} S_t > 0\} = \Pr\{\varepsilon_T - \mu_T < MC_T^* - MB_T^*\}$$

$$= H(MC_T^* - MB_T^*) = H(T).$$

In this case $H(T)$ is increasing in $MC_T^* - MB_T^*$.

4. Data and Empirical Model

In this section we discuss our data and the empirical model adopted. Our data comes from a survey known as the Saffron Survey which was carried out in 1998 by the Centre for Health Economics at University College Dublin.[5] The Saffron Survey's aim was to survey women's knowledge, understanding and awareness of their lifetime health needs. Much of the focus of the survey was on the issue of hormone replacement therapy[6] but other information regarding health, lifestyle choices and demographics was also collected. For our purposes in this paper the relevant questions regarding smoking were as follows: " Do you currently smoke?". People who answered "yes" to this question were then asked "For approximately how many years have you smoked?". People who replied that they did not currently smoked were asked had they ever smoked and if they answered yes to this question they too were asked for approximately how many years they had

[5] I am grateful to Joe Durkan and the Centre for Health Economics for supplying this data.
[6] See Thompson, 2000.

smoked, and in what year they had stopped smoking. From the answers to these questions it is possible to calculate the years people started (and stopped if applicable) smoking. The great advantage of this type of information is that it is possible to examine the effect of the tax rate in each given year on the probability of starting/quitting smoking.

One problem which potentially arises in this analysis is the use of the word "approximately" in the question regarding the duration of smoking. There is a danger here of "heaping" in the sense that people will round off their answer to this question to the nearest 5/10 years. There are a variety of techniques of addressing this issue (see Torelli and Trivellato, 1993, for a comprehensive discussion) but here we adopt the ad hoc approach of simply including dummy variables for the years where heaping is likely (viz. five, ten, fifteen and twenty years before the date of the survey).

Before the formal analysis it is useful to look at some summary information on our sample. The original sample size for the Saffron survey was 1260. However, since we only have tax and price data going back as far as 1960, we have dropped all women who were aged 10 or more in 1960. We are effectively assuming that subjects were at risk of starting smoking from the age of ten. Our data suggests that this is a reasonable assumption since the number of subjects who reported starting smoking before ten was miniscule. Thus we only have women who were born after 1950, leaving us with a total sample of just over 700. Of these, about half have smoked at some stage of their lives and about 35 per cent were smoking at time of interview. In table 1 we give summary statistics (with standard errors in brackets) for a number of key variables for the various subgroups in our sample.

There is relatively little difference across the groups by age except for ex-smokers who tend to be older. As might be expected this group also tends to have worse health (which perhaps prompted them to quit smoking). They also show a higher proportion of married, which may reflect people giving up smoking on getting married. Probably the biggest difference across the columns is to be observed in educational attainment. Of the total population (including smokers) over 60 per cent have obtained Leaving Cert or higher, but of those who have ever smoked only about 47 per cent have. This drops to about 44 per cent when we examine those people still smoking in 1998. Thus getting beyond Junior Cert appears to not only lower the chances of starting smoking, but also increases the chances of quitting if you do start to smoke.

As explained above, the Saffron survey was a cross-section survey carried out in 1998. However, we are exploiting the retrospective information which enables us to examine the impact of a time-varying covariate such as tax or price on the decision to start/quit smoking. One issue which must first be discussed in the choice of tax/price. The choice of such a variable is motivated by the theory of consumer demand which suggests that the quantity consumed (or in this case the decision to consume) will be influenced by a number of factors, including the consumer price (which in turn is influenced by the tax on tobacco).

The tax element in the retail price of a packet of cigarettes has two components, excise duty and value-added tax (VAT). Thus excise duty is added to the producer price and VAT is then applied at the appropriate rate to obtain the retail price. While the retail price is thus influenced by two tax instruments (the rate of excise duty and VAT) it is arguable that only excise duty can be regarded as a specific tax instrument to address smoking, since any increase in the rate of VAT will also cause the prices of many other goods to rise. To engineer a rise in the relative price of tobacco, a rise in excise duty is appropriate. Unfortunately the data supplied to us by the Revenue Commissioners does not break down the tax component into excise and VAT for the period up to 1973. Thus we have taken the total tax component of the retail price and deflated it by the personal consumption deflator to arrive at a real tax on tobacco. This sidesteps the need for such a breakdown since any excise tax increase in excess of overall inflation will appear as an increase in the real tax whereas increases in VAT will also be reflected in increases in the overall price level and thus contribute less to any increase in the real tax.

We thus have a choice between using the real tax content or the consumer price as the relevant time-varying covariate. It can be argued that from the point of view of the decision which the consumer makes re starting or quitting it is the consumer price which is relevant. On the other hand, from the point of view of government it is the tax content which is the policy variable. However, from a practical point of view, the choice between them is largely irrelevant. As figure 1 below shows, the two series move pretty much in tandem and the correlation coefficient between them is 0.97.

We now turn to discuss the more formal analysis of starting and quitting, dealing with starting first.

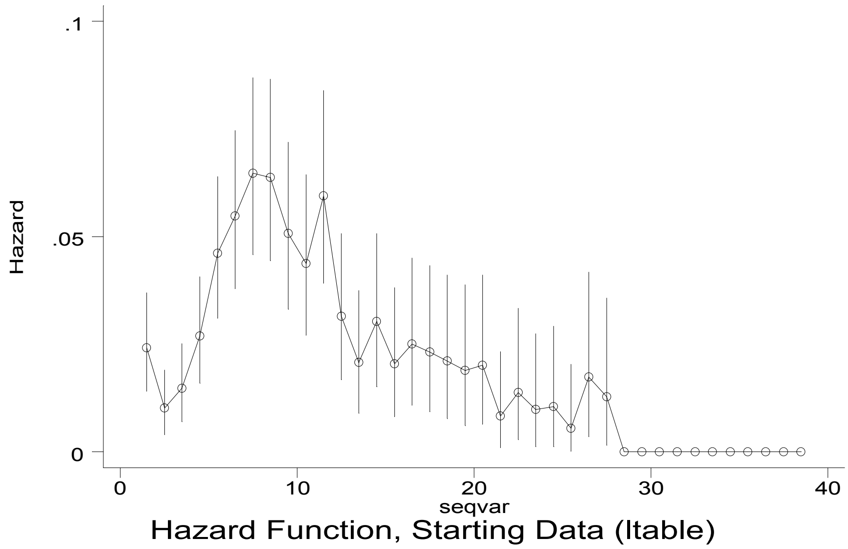
4.1 Starting Smoking

To analyse the decisions to start/quit smoking, we employ duration analysis, with the extra proviso that when examining the decision to start smoking we employ a split population model. When modelling the decision to smoke, we include as one of our covariates the tax rate for the year in question. Thus say we observe woman A, aged 40 in 1998 (the year of the survey) who commenced smoking aged 20 (i.e. in 1978). We assume people are at risk of starting smoking from the age of ten (1968 in the case of woman A). Thus we will have ten observations on woman A where she does not smoke, followed by the transition in year 11 where she does smoke. Each observation for each year for this woman (up to when she starts smoking) is regarded as a separate observation. Thus the observation for 1968 for woman A has a duration of one, with the tax rate for 1968 as one of the covariates and is regarded as right-censored. The observation for 1969 for woman A has a duration of 2, is still right-censored and has the tax rate for 1969 as a covariate. This continues up to the observation for 1978 where there is a “failure” or transition to smoking.

