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Abstract: This paper uses duration analysis to investigate the role of tobacco taxes in starting and quitting smoking. Applying a variety of parametric duration models to a sample of Irish women, it finds that in general tobacco taxes do influence starting and quitting smoking in the expected direction. It also finds that the effect for starting differs by education but in a non-monotonic way, with the greatest effect for women with intermediate levels of education. The results for quitting suggest the greatest effect for women with the lowest level of education. These results are unchanged when account is taken of unobserved heterogeneity.

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1. Introduction

There is ample medical evidence indicating the adverse effects of tobacco consumption upon health (see Mooney, 2000, for a summary). Recent Government publications in Ireland have suggested the long-term goal of a "tobacco-free society". As the accompanying letter to a 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 start smoking and the decision to quit is crucial in terms of formulating policy.

Given this background, this paper has two principal aims. First, it examines the effect of tobacco taxes on starting and quitting smoking, applying duration analysis to a sample of Irish women. Secondly, it explores the extent to which such a tax effect differs by educational background.[1]

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.

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

[1] Note that we are not trying to estimate what the optimal tax on tobacco should be. For a discussion in the Irish case, see Madden (2002).

2. Review of Literature[2]

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.

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-

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

logistic and Weibull specification 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. Finally, Lopez-Nicolas (2002) analyses Spanish data, once again using a split-population model, and finds elasticities of delay with respect to starting of 0.07 and elasticities of duration before quitting of –1.3 to –1.5.

One feature of the above duration studies is that, while they include measures of education or income as covariates, they do not interact such variables with the tax, thus constraining the tax/price response to be identical across the distribution of education/income. This is despite evidence from cross-section studies that such a response does differ according to socio-economic characteristics such as income and education. For example, Evans et al. (1999) note that in the US higher-income individuals are less responsive to tax changes than others. Townsend et al (1994), using UK data, found that men and women in lower socio-economic groups are more responsive than are those in higher socio-economic groups to changes in the price of cigarettes and less to publicity concerning the adverse health effects of smoking (this is also implied in the celebrated model of Becker and Murphy, 1988). Borren and Sutton (1992) find evidence of an "inverse-U" relationship in terms of price responsiveness, with a higher elasticity for middle-income men compared to lower and higher-income men. Their evidence for women, while less clearcut, appears to indicate that elasticity declines as income increases. We explicitly investigate this issue in this paper by including interaction terms which permit the effect of taxes to differ across the education spectrum.

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). 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 discuss our data and the empirical approach we adopt.

3. 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. 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[3] 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 smoke 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 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.

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, we only have tax and price data going back as far as 1960 and so we drop all women who were aged 10 or more in 1960. This is because we are effectively assuming that subjects were at risk of starting smoking from the age of ten, and for women aged ten or over in 1960 we do not have the relevant tax and price data for part of the time when they were at risk of starting smoking (i.e. the period before 1960). Our data suggests that a starting age of ten or over 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

[3] See Thompson (2000).

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.[4] 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). In Ireland there is a specific and an *ad valorem* excise duty as well as VAT. Thus the specific excise duty is added to the

[4] The default category for education is "Primary Cert" indicating that formal schooling ended at approximately the age of 12. "Junior Cert" indicates formal schooling ceased at approximately 16, while "Leaving Cert" indicates schooling ended at approximately 18.

producer price and the *ad valorem* excise duty 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 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.

3.1 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.[5] 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 proportion of the population never smoke at any stage of their lives. In this case a split population model is appropriate

[5] This expansion of the data has the effect of increasing the sample size. Hence the sample sizes in tables 2-6 differ from that in table 1. Standard errors are adjusted to take account of such clustering.

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.

We also estimate log-logistic duration models where the population is not split. We estimate then for the population as a whole and also for the population of smokers only.

Before discussing the appropriate parametric duration model we first present in figure 2 the plot of the empirical hazard function. 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.

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, $\Phi(\alpha' z_i) S(.)$.

In table 2 we present estimates of the above split population model and in tables 3 and 4 we present estimates of the log-logistic model where the population is not split. In tables 3 and 4 we apply the log-logistic model to the whole sample and also to the sample of smokers only. 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, Leaving Certificate 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. 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.[6]

However, in an attempt to distinguish between these influences to some degree, we 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?". [7] Clearly this question refers to a dimension of health which differs from smoking, but we do not believe it is unreasonable to expect that knowledge regarding osteoporosis may be correlated with other aspects of health knowledge, including the health effects of smoking.

