Panel Count Data Analysis of Determinants of Cigarette Smoking: Evidence from British Household Panel Survey, 2001-2009,

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1. Introduction
Numerous econometric models have been developed to analyse count data to identify factors affecting individual level participation decisions or incidence rates. Containing relatively a larger number of nonnegative integer-valued realizations is an interesting and a distinguished feature of the count data. Such characteristic of the count data necessitates modifying the classical ordinary least square regression models are based on normal distribution. Count data models make an allowance for conditioning the count on its mean to take specific values. Instead of simple linear regression models based on the normal distribution, count data models are based on Poisson, Zero-Inflated Poisson or Zero-Inflated Negative Binomial density functions to capture the conditioning nature of the data.
Models based on Poisson and related distributions have been extended to time series, cross sectional or panel data to capture conditions and variations in many social and economic phenomena and its effects on the count dependent variable. Winkelmann (2008) has summarized a few important research areas where the use of count data techniques has been carried out including the analysis of accidents, issues in health economics, dynamics in the labour economics, studies in criminology and nature of tourism. In health economics the demand for health care in terms of determinants of visiting the doctors/clinic is the most commonly investigated field where count data techniques has been applied. Furthermore cigarette smoking has been studied using cross sectional or panel data from countries other than UK. Current paper is aimed to provide empirical evidence on what important labour market and socio-economic determinants of the individual’s smoke decision making. Panel count data techniques have been applied to deduce the results. The data has been derived from British Household Panel Survey. Further details are presented in the section devoted to data description and empirical results.
To the best of authors’ knowledge, there is no piece of research employing the panel data from the UK to identify socio-economic determinants of smoking decisions. Rather most of the research is devoted to analyse demand for smoking in context of health consequences or in context of social or public policy perspective. The current research will contribute to the field of research by filling the gap in literature in terms of an application of fixed effects to the panel count data to identify the social and economic determinants of the participation decisions. It is thus complementing the research of Becker and Murphy (1988) analysing the addictive nature of smoking behaviour using panel dynamic data on the prices and consumption of cigarette. Considering the nature of smoking decisions, inclusion of socio-economic factors into the analysis is the special case where empirical work is very rare.
Studies analysing individual level data to investigate determinants of the overall smoking decisions to identify different contexts of psychological behaviour, are important to develop anti-smoking policies (Bauer, et al. 2006).

An overview of the available literature reveals that regression models based on either Poisson or Negative Binomial distribution will efficiently capture the impact significant socio-economic factors affecting smoking decisions of an individual. Models based on Poisson family of distributions have the problem of inconsistency if applied to over or under dispersed data as the Poisson regression is based on the assumption of equidispersion where mean equals variance of the count indicator. In case the assumption of equidispersion is violated, application of models based on the Negative Binomial regression can be implemented to estimate the parameter of the regression models. These models have the advantages over the standard Poisson regressions but are not free from limitations. It is discussed in more details in the section devoted to econometric modelling.

2. Literature review

Literature on the use of count data models for estimation of the unknown parameters and inferences thereon has increased in the past decade. Count data models are applied to a range of data types including cross sectional, discrete longitudinal, dynamic panel and bivariate and univariate time series datasets. Molenberghs and Verbeke (2005) present a good overview of the models for discrete longitudinal data in a general context, discussing the application of count data models and present related computational issues to binary or even in incomplete longitudinal data. Xu et al. (2007) adds to literature listing the application of state space models to the longitudinal data with existence of serial correlation. Cameron and Trivedi (1998) account the application to the univariate time series data while Denuit et al. (2007) presents a survey on the application of count data models for cross sectional data. Health economics and the related literature have rich examples of models developed for various types of count data models which are listed in the previous paragraphs. Cameron and Trivedi (1998) has presented in a way that best describes the nature of count data techniques showing how to use such techniques to data in their well-known book titled “Regression analysis of the count data”. Cameron and Trivedi (1998) define that a non-negative valued variable might be considered as a count and that economic modelling of such type of data will necessitate estimation of the theoretical models and their parameters to draw inferences. Given the probability distribution for the count data, specification of such models involves nonetheless any other variable and the number of events is assumed to be independently and identically distributed (iid).
This paper adds to the literature in health economics and public policy identifying important determinants of cigarette smoking in UK and utilizes panel data techniques to the data acquired from the British Household Survey from 2001 to 2009. The choice of technique is dependent on the nature of the count variable, if it has the characteristics describing the Poisson distribution in terms of equal mean and variance, then panel Poisson distribution could be a better choice. If any disparity exists in the mean and variance of the count variables, evidencing the existence of overdispersion or underdispersion, then negative binomial regression is applied to deduce the results. Further details on the issue are presented in the methodology section of the same paper.