Consider now the case of woman B with the same age as woman A but who has not started smoking by 1998. In this case there are thirty observations for woman B, all of them right-censored. No "failure" or transition to smoking is observed. Standard duration models assume that failure will eventually take place. Thus even if the last observation for an individual is right-censored (i.e. in our case they have not started smoking by 1998) it is assumed that at some stage they will start smoking. If, say, we were trying to model the duration of a light bulb then this assumption is realistic. At some stage the light bulb will fail. But the assumption is not realistic for the case of starting smoking, since a substantial prportion of the population never smoke at any stage of their lives. In this case a split population model is appropriate where the likelihood of each observation is weighted by the probability that the individual will ever start to smoke and so the duration analysis is applied only to those individuals predicted to start smoking.

It is also possible to estimate standard duration models where the population is not split. We present estimates for both models below.

Before discussing the appropriate parametric duration model we first present the plot of the empirical hazard function below. This is particularly useful when choosing a parametric hazard function. We use the lifetable estimate of the hazard function (with confidence intervals as shown) and this is qualitatively very similar to the Kaplan-Meier estimate of the empirical hazard.



Hazard Function, Starting Data (ltable)

This figure shows that the hazard increases at first and then decreases. It reaches its peak when the time period equals seven, which corresponds to age seventeen since we assume subjects are at risk of smoking from age ten. There is another local peak at age twenty-one and then a fairly sharp decrease. What this suggests is that a monotonic hazard function is not appropriate for this dataset. A hazard function which at first increases and then decreases seems most appropriate, suggesting the log-logistic model is worth trying.

For the smokers in our sample we infer the age of starting as outlined above and the duration data can be viewed as a complete spell. The sample, of course, also contains individuals who are not observed to have started smoking. A parametric duration model would interpret these individuals as incomplete spells and assume that they will eventually fail and start smoking. They are viewed as "right-censored" at the time of the survey. As explained above this does not appear reasonable when dealing with smoking and consequently Douglas and Harihan (1994) in their analysis of US data and Foster and Jones (2000) in their analysis of UK data have argued that a split population model be used. In this model duration analysis is applied only to those individuals who are predicted to eventually start smoking.

Following Foster and Jones (2000) suppose we define $s=1$ for an individual who will eventually start smoking and modelling eventual failure (i.e. starting smoking) using a probit specification we have

$$\Pr(s=1)=\Phi(\alpha' z_i) \text{ and } \Pr(s=0)=1-\Phi(\alpha' z_i)$$

where z_i is a vector of time invariant covariates, Φ is the cumulative density function for the standard normal distribution and α is a parameter vector. Thus the probability of starting smoking at a given time *t* is defined conditional upon eventually starting.

Given the plot of the empirical hazard function above the most appropriate parametric duration model is the log-logistic. The probability density function $f(.)$ and the survival function $S(.)$ of the log-logistic distribution for those individuals who eventually start smoking are

$$f(t \mid s=1; x_i(t)) \equiv \frac{\lambda^{\frac{1}{\gamma}} t^{\frac{1}{\gamma}-1}}{\gamma[1+(\lambda t)^{\frac{1}{\gamma}}]^2}$$

$$S(t \mid s=1; x_i(t)) \equiv \frac{1}{1+(\lambda t)^{\frac{1}{\gamma}}}$$

where $\lambda=\exp(-\beta' x_i(t))$, $x_i(t)$ is a vector of time variant and time-invariant covariates and γ is a scale parameter.

Then the contribution to the log-likelihood function for the split population model becomes, for individual *i*:

$$c_i \ln[\Phi(\alpha' z_i) f(t \mid s=1; x_i(t))]+(1-c_i)\ln[1-\Phi(\alpha' z_i)+\Phi(\alpha' z_i) S(t \mid s=1; x_i(t))]$$

For those who are observed as smokers in the sample, $c_i=1$ and their contribution to the likelihood function is simply the log of the probability of being a smoker $\Phi(\alpha' z_i)$ times the probability density function of starting at the observed starting age, $f(.)$. For those who are observed as not starting

($c_i = 0$), the contribution is the log of the probability of never starting $1-\Phi(\alpha' z_i)$ plus the probability of starting after the age observed at the time of the survey, $\Phi(\alpha' z_i)S(.)$.

We also estimate a version where the population is not split and we employ the log-logistic model.

In table 2 we present estimates of the above split population model and in table 3 we present estimates of the log-logistic model where the population is not split. We include both time-varying and non-time-varying covariates in these models. Education is frequently regarded as an important determinant of health and smoking habits (see Meara, 2000) and we include categorical variables for Junior Certificate (essentially leaving formal education at around sixteen years of age), Leaving Certificate (where the secondary cycle is completed and education ceases at about eighteen years of age) and third level. The default category is Primary Education whereby formal schooling ends at about twelve years of age.

The mechanism whereby education affects smoking behaviour is unclear. It may indicate that more educated people simply have more information regarding the effects of smoking upon health. It may also indicate that more educated people are better able to process or act upon information on regarding the health effects of smoking. Finally it may reflect the presence of a "third" variable whereby which simultaneously influences attitudes towards both education and smoking/health. Thus individuals with a low discount rate (i.e. they are more "future-oriented") will invest in both their health capital (by refraining from activities such as smoking) and their human capital. While we do include a measure of health knowledge (see below) in the absence of reliable measures of such discount rates it is difficult to distinguish between these different mechanisms but it is likely that all three (and perhaps others) are at work.[7]

To try and capture the influence of government campaigns to deter smoking we also include dummy variables for both the TV and radio bans on tobacco advertising. We also include a variable which we label health knowledge. As mentioned above, the Saffron survey collected a variety of information regarding the health habits and needs of women. Owing to its concentration on hormone replacement therapy, a number of questions were asked regarding health knowledge in this area. As our measure of health knowledge we include a dummy variable which measures the response to the question "Have you ever heard of osteoporosis?".[8] Clearly this question refers to a dimension of health which differs from smoking, but we do not believe it is unreasonable to expect

[7] For a discussion on the relative importance of these mechanisms for the link between smoking, health and socio-economic status, see Meara (2001).

[8] In future research we hope to include other measures of health knowledge apart from osteoporosis. Nevertheless, osteoporisis may be a suitable measure of health knowledge for our sample since typically it is more common amongst older women thus reducing the chances that knowledge regarding it comes from direct experience but rather instead from being generally well-informed on health issues. Also since smoking increases the risk factor for osteoporosis it may be a good proxy for health knowledge specifically related to smoking.

that knowledge regarding osteoporosis may be correlated with other aspects of health knowledge, including the health effects of smoking. The inclusion of this variable may also help to disentangle, to some extent at least, the mechanism whereby education affects smoking (see discussion above).