There is one further point which must be borne in mind in terms of interpreting the effect of education on the hazard of starting smoking. Some people will have started smoking *before* completing the higher levels of education, such as Leaving Cert or Third Level. In that respect education is endogenous and could not be regarded as a pre-determined variable. In fact, if we allow for an effect of health upon education as well as an effect of education upon health, it is possible that the very act of starting to smoke will affect future educational achievement. Ideally we would like to instrument for education to remove this endogeneity. However, our

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

[7] While knowledge about osteoporosis may appear to be a narrow definition of health knowledge, it may be a suitable measure for our sample. Typically osteoporosis is more common amongst older women. Given that our sample are all aged 48 or less, this reduces the chances that knowledge regarding it comes from direct experience but instead comes 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.

data does not include any obvious instrumental variable. Thus for these people education may be capturing the effect of other unobserved factors, which influence not just the probability of starting to smoke, but also the degree of education obtained (e.g. such as the rate of time-preference referred to above). Such an effect is less relevant for the analysis of quitting smoking, since in this case, the vast majority of smokers quit *after* they have achieved their highest level of education.[8]

Ideally we would like to include income as a covariate also. However, the income variable for the data in question is not very satisfactory for a couple of reasons. Firstly, data on this variable is missing for over 20% of the observations whereas data for education is available for all observations. Secondly the income data which is available is presented in the form of income ranges. Thus it is not possible to construct a variable for equivalised income (unless we assume income is at the midpoint of the range), since we do not know the precise value of income which must be equivalised. On balance, it was felt best not to include income, though this runs the risk that the estimated effect of education may be confounded with that of income, presuming the two to be highly correlated. On the other hand, it could be argued that the specification we adopt here be regarded as a reduced form, since it is likely that income itself will be a function of education.

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. 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 include a higher-order polynomial in time, which allows for a smooth but flexible

[8] I am grateful for the comments of an anonymous referee with regard to this point.

time trend. Finally, we also include a cohort dummy, which takes on a value of one if the individual is aged 33 or less and a dummy variable for marital status.

Before discussing the results it is important to point out that while educational achievement and marital status are factors which clearly will vary over a woman's lifetime, we are not treating them as time-varying covariates in this analysis. We do not have information on age of marriage nor on age of completion of education. Thus even though a women may be classified as "married" she will not have been married for at least part of the time during which her smoking behaviour is analysed (e.g. during her early teens). However, if education and/or marital status is correlated with some more fundamental attribute such as an individual's underlying rate of time preference then the use of "ultimate" educational/marital status is justified, to a degree at least.

Bearing in mind the evidence cited above that tax responsiveness may differ by education or socio-economic characteristics we also include specifications with interaction terms which attempt to capture such an effect.

3.2 Unobserved Heterogeneity or "Frailty"

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.

3.3 Starting Smoking: Results and Discussion

We first of all discuss the results in tables 2, the split-population model and table 3, the log-logistic model applied to smokers only (thus there are no right-censored observations). The results from the probit for becoming a smoker show the expected negative effect for Leaving Cert (and to a lesser extent for third level education) compared to the default category of primary education only. What is also of interest is the positive coefficient on Junior Cert indicating a non-monotonic effect of education on the probability of becoming a smoker. The results also show that marriage has a negative effect while younger cohorts are more likely to become smokers.

Turning now to the duration part of the split population model, when no interaction terms between tax and education are used, the coefficient on tax is in the expected direction (i.e. positive, indicating that higher taxes delay the period before starting), but is not significant. When the interaction terms are used, the coefficient on tax alone is negative but even less well-determined that when no interactions terms are used. The interaction term with Junior Cert is statistically significant however, albeit at only the 10% level. The interaction term with Leaving Cert is similar in magnitude and very near conventional significance levels, while the interaction term with third level is smaller and insignificant. Thus tax has no significant effect on duration for the default group, followed by a positive effect on duration for those with Junior Certificate education. When we test the null hypothesis of equality of any two of the tax interaction coefficients with Junior Cert, Leaving Cert and Third Level with each other, we find we cannot reject the null.

Thus the tax effect for Junior Cert is higher (and statistically significant) than for those with minimal education but not statistically significantly different than the tax effect for Leaving Cert and Third Level. In turn the tax effect for Leaving Cert is almost significantly different than for those with minimal education but different than the tax effect for Third Level, while the tax effect for Third Level is not significantly different than that for minimal education.

These results are partly in line with those of Townsend and Borren and Sutton in that the tax effect for those with least education appears smallest. However, our evidence does not clearly support the second part of the "inverse U" type argument, in that we don't find significantly different tax effects between Junior Cert and higher education groups.[9]

Turning now to the duration model for smokers only in table 3, we see that in general, the coefficients are better determined. In the model without the interaction terms, the coefficient on tax is similar to that in the split population model, and this time it is statistically significant. Perhaps surprisingly, education has little or no effect. This broadly carries through to the model with interaction terms. Even though the coefficient on third level education is positive and significant, the overall effect of third level education is given by this coefficient plus the product of the coefficient on the interaction term between tax and third level education and the average value of tax. Since it is the log of tax which is used, this second term will be negative, thus offsetting to some degree the positive effect of third level education on duration.