Individual smoking decisions are affected by socio-economic conditions which are also the major causes of stress to an individual in their personal and social lives. Castro et al. (1987) summarize the factors into four broad categories as potential, disruptive events, disposition or personality traits and social factors. Social factors lead to stress in the sense that individuals have less access to routine activities into their household and market productivity related activities (Cervantes and Castro, 1985). Disruptive life events include family or household characteristics like conflicts in parents’ marital lives, socio-economic status and religion which antecedent might consider before committing smoking decisions as adolescents relate such factors with their efforts in coping and relaxation (Russell, 1979).

Furthermore smoking decisions might be a cause of low level of education, lower expectations from future achievements and short term future perspective. It is also expected that individual believing in self-image promoted through smoking and or smoking might also be the cause of some chronic diseases (Brunswick and Messeri, 1984; Horn, 1979 and Weinstein, 1982). Individual’s decisions to smoke is also motivated by one’s behaviour that can be summarized into rebelliousness and socially nonconforming activities with an attitude towards risk-taking attitude like using drugs and other pharmacological agents, also affects one decisions to smoke (Jessor and Jessor, 1977; Williams, 1973 and Huba and Bentler, 1982).

Various examples are present in studies in Social Psychology on factors causing stress and depression. Smoking has been studied in a similar context to identify social, economic and health related factors. Health related determinants include some negative effects of smoking like diseases as a result of smoking and its effect on the passive smokers on the assumption that those who have acquired these diseases will be more cautious of the effects and will be less likely to smoke (Office of the U.S. Surgeon General, 2010). The effects and causal nature of health related issue is important from perspective of its direct and indirect economic
costs to the smoker. The chances of higher costs to visit the medical practitioners and other heads will contribute to the higher per month cost of living (Kopstein, 1984). Further smoking has been investigated as remedial in cases when the individuals are depressed are anxious and results indicates relationship between smoking and subclinical depression and anxiety (Morrell and Cohen, 2006).

It has been developed that stress and anxiety is also developed by degraded social and economic conditions which the individuals presumably trying to relax while smoking. Such factors include financial condition, type and level of education, types of jobs, likeliness of the individuals of the neighbourhood (Duncan et al. 1999), family background and peers effect on the development of habitual smoking including fathers’ and also include mothers’ social and economic class, person’s own household behaviour including relationships with the spouse and other family members etc (Powell et al., 2005). These factors are included in our study to identify significance in context to estimate prevalence of smoking.

Furthermore the public policies are affecting individuals smoking behaviour or the extent of smoking in terms of number of cigarettes smoked per day. It depends on where he performs his work as if he works at the employers premises, more chances are there that the rate will be low as compared to his work at home, travelling and other locations (Borland et al., 1990; Farkas et al., 1999 and Evan et al., 1998). Research has been conducted to investigate the efficacy of policies implementations checking the suitability of actions like smoking bans in public place with promotions of not to smoke in front of kids due to several social and health effects on them. These factors have been included in the current study and categories for workplace locations and presence of children in the family are utilized to check the smoking patterns in such conditions.