The results in tables 2 and 3 confirm the importance of education as an explanatory factor in smoking behaviour. The coefficient on the probit in table 2 for Leaving Cert is negative, indicating that compared to those having completed primary education, obtaining the Leaving Cert reduces the probability of becoming a smoker. Perhaps unusually, the coefficient on Junior Cert is positive. Typically the relationship between the probability of smoking and educational achievement is monotonic (for example, see Madden, 2001) but the evidence here suggests otherwise. Curiously, the coefficient on those with third level education, while of the expected sign, is not significant. The coefficient on third level education for the duration part of table 2 is positive but not significant. A positive coefficient indicates that conditional upon eventually starting smoking, third level education will delay the process i.e. it has a positive effects upon the length of time before "failure", the transition to smoking. Surprisingly, the coefficient on Leaving Cert is negative, though not significant. Note also that the education variable here refers to the highest level achieved, a level which will not have been achieved by the subject for a number of the years at which she was at risk of starting smoking e.g. from age ten to twenty it is very unlikely that any person would have a third level degree. However, if the highest level of education achieved acts as a proxy for a variable such as a person's discount rate (see the argument above) then its inclusion for all years at which the subject was at risk is valid.

For the most part, the coefficients on the duration part of table 2 are not significant. One exception is the ban on radio advertising. However, the sign of this coefficient is negative, contrary to intuition i.e. the ban on radio advertising shortened the duration before starting to smoke. Another factor which is significant is health knowledge, and here the coefficient is of the expected sign. Greater health knowledge increases the delay before starting smoking. Turning now to the key factor we wish to examine in this paper, we see that for the split-population model the tax rate on tobacco has the "wrong" sign and is not statistically significant. Thus for those people who will eventually smoke, the tax rate on tobacco has no effect upon the duration of time before they start smoking. We also notice evidence of "heaping" in that the dummy variables for ten, fifteen and twenty years all have significant negative coefficients. This indicates that with the retrospective data we have, people have a tendency to "round off" when they started smoking by indicating it was twenty, fifteen or ten years ago.

To allow for the possibility of a secular drift in smoking habits over time, perhaps related to increased health awareness or general public intolerance towards smoking we also include a time trend. However, given that all the variation in tax rates is attributable to variation across calendar years there may be an identification problem in separating the time trend and tax effects. Following Foster and Jones (2000) we thus include a fourth-order polynomial in time, which allows for a smooth but flexible time trend. We also experiment with other specifications regarding time. These include a linear spline with three knots and in the third specification we simply exclude time altogether. Finally, we also include a cohort dummy, which takes on a value of one if the individual is aged 33 or less.

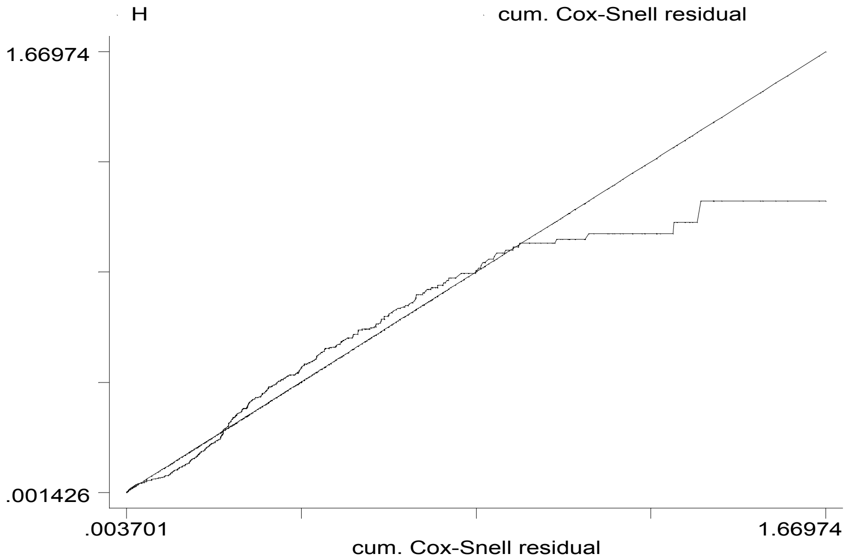
The results in table 2 show that the estimates for the effect of taxation are quite sensitive to the specification for time. When a linear spline is used, and when time is excluded altogether, the coefficient on tax is significant but not in the expected direction. The coefficients on the other variables are all fairly robust to the specification for time.

Table 3 shows the results for the log-logistic model where the population is not split, and with the three different specifications for time. Thus this approach assumes that at some stage every subject will "fail" and make the transition from non-smoking to smoking. The coefficients in this model are in general much better determined than in the split population model. The effect of education is to lengthen the duration before smoking, with significant effects (of the same magnitude) observed for both the Leaving Cert and third level. The coefficient on the ban on TV advertising is significant when the fourth order polynomial is used but is insignificant elsewhere. Once again the coefficient has the opposite sign to what intuition would suggest. The coefficient on health knowledge once again has the expected sign for all specifications and is just off conventional significance levels (the p-value is about 12%). Interestingly, the inclusion of health knowledge reduces the size of the coefficients on education compared to the case where it is excluded (results not reported here but available on request), suggesting that at least part of the impact of education reflects knowledge regarding health. The cohort effect is also significant, indicating that younger people (those aged 33 or less) started to smoke earlier than their older counterparts.

Marriage prolongs the duration before starting smoking, and perhaps most interestingly, so too does the tobacco tax for two of the specifications. Since the dependent variable is actually the log of real tax on tobacco, the coefficient can be interpreted as an elasticity. At first glance the estimated elasticities of 1.2 and 0.7 appear high, but it is well to translate it into the metrics actually used. An elasticity of about 1.2 suggests that an increase in the *real* tax on tobacco of five per cent (which would require an even bigger nominal tax increase, given some general inflation) would increase duration before smoking by about five to six per cent. Given that the average value of the duration variable for those who eventually smoke is about nine years, this indicates a delay of around six to seven months following a five per cent real tax increase. Once again there is evidence of heaping at five year intervals.

When using a parametric duration model it is important to determine whether the data support the particular parametric form of the hazard function. Probably the most frequently employed method is to use the model based estimate of the cumulative hazard function to form what is known as the Cox-Snell (1968) residuals. The Cox-Snell residual for subject *j* at time t_j is defined as $\hat{H}_j(t_j) = -\ln \hat{S}_j(t_j)$, the estimated cumulative hazard function obtained from the fitted model, given that $\hat{S}_j(t_j)$ is the estimated survival function. Cox and Snell argued that if we have *n* subjects then if the correct model has been fitted to the data, these residuals are *n* observations from an exponential distribution with unit mean. Thus a plot of the model-based cumulative hazard against the cumulative hazard function obtained from a nonparametric or empirical estimator should yield a straight line with slope equal to one if the parametric model is correct.

Below we show such a plot for the log-logistic model for starting smoking.