Similarly, the effect of tax for each educational group is given by the sum of the overall coefficient for tax and the interaction coefficient. In this respect we see tentative evidence once again of the first part of an "inverse-U" effect with the greatest impact of tax upon those with Junior Cert education. Evidence of the second part of the inverse U is much less clearcut since once again when we test the null hypothesis of equality of any two of the tax interaction coefficients with Junior Cert, Leaving Cert and Third Level with each other, we find we cannot reject the null.

In table 4 we present evidence for the log-logistic model, this time applied to the population as a whole i.e. there are some right-censored observations. We also

[9] I am grateful for the comments of an anonymous referee with regard to this point.

include the frailty models here, given that the p-values for the LR test for frailty indicates its presence.[10] For the models without interaction terms, the coefficient on tax is in the expected direction and for the model without frailty and the model with inverse gauss frailty the coefficients are significant (and similar in magnitude). The results when interaction terms are used are similar across models and once again indicate non-monotonicity but interestingly the greatest effect of tax is now seen for those with Leaving Cert rather than Junior Cert. What is also of interest is that here we see much clearer evidence of the full "inverse U "effect in that not only is the coefficient on the tax/Leaving Cert variable significantly different from zero, it is also significantly different from that on tax/Third Level (p=0.0815) and very near to being significantly different from the tax/Junior Cert variable (p=0.1227). Results for the models with frailty are qualitatively similar and available on request.

Summarising the results from tables 2-4 it seems fair to say that tax does appear to have an effect on duration before starting and there is evidence that the effect for Junior Cert is greater than the effect for minimal levels of education. However the evidence that this effect diminishes again as we move to higher levels of education is much less clearcut.

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

[10] The presence of frailty was decisively rejected for the models run on smokers only. Hence we do not include them. They are available on request.

$\hat{S}_j(t_j)$ 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.

Figures 3 and 4 show such plots for the log-logistic model for starting smoking for smokers only and then for the total population (for brevity we include only the specifications with the interaction terms with education. The plots for the other specifications are available on request).

In evaluating these plots care must be taken regarding the scale of the axes. For the case of smokers only, the residuals deviate from the 45 degree line after the estimated cumulative hazard takes a value of around 1.3 indicating a limited degree of misspecification. For the whole population this deviation is observed when the cumulative hazard is around 0.9, suggesting a greater degree of misspecification for this model.

3.4 Quitting Smoking: Results and Discussion

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. Also as Forster and Jones (2000) point out, it may be extremely difficult to identify the separation between those who will eventually quit and those who will never quit from data of this sort.[11] Figure 5 shows the plot of the empirical hazard function for quitting, once again using the lifetable estimate with confidence intervals.

Apart from the spikes at ten and twenty years there is relatively little evidence of an increasing or decreasing hazard.[12] 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 are $S(t) = \exp(-(\lambda t)^p)$ 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

[11] We estimated a split population model for quitting and obtained results qualitatively similar to those in tables 5 and 6. Results are available on request.
[12] These spikes suggest that "heaping" may be present i.e. when asked when they quit smoking respondents round off their answers to "ten years ago" or "twenty years ago". Following one of the strategies proposed in Forster and Jones (2000) we include dummy variables for 10, 20 and 30 years in the models estimated in tables 5 and 6. The results are virtually identical to those presented here and are available on request.

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.

Table 5 gives the results for the exponential and gamma models while table 6 gives results for the Weibull model where we have also included frailty models (with the results presented in accelerated time format).[13] 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. Looking at the models first of all without interaction effects, we note that in all cases the coefficient on tax has the expected negative sign i.e. higher tax *reduces* the delay before quitting. The magnitude of the coefficient is also very similar across models but in no case is it statistically significant.

When the interaction terms are included the coefficient on tax increases in absolute size and becomes statistically significant for the non-frailty specifications. The coefficients on the interaction terms are only significant for Junior Cert for the gamma and Weibull models. For all models it is also the case that when we test the null hypothesis of equality of any two of the tax interaction coefficients with Junior Cert, Leaving Cert and Third Level with each other we do not reject the null. Thus there is reasonable evidence that the tax effect for Junior Cert is less than that for those with minimal education, but no evidence that the tax effect for Junior differs significantly from that for Leaving and Third Level. This is somewhat at odds with the evidence for starting. However, given that relatively few of the coefficients are well determined such statements must be made with caution.

Since the parametric models are nested it is possible to check their validity against each other, which is carried out in table 7. In all cases of the test for σ=1 i.e.

[13] The null hypothesis of no frailty was not rejected for the gamma and exponential models

between Weibull and exponential, the null is rejected, indicating the Weibull is to be preferred over the exponential. For the test κ=1. i.e. between gamma and Weibull, the null is rejected for the case with interaction terms, indicating a choice of gamma over Weibull, while it is not rejected when interaction terms are not included. We also present values of the Aikake information criterion, whereby AIC=-2 log likelihood +2(c+p+1) where c is the number of model covariates and p the number of model specific ancillary parameters. The model with the lowest AIC is to be preferred. We see that in terms of AIC the exponential model has values well in excess of the gamma or Weibull, but there is very little to choose between the Weibull and gamma specifications. The estimated coefficients for these models are also quite similar in sign and magnitude. We also note that all models have a Ramsey RESET p-value in excess of 0.8.

What about the Cox-Snell residuals? Figures 6 to 8 present Cox-Snell residuals and once again for the sake of brevity we present only the residuals where the interaction terms are included (the residuals for the models without interaction terms are available on request).

Casual eyeballing of these plots suggests the greatest degree of misspecification for the exponential model with relatively little to choose between the gamma and Weibull models, though perhaps the gamma model is to be marginally preferred. This is entirely consistent with the results from table 7.

4. 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 inclusion of interaction terms with education also permits analysis of how the effectiveness of taxation differs according to education. The evidence presented here is mixed. In terms of starting smoking, there is limited evidence of at least the first part of an “inverse-U” effect, with the strongest effect of taxation on those with intermediate levels of education and weaker effects for those with least education. Evidence on the second part of the inverse U effect i.e. a stronger effect for intermediate education than for higher levels of education is less convincing. It has to be stressed however, that these results are relatively tentative given the calculated significance levels. There is also some evidence of misspecification in the diagnostics.

The evidence for quitting suggests an even more complex relationship between education and the effectiveness of taxation. Tax seems to be most effective in terms of encouraging quitting for those with the least education. However, there seems to be little evidence of any significant difference in the effectiveness of taxation between Junior, Leaving and Third Level.

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.

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

Table 2: Split Population Duration Model for Starting Smoking (N=11733)

	Duration	Probit	Duration	Probit
Junior Cert	0.019	0.212	0.482	0.206
	(0.168)	*(0.090)***	*(0.330)*	*(0.092)***
Leaving Cert	-0.097	-0.231	0.372	-0.234
	(0.178)	*(0.089)****	*(0.346)*	*(0.090)****
Third Level	0.291	-0.158	0.516	-0.177
	(0.207)	*(0.103)*	*(0.383)*	*(0.105)**
Ln (Tax)	0.451		-0.268	
	(0.391)		*(0.728)*	
Cohort	0.258	0.205	0.232	0.206
	(0.267)	*(0.065)****	*(0.296)*	*(0.067)****
Health Knowledge	0.211	-0.077	0.206	-0.080
	(0.144)	*(0.079)*	*(0.155)*	*(0.080)*
Married	0.054	-0.115	-0.034	-0.122
	(0.123)	*(0.063)**	*(0.131)*	*(0.065)**
Tax*Junior Cert			1.214	
			*(0.728)**	
Tax*Leaving Cert			1.123	
			(0.763)	
Tax*Third Level			0.681	
			(0.793)	
Time	0.074		0.064	
	(0.077)		*(0.083)*	
Time^2/100	-0.310		-0.216	
	(0.470)		*(0.499)*	
Time^3/1000	0.012		-0.013	
	(0.085)		*(0.090)*	
Constant	1.618	-1.553	1.494	-1.528
	*(0.386)****	*(0.100)****	*(0.448)****	*(0.102)****
Gamma	0.412		0.434	
	*(0.032)****		*(0.035)****	

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

Table 3: Log-Logistic Duration Model for Starting Smoking, Smokers Only (N=3202)

Junior Cert	-0.094	0.312
	(0.114)	*(0.200)*
Leaving Cert	-0.104	0.273
	(0.120)	*(0.213)*
Third Level	0.084	0.454
	(0.122)	*(0.217)***
Ln (Tax)	0.523	-0.321
	*(0.293)**	*(0.472)*
Cohort	-0.143	-0.154
	(0.138)	*(0.140)*
Health Know.	0.205	0.203
	*(0.092)***	*(0.096)***
Married	0.038	0.031
	(0.071)	*(0.072)*
Tax*Junior		0.994
		*(0.441)***
Tax*Leaving		0.932
		*(0.491)**
Tax*3rd Level		0.907
		*(0.467)**
Time	0.074	0.066
	(0.062)	*(0.063)*
Time^2/100	-0.150	-0.106
	(0.329)	*(0.335)*
Time^3/1000	-0.023	-0.030
	(0.053)	*(0.054)*
Constant	1.730	1.441
	*(0.324)****	*(0.336)****
Gamma	0.349	0.348
	*(0.022)****	*(0.022)****
Observations	3202	3202

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

Table 4: Log-Logistic Duration Model for Starting Smoking, Total Population (N=11733), S.E. in parentheses, * significant at 10%; ** significant at 5%;* significant at 1%**