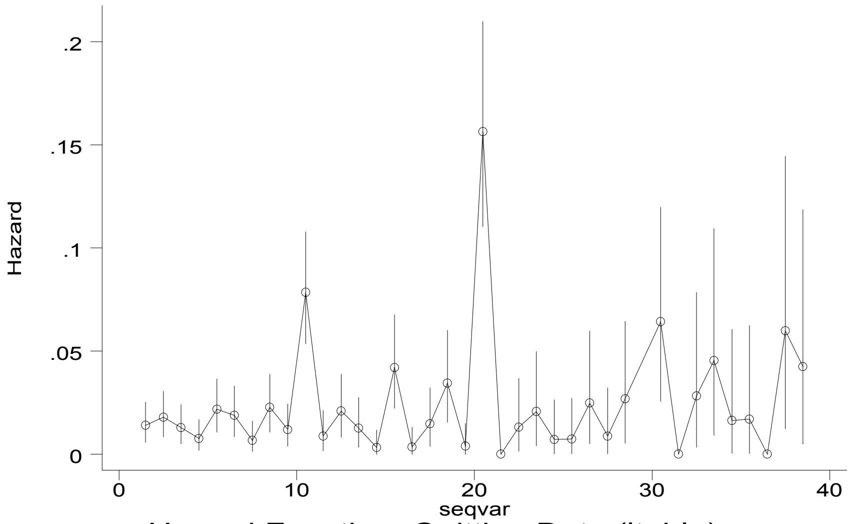
The departure of the plot from the reference line after the cumulative hazard takes on a value of about 0.37 gives some indication of misspecification.[9] The Ramsey RESET test however gives no indication of model misspecification with a p-value for the inclusion of higher powers of the fitted duration of 0.469. Comparing the different specifications with regard to time, we see in table 3 that the RESET tests for the specifications with a linear spline and where we do not take account of time at all both show signs of misspecification[10]. Overall then it seems as though the specification with the fourth-order polynomial in time performs best, while the other two specifications perform relatively poorly.

[9] From the graph it can be seen that the deviation from the reference line becomes severe at a value of the Cox-Snell residual of just over 1.0. The cumulative hazard is then exp(-1) i.e. about 0.37.

[10] We do not present them here, but the graphs of the Cox-Snell residuals for the specifications with a linear spline in time, and where no account is taken of time, also reveal evidence of misspecification.

4.2 Quitting Smoking

For the case of quitting smoking the analysis is in many ways the mirror image of the analysis reported above. In this case the transition, or "failure" is the act of quitting smoking. Thus a person who has smoked for say 10 years and then quits represents ten observations, where the duration variable increases by one each year. Each year up to the point of quitting is regarded as right-censored and then the quitting year is the transition year. A person who say starts smoking in 1988 and has not quit by 1998 (the year of the survey) is simply treated as having ten right-censored observations. We do not employ the split-population model for quitting since it seems more reasonable to assume that from a population of smokers, all, or at least a majority of them, will quit or would eventually quit if they could be observed for long enough, than to assume that from a population of non-smokers, all will eventually start smoking. Below we show the plot of the empirical hazard function for quitting, once again using the lifetable estimate with confidence intervals.



Hazard Function, Quitting Data (ltable)

There are clear spikes at the ten and twenty year mark which suggests heaping. Apart from those spikes there is relatively little evidence of an increasing or decreasing hazard. This suggests that amongst parametric duration models, the exponential or Weibull might be an appropriate choice. The survival function for the exponential model (in accelerated failure time format) is: $S(t) = \exp(-\lambda t)$ where $\lambda_j = \exp(-x_j \beta)$ and x_j and β represent a vector of covariates and regression coefficients respectively. The corresponding functions for the Weibull model is $S(t) = \exp(-(\lambda t)^p)$ where $\lambda_j = \exp(-x_j \beta / p)$ and x_j and β are as before. Clearly the exponential model is a special case of the Weibull model, where $p = 1$. We also include estimates from the generalised gamma model. This is an extremely flexible model which nests both the exponential and Weibull model. Its survival function is $S(t) = 1 - I(\kappa \exp(\frac{z}{\sqrt{\kappa}}))$ where I is the incomplete gamma function and $z = \frac{\ln t - \lambda}{\sigma}$. When $\kappa = 1$ this reduces to the Weibull distribution, while $\kappa = 1$ and $\sigma = 1$ gives the exponential distribution.

Tables 4-6 gives the results for the estimation of gamma, Weibull and exponential duration models (with the results presented in accelerated time format), where once again we have included different specifications of time. Note that in terms of intuition, we expect coefficients to be of opposite sign to the starting models, since here we are estimating the effect of variables on the delay before quitting. We note that there is very little to choose between the three models in terms of estimates of the non-tax coeffcients, with the possible exception of a larger effect for health knowledge in the exponential model. Once again we see the importance of education. Compared to completing only primary education, having a Leaving Certificate or third level education exerts a statistically significant and negative impact on the delay before quitting. Perhaps surprisingly the higher coefficient on health knowledge in the exponential model is not accompanied by a relatively smaller coefficient on education.

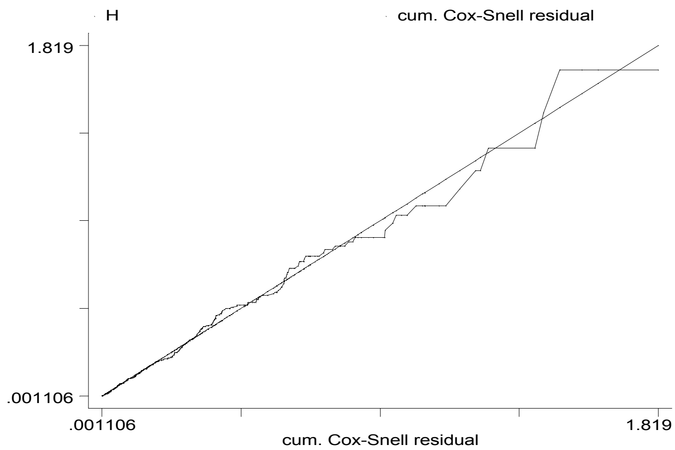
The coefficient on the tax rate is of the expected sign in all three models when the fourth order polynomial in time is used and when no account is taken of time. When the linear spline is used the coefficient is not of the expected sign, but neither is it significant. In fact only when the exponential model is used with no time trend is the coefficient statistically significant, with a value of –0.9. However, in the Weibull and gamma models with no time trend, the coefficient on tax is not too far off conventional significance levels. Given an elasticity of –0.9, since the average duration before quitting for those who quit is about 14 years, this suggests that a five per cent increase in the tax on tobacco would lead to a decrease in smoking duration of about seven to eight months.