			Gamma Frailty	Gamma Frailty	Inv Gauss Frailty	Inv Gauss Frailty
Junior Cert	-0.268 *(0.154)**	-0.042 *(0.305)*	-0.131 *(0.156)*	0.094 *(0.268)*	-0.171 *(0.156)*	0.048 *(0.281)*
Leaving Cert	0.318 *(0.158)***	0.778 *(0.315)***	0.171 *(0.192)*	0.765 *(0.280)****	0.296 *(0.159)**	0.811 *(0.286)****
Third Level	0.283 *(0.172)*	0.451 *(0.325)*	0.307 *(0.181)**	0.609 *(0.291)***	0.329 *(0.175)**	0.605 *(0.300)***
Ln (Tax)	0.576 *(0.329)**	-0.170 *(0.667)*	0.356 *(0.339)*	-0.409 *(0.548)*	0.510 *(0.284)**	-0.322 *(0.572)*
Cohort	-0.516 *(0.134)****	-0.513 *(0.137)****	-0.025 *(0.453)*	-0.239 *(0.215)*	-0.350 *(0.185)**	-0.350 *(0.177)***
Health Know	0.204 *(0.121)**	0.198 *(0.122)*	0.213 *(0.125)**	0.186 *(0.121)*	0.199 *(0.124)*	0.186 *(0.125)*
Married	0.278 *(0.102)****	0.267 *(0.103)****	0.200 *(0.162)*	0.245 *(0.108)***	0.286 *(0.105)****	0.274 *(0.105)****
Tax*Junior		0.609 *(0.667)*		0.631 *(0.558)*		0.600 *(0.591)*
Tax*Leaving		1.211 *(0.672)**		1.366 *(0.567)***		1.345 *(0.593)***
Tax*3rd Level		0.363 *(0.737)*		0.764 *(0.599)*		0.672 *(0.627)*
Time	0.095 *(0.063)*	0.087 *(0.065)*	0.133 *(0.062)***	0.124 *(0.061)***	0.131 *(0.061)***	0.122 *(0.063)**
Time^2/100	-0.488 *(0.326)*	-0.457 *(0.332)*	-0.719 *(0.335)***	-0.632 *(0.322)***	-0.652 *(0.319)***	-0.606 *(0.326)**
Time^3/1000	0.088 *(0.049)**	0.084 *(0.050)**	0.112 *(0.054)***	0.100 *(0.050)***	0.106 *(0.049)***	0.098 *(0.050)**
Constant	2.277 *(0.347)****	2.060 *(0.393)****	1.565 *(0.359)****	1.292 *(0.359)****	1.515 *(0.353)****	1.286 *(0.384)****
Gamma	0.620 *(0.037)****	0.620 *(0.037)****	0.411 *(0.036)****	0.417 *(0.036)****	0.426 *(0.043)****	0.426 *(0.042)****
Theta			2.204 *(0.679)****	1.818 *(0.413)****	2.761 *(1.121)***	2.780 *(1.044)***
LR Test, θ=0, p-value			0.000	0.000	0.000	0.000

Table 5: Gamma and Exponential Models for Quitting (AFT format, N=8625), S.E. in parentheses, * significant at 10%; ** significant at 5%;* significant at 1%**

	Gamma	Gamma	Exponential	Exponential
Junior Cert	-0.133	0.205	-0.113	0.217
	(0.165)	*(0.253)*	*(0.200)*	*(0.311)*
Leaving Cert	-0.498	-0.262	-0.548	-0.359
	*(0.163)****	*(0.240)*	*(0.193)****	*(0.290)*
Third Level	-0.799	-0.486	-0.804	-0.527
	*(0.319)***	*(0.276)**	*(0.254)****	*(0.334)*
Ln (Tax)	-0.380	-1.170	-0.614	-1.379
	(0.453)	*(0.639)**	*(0.588)*	*(0.814)**
Cohort	0.067	0.018	0.594	0.560
	(0.267)	*(0.238)*	*(0.275)***	*(0.276)***
Health Know	-0.546	-0.541	-0.791	-0.791
	*(0.242)***	*(0.216)***	*(0.298)****	*(0.298)****
Married	-0.099	-0.097	-0.044	-0.041
	(0.129)	*(0.128)*	*(0.163)*	*(0.163)*
Tax*Junior		1.140		1.209
		*(0.644)**		*(0.851)*
Tax*Leaving		0.798		0.694
		(0.639)		*(0.817)*
Tax*3rd Level		1.136		1.060
		(0.781)		*(0.980)*
Time	0.006	-0.001	0.019	0.015
	(0.070)	*(0.069)*	*(0.090)*	*(0.091)*
Time^2/100	0.040	0.080	-0.060	-0.038
	(0.386)	*(0.377)*	*(0.486)*	*(0.489)*
Time^3/1000	-0.014	-0.020	-0.002	-0.005
	(0.063)	*(0.060)*	*(0.076)*	*(0.076)*
Constant	4.125	3.902	4.560	4.363
	*(0.364)****	*(0.369)****	*(0.470)****	*(0.498)****
Ln(σ)	-0.152	-0.141		
	(0.312)	*(0.136)*		
κ=1 (Wald p)	0.534	0.064		
	(0.608)	*(0.226)****		
Log Likelihood	-424.44	-422.769	-435.573	-434.554
AIC	861.9	861.5	882.1	883.1
RESET (Wald *p*)	0.961	0.963	0.958	0.823

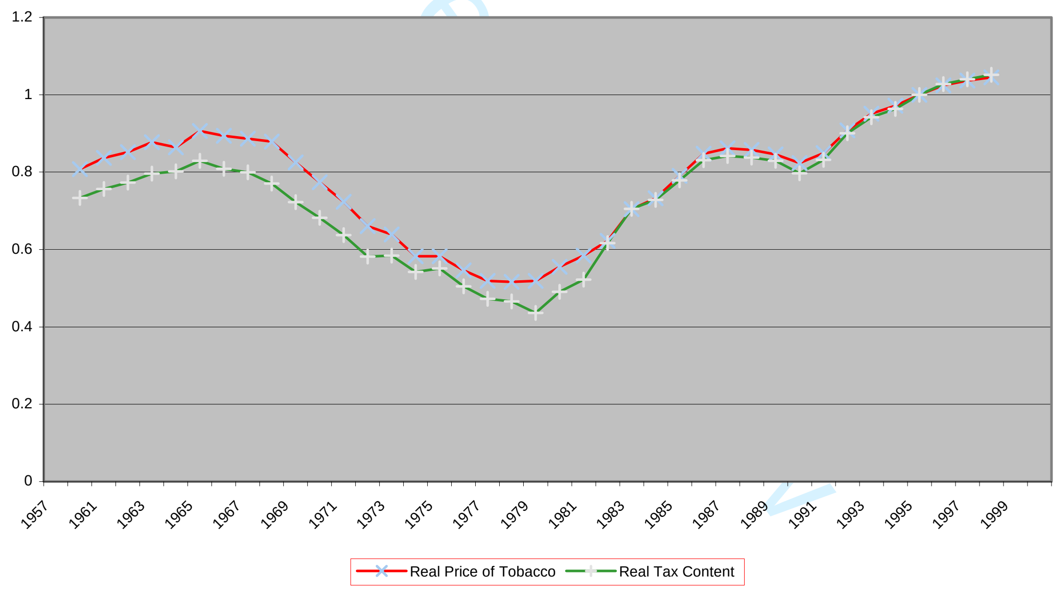
Table 6: Weibull Models for Quitting (AFT format, N=8625), S.E. in parentheses, * significant at 10%; ** significant at 5%;* significant at 1%**

			Gamma Frailty	Gamma Frailty	Inv Gauss Frailty	Inv Gauss Frailty
Junior Cert	-0.158	0.126	-0.127	0.091	-0.131	0.090
	(0.148)	*(0.224)*	*(0.160)*	*(0.216)*	*(0.158)*	*(0.217)*
Leaving Cert	-0.473	-0.276	-0.483	-0.336	-0.487	-0.329
	*(0.143)****	*(0.207)*	*(0.153)****	*(0.216)*	*(0.152)****	*(0.214)*
Third Level	-0.693	-0.446	-0.826	-0.569	-0.795	-0.536
	*(0.195)****	*(0.241)**	*(0.228)****	*(0.281)***	*(0.202)****	*(0.263)***
Ln (Tax)	-0.372	-1.057	-0.339	-0.901	-0.349	-0.929
	(0.424)	*(0.593)**	*(0.404)*	*(0.595)*	*(0.403)*	*(0.594)*
Cohort	-0.001	-0.043	0.045	-0.003	0.033	-0.017
	(0.220)	*(0.217)*	*(0.220)*	*(0.218)*	*(0.216)*	*(0.214)*
Health Know	-0.589	-0.588	-0.555	-0.556	-0.559	-0.564
	*(0.213)****	*(0.212)****	*(0.213)****	*(0.211)****	*(0.211)****	*(0.209)****
Married	-0.099	-0.098	-0.130	-0.127	-0.121	-0.119
	(0.119)	*(0.118)*	*(0.129)*	*(0.127)*	*(0.127)*	*(0.125)*
Tax*Junior		1.027		0.799		0.826
		*(0.607)**		*(0.599)*		*(0.605)*
Tax*Leaving		0.705		0.526		0.568
		(0.584)		*(0.589)*		*(0.583)*
Tax*3rd Level		0.917		1.048		0.999
		(0.712)		*(0.692)*		*(0.692)*
Time	0.013	0.010	-0.002	-0.006	-0.004	-0.006
	(0.064)	*(0.064)*	*(0.064)*	*(0.063)*	*(0.065)*	*(0.065)*
Time^2/100	-0.010	0.009	0.054	0.079	0.064	0.079
	(0.345)	*(0.346)*	*(0.335)*	*(0.333)*	*(0.341)*	*(0.341)*
Time^3/1000	-0.003	-0.006	-0.013	-0.017	-0.014	-0.016
	(0.054)	*(0.054)*	*(0.051)*	*(0.051)*	*(0.052)*	*(0.052)*
Constant	4.183	3.999	4.108	3.960	4.087	3.947
	*(0.338)****	*(0.354)****	*(0.334)****	*(0.340)****	*(0.345)****	*(0.347)****
Theta			0.802	0.817	1.128	0.981
			*(0.869)***	*(0.862)*	*(1.773)*	*(1.489)*
LR Test, θ=0, p-value			0.086	0.087	0.092	0.102
Ln(σ)	0.345	0.351	0.466	0.477	0.472	0.467
	*(0.066)****	*(0.066)****	*(0.139)****	*(0.140)****	*(0.158)****	*(0.147)****
Log Like.	-425.248	-423.78	-424.311	-422.860	-424.362	-422.977
AIC	862.5	862.6	861.6	861.7	861.7	861.9
RESET (Wald *p*)	0.997	0.921	0.993	0.743	0.993	0.787