Surprisingly, the coefficients on the dummy variables for heaping are not significant, despite the plot of the empirical hazard function above. In terms of nested tests, we note that the exponential model is rejected in favour of the Weibull (log p is significantly different from zero) and in turn the Weibull is rejected, though less decisively, in favour of the gamma (κ is not significantly different from unity except when no time trend is employed). The correspondence between the gamma and Weibull models is confirmed by the Akaike information criterion (AIC) which gives a marginally lower value to the Weibull compared to the gamma model, except once again when no time trend is used.[12]

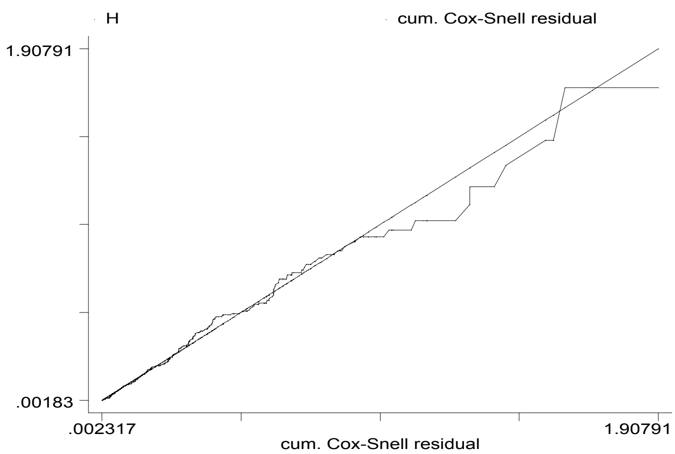
[12] The AIC is typically used to discriminate between non-nested models and proposes penalizing the log likelihood function to reflect the number of parameters estimated in a particular model and then comparing them. The model with the smallest AIC value is preferred.

This correspondence between the gamma and Weibull models and the difference compared to the exponential model is confirmed by examination of the Cox-Snell residuals for these models. Visual inspection indicates that the residuals for the gamma and Weibull models are very similar, while there is considerably greater deviance from the reference line in the case of the exponential model. The results of the Ramsey RESET test do not indicate misspecification with high p-values for both the Weibull and exponential models for the inclusion of higher powers of the fitted duration. The gamma model with higher powers of the fitted duration would not solve owing to infeasible starting values, but given the p-value of 0.868 for the Weibull it seems highly likely that a similar figure would have been obtained for the gamma model.

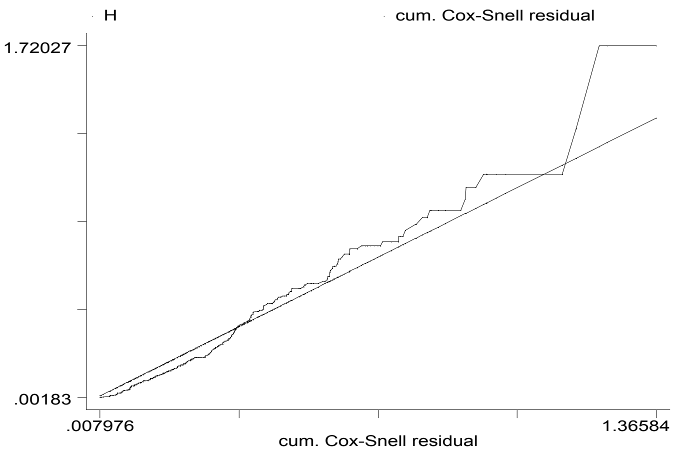
Cox-Snell Residuals for Gamma Model



Cox-Snell Residuals for Weibull Model



Cox-Snell Residuals for Exponential Model



5. Frailty Models

The specifications we have outlined above, plus the included covariates may still not explain all the variability in observed time to failure. The excess unexplained variability, or overdispersion, may be caused by misspecification or omitted covariates. In survival analysis this is known as "frailty" since the model is unable to explain fully why subjects with shorter time to failure are more frail than others. A frailty model attempts to measure this overdispersion by modelling it as resulting from a latent multiplicative effect on the hazard function. Thus given a hazard function $h(t)$ the hazard becomes $\alpha h(t)$.

Frailty may also be "shared" in the sense that the subjects in a given group may experience the same unobserved heterogeneity e.g. the group may represent a family, or, as is the case here, a single subject for which multiple episodes are observed.

Recall that in the case of frailty the hazard function becomes $\alpha h(t)$. For purposes of identifiability it is usually assumed that α is distributed with mean one and variance θ. The issue then becomes the estimation of the additional frailty variance, θ. Probably the two most common parametric choices for $g(\alpha)$, the probability density function for α are the gamma and the inverse gaussian. While the associated hazard function for the two distributions are quite alike there is one important distinction. Suppose we have two individuals with common frailty. Conditional on the given frailty their respective hazards are proportional with, say, $h^{(2)}(t)/h^{(1)}t = c$. Marginally however, for gamma frailties the hazard ratio $h_\theta^{(2)}(t)/h_\theta^1(t) = c$ at $t = 0$, but diminishes with time so that in the limit the ratio becomes unity. For the inverse-Gaussian once again suppose that $h_\theta^{(2)}(t)/h_\theta^1(t) = c$ at $t = 0$. However, in this case the limit of this ratio is not unity but $c^{1/2}$ so that the frailty effect does not diminish completely over time.

Tables 3A and 3B show the log-logistic starting model estimated with both gamma and inverse-Gauss shared frailty. Note that in all cases the null hypothesis that the additional frailty variance $\theta = 0$ is rejected. However, it is also worth noting that qualitatively the results for starting are not affected, although the tax elasticities are slightly smaller. We do not present the results for the parametric frailty models for quitting since in no case was the null hypothesis that $\theta = 0$ rejected. Once again the qualitative results were unchanged.[13]

6. Discussion and Conclusion

This paper has examined the factors influencing starting and quitting smoking for a sample of Irish women using duration analysis. The innovation in the paper is that retrospective data in the sample allows for the inclusion of the real tax on tobacco as a time-varying covariate, thus permitting analysis of the effectiveness of a major policy variable in terms of combating smoking. The evidence presented here is mixed. In terms of starting smoking, the results from a split population model appear to indicate either no role or else a highly counterintuitive role for tobacco taxes in starting quitting. The evidence from a non-split log-logistic model suggested quite a considerable role for taxes in delaying duration before starting smoking. The analysis for quitting showed that the effect of tobacco taxation was in the expected direction in terms of accelerating the quitting decision. However in general this effect was not statistically significant. One problem which featured in the analysis of quitting, and to a lesser extent starting, was the sensitivity of the influence of taxes to the treatment of time. This suggests problems of identification and difficulty in discriminating between the effects of the variation over time in tax and the influence of other secular factors.

Results for other variables were also of interest. Predictably education played an important role, with higher lifetime educational achievement delaying the duration before starting and accelerating the duration before quitting. The inclusion of a proxy for health knowledge tended to lower the coefficient on education indicating that part of the traditional role assigned to education reflects greater health knowledge among higher educated people. The precise mechanism whereby education affects health behaviour and smoking in particular is something we hope to return to in future research. Finally, the inclusion of variables reflecting advertising bans on tobacco produced results contrary to intuition with these variables either having no effect or else *delaying* the duration before starting smoking.

Overall, the results in this paper are probably more suggestive than definitive in terms of the role of tobacco taxes in influencing starting and quitting. It should also be borne in mind that the results here apply only to a sample of women aged 48 or under. However, given the wealth of results from other countries and time periods regarding the effect of taxes and prices on tobacco consumption, it is clear that tobacco taxation is likely to remain a major instrument in public policy to discourage smoking.

[13] The results are available on request.

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Table 1: Summary Statistics for Sample

Variable	Total (N=703)	Ever Smoked (N=348)	Smokers (N=246)	Ex-Smokers (N=102)
Age	34.38265	34.70977	33.02846	38.76471
	(8.697518)	(8.701864)	(8.511409)	(7.806035)
Age Started Smoking		19.35777	19.37295	19.31959
		(5.294379)	(5.169976)	(5.622771)
Health Problem	.1038407	.1264368	.1178862	.1470588
	(.305271)	(.3328195)	(.3231307)	(.3559135)
Single	.3499289	.3390805	.4065041	.1764706
	(.4772868)	(.4740788)	(.4921821)	(.3831026)
Married	.5860597	.591954	.5284553	.745098
	(.4928887)	(.4921794)	(.5002074)	(.4379582)
Widowed	.0085349	.0057471		.0196078
	(.0920547)	(.0757005)		(.1393331)
Separated	.0554765	.0632184	.0650407	.0588235
	(.229071)	(.2437058)	(.2471003)	(.2364561)
Primary Education	.1052632	.1293103	.1463415	.0882353
	(.3071107)	(.3360263)	(.3541688)	(.2850375)
Junior Cert	.2745377	.3821839	.4146341	.3039216
	(.4465988)	(.4866208)	(.4936632)	(.4622205)
Leaving Cert	.4054054	.3189655	.2723577	.4313725
	(.4913199)	(.4667468)	(.4460806)	(.4977137)
Third Level	.2147937	.1695402	.1666667	.1764706
	(.4109716)	(.3757687)	(.3734378)	(.3831026)
Working	.5504979	.4971264	.4756098	.5490196
	(.4977976)	(.5007117)	(.5004229)	(.5000485)
Cigarettes per Day		15.47977	15.0449	16.53465
		(8.827224)	(8.063403)	(10.42071)

Table 2: Split Population Duration Model for Starting Smoking

	Duration	Probit	Duration	Probit	Duration	Probit
Junior Cert	-0.014	0.318	-0.022	0.315	-0.113	0.269
	(0.258)	*(0.168)**	*(0.260)*	*(0.170)**	*(0.233)*	*(0.156)**
Leaving Cert	-0.330	-0.370	-0.345	-0.377	-0.288	-0.334
	(0.258)	*(0.156)***	*(0.260)*	*(0.158)***	*(0.236)*	*(0.149)***
Third Level	0.348	-0.081	0.331	-0.083	0.202	-0.063
	(0.287)	*(0.180)*	*(0.291)*	*(0.184)*	*(0.271)*	*(0.182)*
Ln (Tax)	-0.933		-2.902		-1.217	
	(0.786)		*(1.277)***		*(0.286)****	
TV Ban	-0.389		-0.636		-0.372	
	(0.274)		*(0.282)***		*(0.169)***	
Radio Ban	-0.832		-0.829		-0.082	
	*(0.321)****		*(0.306)****		*(0.127)*	
Married	-0.207	-0.295	-0.215	-0.302	-0.162	-0.329
	(0.170)	*(0.095)****	*(0.171)*	*(0.097)****	*(0.164)*	*(0.100)****
Health Knowledge	0.355	0.002	0.357	0.004	0.243	-0.049
	(0.203)*	(0.121)	(0.206)*	(0.123)	(0.184)	*(0.122)*
Time	0.141					
	(0.227)					
Time^2/100	-2.836					
	(3.073)					
Time^3/1000	1.847					
	(1.438)					
Time ^4/10000	-0.343					
	(0.213)					
Time 1			-0.038			
			(0.060)			
Time 2			-0.015			
			(0.079)			
Time 3			0.330			
			*(0.172)**			
Time 4			-0.579			
			*(0.147)****			
5 Years	0.105		0.042		-0.760	
	(0.485)		*(0.425)*		*(0.310)***	
10 Years	-1.143		-1.279		-0.583	
	*(0.237)****		*(0.248)****		*(0.184)****	
15 Years	-0.485		-0.237		-0.176	
	*(0.248)**		*(0.257)*		*(0.198)*	
20 Years	-1.616		-1.404		-1.205	
	*(0.293)****		*(0.277)****		*(0.199)****	
Constant	2.838	-0.995	2.743	-0.982	2.776	-0.991
	*(0.796)****	*(0.184)****	*(0.590)****	*(0.188)****	*(0.350)****	*(0.187)****
Gamma	0.577		0.578		0.521	
	*(0.049)****		*(0.049)****		*(0.043)****	
Observations	11733	11733	11733	11733	11733	11733

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Log-Logistic Duration Model for Starting Smoking (N=11733)

Junior Cert	-0.232	-0.229	-0.225
	(0.147)	(0.148)	(0.159)
Leaving Cert	0.313	0.310	0.365
	(0.150)**	(0.151)**	(0.162)**
Third Level	0.301	0.290	0.362
	(0.164)*	(0.166)*	(0.177)**
ln(Tax)	1.171	0.802	0.699
	(0.539)**	(0.983)	(0.257)***
TV Ban	-0.608	-0.418	0.257
	(0.281)**	(0.273)	(0.194)
Radio Ban	-0.419	-0.247	0.341
	(0.314)	(0.291)	(0.160)**
Married	0.239	0.257	0.268
	(0.100)**	(0.100)**	(0.108)**
Health Knowledge	0.186	0.195	0.191
	(0.119)	(0.120)	(0.128)
Young Cohort	-0.598	-0.620	-0.522
	(0.129)***	(0.125)***	(0.137)***
Time	-0.551		
	(0.217)**		
Time^2/100	7.366		
	(2.030)***		
Time^3/1000	-2.950		
	(0.724)***		
Time ^4/10000	0.374		
	(0.087)***		
Time 1		0.023	
		(0.047)	
Time 2		0.124	
		(0.074)*	
Time 3		-0.150	
		(0.130)	
Time 4		0.023	
		(0.070)	
5 Years	-0.566	-0.813	-0.823
	(0.257)**	(0.247)***	(0.270)***
10 Years	-0.945	-0.981	-1.075
	(0.184)***	(0.193)***	(0.186)***
15 Years	-0.735	-0.535	-0.595
	(0.213)***	(0.220)**	(0.193)***
20 Years	-1.336	-1.344	-0.853
	(0.257)***	(0.260)***	(0.181)***
Constant	3.898	2.569	2.764
	(0.820)***	(0.422)***	(0.233)***
Gamma	0.596	0.595	0.632
	*(0.036)****	*(0.036)****	*(0.037)****
RESET (Wald *p*)	0.469	0.002	0.000

* significant at 10%;
** significant at 5%;
*** significant at 1%

Table 3A: Log-Logistic Duration Model for Starting Smoking, Gamma Frailty (N=11733)