Table 7: Specification Tests for Parametric Models for Duration up to Quitting

	Gamma		Exponential		Weibull	
		Interaction		Interaction		Interaction
Log L	-424.44	-422.769	-435.573	-434.554	-425.248	-423.78
Reset (p)	0.961	0.963	0.958	0.823	0.997	0.921
AIC	861.9	861.5	882.1	883.1	862.5	862.6
Test G-W	0.534 *(0.608)*	0.064 *(0.226)******				
Test W-E					0.345 *(0.066)******	0.351 *(0.066)******

Figure 1: Tobacco Taxes and Prices 1960-1998



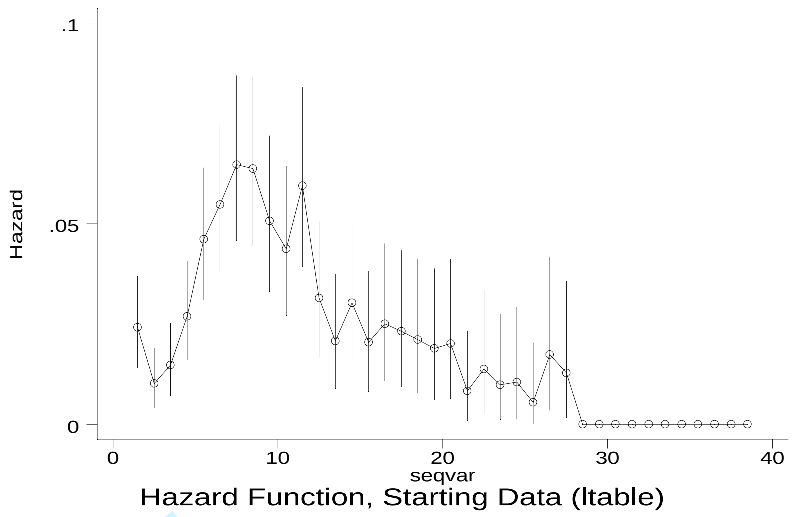


Figure 2: Empirical Hazard, Starting Smoking