Junior Cert	-.1633823	-.1435141	-.1300369
	(.1495151)	(.1503846)	(.1647115)
Leaving Cert	.2931357	.2919128	.3365944
	(.1513668)*	(.1532283)*	(.1703861)**
Third Level	.3158465	.3176985	.4025167
	(.1667149)*	(.1680929)*	(.1815995)**
ln(Tax)	.9472032	.5028625	.4534907
	(.4568205)**	(.8046398)	(.2936153)
TV Ban	-.4750968	-.3196387	.231222
	(.2498986)*	(.2350651)	(.1703292)
Radio Ban	-.3672872	-.2691238	.2018518
	(.2514542)	(.2353237)	(.149304)
Married	.2407566	.2646399	.2666029
	(.1024088)**	(.1028072)**	(.113484)**
Health Knowledge	.1846545	.194825	.191786
	(.1193445)	(.1201916)	(.1310972)
Young Cohort	-.5022454	-.5101896	-.3337266
	(.1508746)***	(.1525738)***	(.1880235)*
Time	-.3727273		
	(.1703213)**		
Time^2/100	5.407485		
	(1.698717)***		
Time^3/1000	-2.208457		
	(.6312929)***		
Time ^4/10000	.2827125		
	(.0777506)***		
Time 1		.0464006	
		(.0441703)	
Time 2		.0646654	
		(.0653838)	
Time 3		-.0943694	
		(.1071291)	
Time 4		-.0014357	
		(.0610422)	
5 Years	-.4325309	-.5700792	-.5850283
	(.2120274)**	(.2090108)***	(.231798)**
10 Years	-.7176406	-.7263485	-.7619172
	(.1730935)***	(.1728355)***	(.1783348)***
15 Years	-.5813774	-.4007129	-.4431371
	(.1960891)***	(.1970436)**	(.1863933)**
20 Years	-1.032392	-1.009541	-.6558081
	(.2415746)***	(.2394744)***	(.1925921)***
Constant	3.012333	1.9355	2.306414
	(.6525642)***	(.3989627)***	(.236654)***
Gamma	.474031	.4600329	.4918141
	(.0449481)***	(.0423093)***	(.0450202)***
Theta	.9112615	1.093052	1.165663
	(.3429947)	(.3655644)	(.4162853)
LR Test, θ=0, p-value	0.001	0.000	0.000

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3B: Log-Logistic Duration Model for Starting Smoking, Inverse Gauss Frailty (N=11733)

Junior Cert	-.1872975	-.1722165	-.1621635
	(.1491109)	(.1501105)	(.165082)
Leaving Cert	.3046791	.3068619	.3678117
	(.1501615)**	(.1510904)**	(.1647285)**
Third Level	.3159859	.3167939	.4054235
	(.167376)*	(.1683078)*	(.1820652)**
ln(Tax)	1.01714	.5870577	.5780025
	(.4774397)**	(.8411236)	(.2643384)**
TV Ban	-.5015285	-.3358255	.2578247
	(.262756)*	(.2477114)	(.172173)
Radio Ban	-.3766794	-.260621	.2523813
	(.2637928)	(.2465065)	(.1457802)*
Married	.2411583	.2650983	.2741738
	(.1014223)**	(.1012547)***	(.1108897)**
Health Knowledge	.1828438	.1911681	.1861933
	(.1198183)	(.1201856)	(.1312186)
Young Cohort	-.5450179	-.5633438	-.4242876
	(.1434413)***	(.1417258)***	(.1617883)***
Time	-.4141189		
	(.1784489)**		
Time^2/100	5.867346		
	(1.777768)***		
Time^3/1000	-2.382722		
	(.6605274)***		
Time ^4/10000	.304259		
	(.0813374)***		
Time 1		.0417342	
		(.0461587)	
Time 2		.0775129	
		(.0686023)	
Time 3		-.1057201	
		(.1121692)	
Time 4		.0042159	
		(.0630978)	
5 Years	-.4637286	-.6232787	-.6441913
	(.2234648)**	(.2200971)***	(.2444849)***
10 Years	-.7677455	-.7780138	-.8396256
	(.1819941)***	(.1826393)***	(.185238)***
15 Years	-.6197943	-.4332288	-.4919891
	(.2047483)***	(.2061768)**	(.1912669)***
20 Years	-1.100372	-1.07858	-.69176
	(.2535472)***	(.2530219)***	(.2027171)***
Constant	3.214076	2.064273	2.419192
	(.6825782)***	(.4187633)***	(.2418422)***
Gamma	.5005525	.4870729	.5247107
	(.0473246)***	(.0453831)***	(.0470591)***
Theta	.8324006	1.04784	1.049775
	(.4636866)	(.5248799)	(.5425983)
LR Test, θ=0, p-value	0.006	0.002	0.002

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Gamma Models for Quitting (AFT format, N=8625)

Junior Cert	-0.138	-0.135	-0.136
	(0.152)	(0.157)	(0.158)
Leaving Cert	-0.492	-0.491	-0.491
	(0.158)***	(0.161)***	(0.153)***
Third Level	-0.793	-0.796	-0.794
	(0.213)***	(0.377)**	(0.281)***
ln(Tax)	-0.187	1.126	-0.570
	(0.698)	(1.172)	(0.360)
TV Ban	0.132	0.151	-0.048
	(0.451)	(0.424)	(0.231)
Radio Ban	0.341	0.432	0.133
	(0.370)	(0.387)	(0.195)
Married	-0.103	-0.099	-0.104
	(0.126)	(0.125)	(0.125)
Health Knowledge	-0.551	-0.546	-0.545
	(0.215)**	(0.252)**	(0.231)**
Young Cohort	0.063	0.065	0.040
	(0.229)	(0.329)	(0.229)
Time	0.056		
	(0.123)		
Time^2/100	-0.494		
	(1.639)		
Time^3/1000	0.117		
	(0.678)		
Time ^4/10000	-0.009		
	(0.087)		
Time 1		0.018	
		(0.047)	
Time 2		0.041	
		(0.122)	
Time 3		-0.203	
		(0.177)	
Time 4		0.116	
		(0.076)	
5 Years	0.365	0.348	0.342
	(0.489)	(0.327)	(0.319)
10 Years	0.535	0.617	0.545
	(0.374)	(0.418)	(0.383)
15 Years	-0.356	-0.532	-0.292
	(0.300)	(0.377)	(0.280)
20 Years	0.573	0.453	0.409
	(0.548)	(0.754)	(0.546)
Constant	4.095	4.472	4.124
	(0.417)***	(0.446)***	(0.314)***
Ln(σ)	-0.161	-0.155	-0.162
	*(0.066)***	*(0.402)*	*(0.299)*
κ	0.640	0.622	0.632
	n/a	*(0.813)*	*(0.442)*
Log Likelihood	-421.416	-420.455	-421.733
AIC	880.832	878.91	873.466
RESET (Wald *p*)	n/a	n/a	n/a

* significant at 10%; ** significant at 5%; ***significant at 1%

Table 5: Weibull Models for Quitting (AFT format, N=8625)

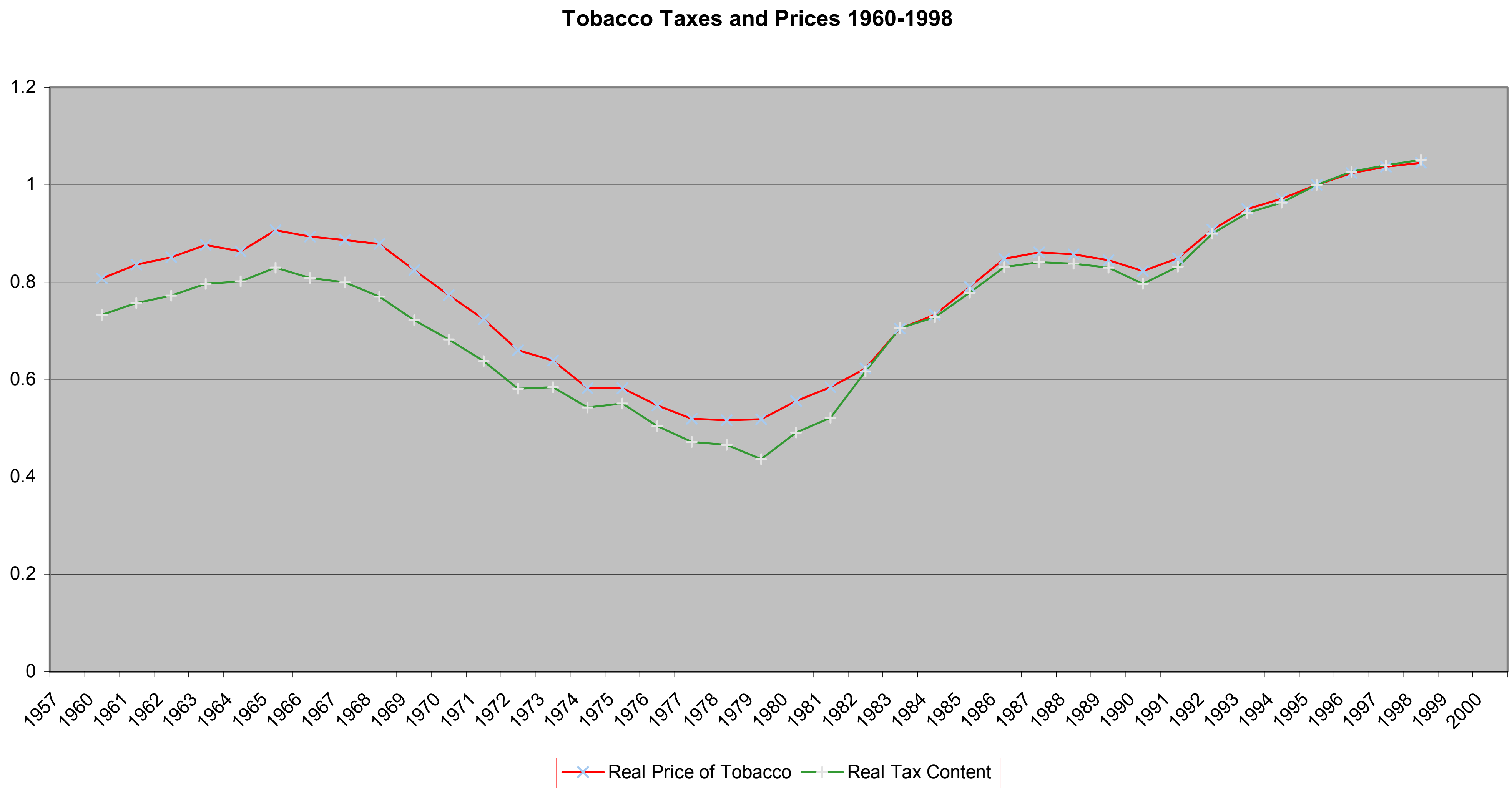
Junior Cert	-0.159	-0.159	-0.159
	(0.148)	(0.148)	(0.147)
Leaving Cert	-0.473	-0.473	-0.472
	(0.143)***	(0.143)***	(0.143)***
Third Level	-0.694	-0.693	-0.695
	(0.195)***	(0.195)***	(0.195)***
ln(Tax)	-0.214	0.915	-0.458
	(0.643)	(1.012)	(0.311)
TV Ban	0.173	0.189	-0.005
	(0.413)	(0.367)	(0.216)
Radio Ban	0.359	0.446	0.120
	(0.364)	(0.367)	(0.189)
Married	-0.100	-0.098	-0.100
	(0.119)	(0.119)	(0.118)
Health Knowledge	-0.590	-0.590	-0.588
	(0.213)***	(0.213)***	(0.213)***
Young Cohort	0.001	-0.005	-0.009
	(0.220)	(0.220)	(0.214)
Time	0.077		
	(0.112)		
Time^2/100	-0.789		
	(1.501)		
Time^3/1000	0.233		
	(0.617)		
Time ^4/10000	-0.022		
	(0.079)		
Time 1		0.022	
		(0.044)	
Time 2		0.016	
		(0.094)	
Time 3		-0.162	
		(0.137)	
Time 4		0.108	
		(0.070)	
5 Years	0.336	0.325	0.323
	(0.303)	(0.297)	(0.296)
10 Years	0.475	0.545	0.464
	(0.370)	(0.373)	(0.361)
15 Years	-0.296	-0.454	-0.256
	(0.269)	(0.285)	(0.244)
20 Years	0.681	0.598	0.521
	(0.547)	(0.565)	(0.515)
Constant	4.124	4.480	4.233
	(0.393)***	(0.440)***	(0.262)***
Ln(p)	0.342	0.344	0.346
	*(0.067)****	*(0.067)****	*(0.066)****
Log Likelihood	-422.122	-421.195	-422.483
AIC	880.244	878.39	874.966
RESET (Wald *p*)	0.868	0.750	0.781

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Exponential Model for Quitting (AFT format)

Junior Cert	-0.061	-0.061	-0.062
	(0.196)	(0.196)	(0.195)
Leaving Cert	-0.496	-0.496	-0.497
	(0.188)***	(0.188)***	(0.189)***
Third Level	-0.703	-0.703	-0.708
	(0.248)***	(0.247)***	(0.247)***
ln(Tax)	-0.471	1.001	-0.900
	(0.910)	(1.441)	(0.402)**
TV Ban	0.194	0.236	-0.154
	(0.573)	(0.522)	(0.299)
Radio Ban	0.536	0.683	0.113
	(0.517)	(0.521)	(0.265)
Married	-0.153	-0.150	-0.150
	(0.153)	(0.153)	(0.153)
Health Knowledge	-0.849	-0.849	-0.845
	(0.294)***	(0.294)***	(0.294)***
Time	0.135		
	(0.156)		
Time^2/100	-1.464		
	(2.116)		
Time^3/1000	0.457		
	(0.873)		
Time ^4/10000	-0.047		
	(0.112)		
Time 1		0.035	
		(0.061)	
Time 2		-0.012	
		(0.133)	
Time 3		-0.196	
		(0.193)	
Time 4		0.148	
		(0.099)	
5 Years	0.479	0.471	0.466
	(0.427)	(0.419)	(0.418)
10 Years	0.718	0.818	0.711
	(0.518)	(0.523)	(0.506)
15 Years	-0.384	-0.598	-0.320
	(0.375)	(0.396)	(0.346)
20 Years	1.070	0.997	0.779
	(0.781)	(0.808)	(0.732)
Constant	4.501	4.988	4.668
	(0.542)***	(0.610)***	(0.368)***
Log Likelihood	-434.570	-433.698	-435.099
AIC	903.14	901.396	896.198
RESET (Wald *p*)	0.740	0.600	0.836
Observations			

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%


Tobacco Taxes and Prices 1960-1998
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1
0.8
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1957 1960 1961 1962 1963 1964 1965 1966 1967 1968 1969 1970 1971 1972 1973 1974 1975 1976 1977 1978 1979 1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000
Real Price of Tobacco
Real Tax Content