Figure 3: Cox-Snell Residuals, Log-logistic model, smokers only

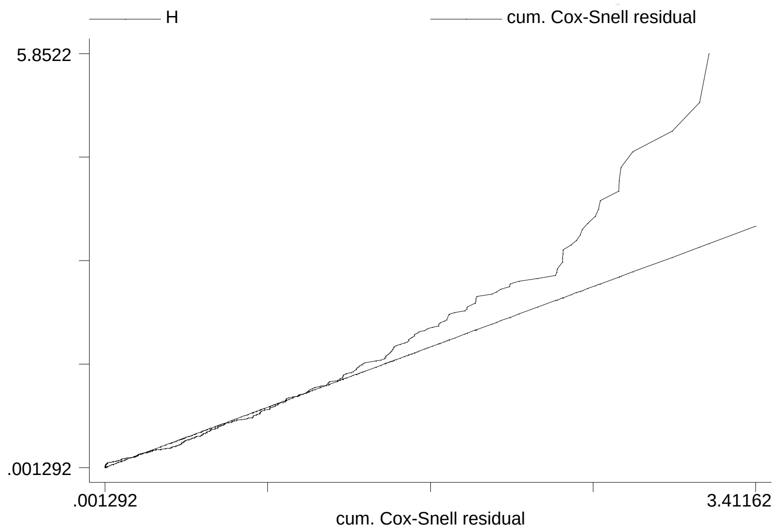


Figure 4: Cox-Snell Residuals, Log-logistic model, smokers and non-smokers

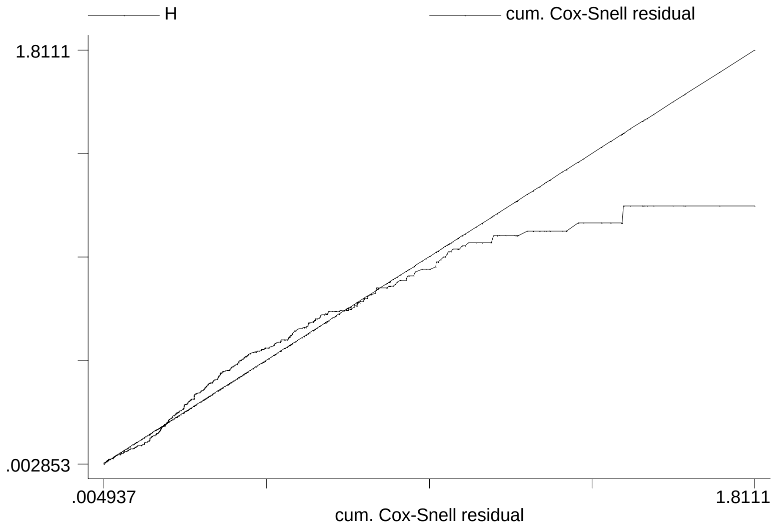


Figure 5: Empirical Hazard Function, Quitting Smoking

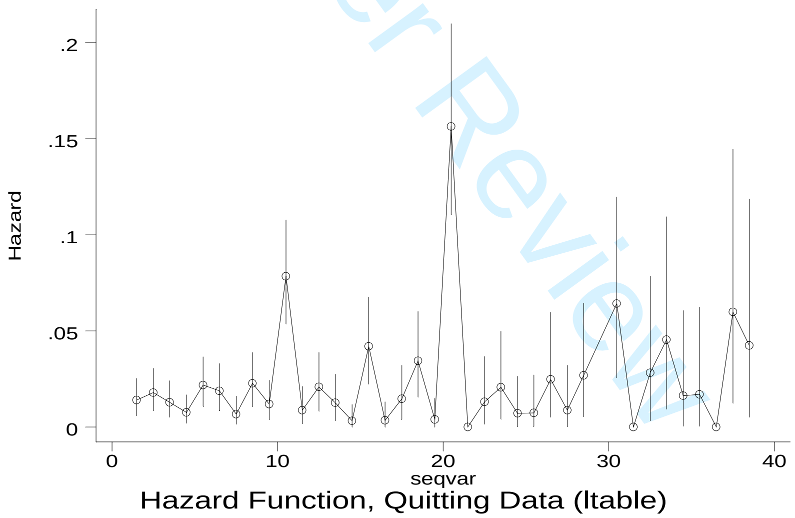


Figure 6: Cox-Snell Residuals for Gamma Model

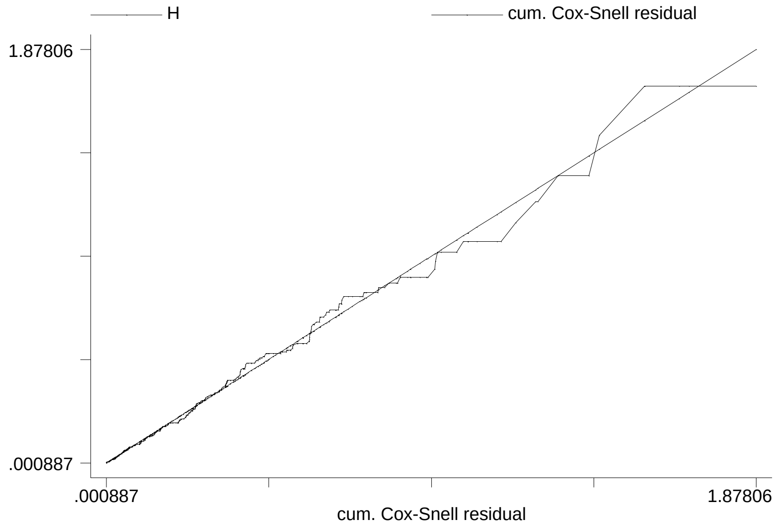


Figure 7: Cox-Snell Residuals for Weibull Model

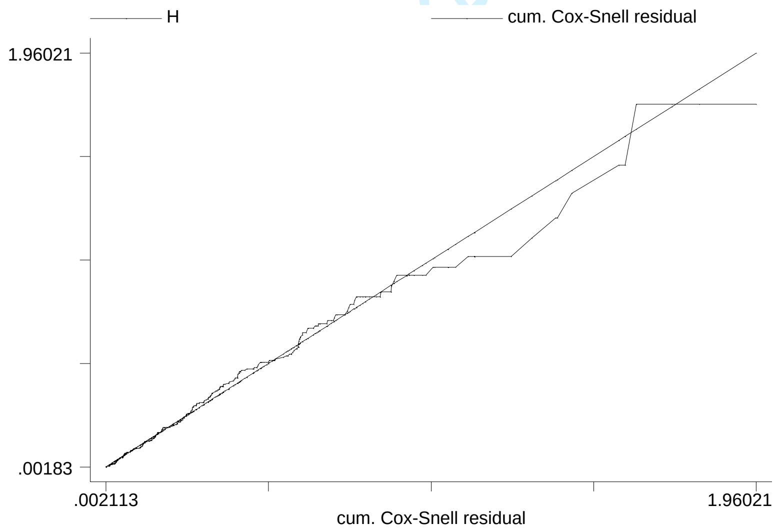


Figure 8: Cox-Snell Residuals for Exponential Model