Although a tendency toward smoking exists as a quick relief from stress by lighting up, there is no empirical evidence that nicotine alleviates stress. In fact, studies have shown the opposite; that smokers have higher stress levels than non-smokers (Warburton, Revell, & Thompson, 1991; Jones & Parrott, 1997; West, 1992). Research shows that adult smokers experience periods of heightened stress between cigarettes, and that smoking only restores their stress levels to normal (Schachter, 1978; Hughes, Higgins, & Hatsuakami, 1990; Parrott, Garnham, Wesnes, & Pincock, 1996 and Office of the U.S. Surgeon General, 1988). However, soon after smoking, they will require another cigarette to keep their stress at normal levels because if they don’t they will experience the stress that comes from nicotine withdrawal. Research suggests that smoking does nothing to relieve stress and can only contribute to increase its prevalence (Parrott, A.C.1999).
Boucher & Guillen (2009), Cameron and Travidi (1998), Hausman et al. (1984) and Winkelmann (2008) summarises issues in the uses of panel count techniques as methods for panel count data differ from standard count data models in at least one of three ways. First, they address the non-standard form of the covariance matrix of the observations that arises since the assumption of independent observations is most likely invalid. Second, and relatedly, they provide a richer framework for addressing the issue of unobserved heterogeneity than do univariate count data. In particular, dependence between the unobserved heterogeneity and the regressors is no longer excluded. Third, models for panel count data allow the introduction of dynamic elements, such as a lagged dependent variable, into the regression part of the model. Further it is also observed that panel methods also differ from multivariate count data models in that panel methods are somewhat more restrictive in their covariance structure, as they frequently assume that dependence is generated by unobserved heterogeneity that is specific to the individual but constant over time. Secondly, panel data models explicitly consider the possibility that the unobserved individual heterogeneity factor is correlated with one or more explanatory variables. In this situation, conditional models are required. The current paper is restricted to the application of recently developed econometric techniques for panel data assuming that such models are consistent and efficient in estimating the parameters of the models, the only objective of current investigation to shed light on some important socio-economic determinants of smoking decisions.

3. Econometric Strategy
The special nature of data needs the count data models are modified to take a deeper account of the nature of the data giving birth to the methods of generalized linear models, including Poisson and Negative Binomial probability distributions. Poisson distribution is based on the probability of the dependent variable conditioned on some observed and/or unobserved characteristic of the $i$th observation. It turns naturally into a standard nonlinear regression with the count variable depending on some exogenous regressors in the system which results in a standard Poisson model. Panel data estimation of the count data is well documented by Boucher & Guillen (2009), Cameron and Travidi (1998), Hausman et al. (1984) and Winkelmann (2008). Hilbe (2011) documents the usage and extensions of negative binomial regression. The paper follows Stata commands from Hilbe (2011) for reporting results from the sample.
3.1. Fixed Effects Poisson

Cameron and Travidi (1998) promoted estimation of fixed effects Poisson regression models for the panel count data. Following standard explanations of fixed effects negative binomial from Allison and Waterman (2002) and Guimaraes (2008), the paper is based on the analysis of; $S_{it}$, the dependent variable in the study with data on individuals ($i = 1, \ldots, n$) across time ($t = 1, \ldots, T_i$) has a Poisson distribution with $\mu_{it}$, and depends on the vector of included exogenous variables $x_{it}$. Log-linear form of the function is given as:

$$ln \mu_{it} = \delta_i + \beta x_{it}$$

with $\delta_i$ is the fixed effect parameter.

The Poisson model can be estimated using conventional approaches using maximum likelihood with including dummies for all the individuals (minus one) to estimate fixed effects model directly. Alternatively conditional maximum likelihood approach can be applied to estimate the model conditioning on the count total $\sum_t S_{it}$ for each individual that yields into a conditional likelihood for the Poisson to be proportional to (2) and is an equivalent of multinomial logit model for grouped data.

$$\prod_t \prod_i \left( \frac{\exp(\beta x_{it})}{\sum_s \exp(\beta x_{is})} \right)^{\delta_{it}}$$

The conditioning eliminates the $\delta_i$, the parameters of fixed effects from the likelihood function. Like logistic regression modelling, the inclusion of dummy variables into the fixed effects models results in inconsistent estimates of $\beta$ (Hsiao, 1986) in form of incidental parameters problem as given by Kalbfleisch and Sprott in 1970. Conditional estimation has been reported as free from such problems (Allison and Waterman, 2002) and the $\beta$ estimates in both the unconditional and conditional models are similar with associated covariance matrix (Cameron and Travidi, 1998). The fixed effects model controls for unrestricted heterogeneity across the individuals and for the given individual restriction is put on the model to strictly use equality of mean and variance:

$$E(S_{it}) = \text{var}(S_{it}) = \mu_{it}$$

with many datasets, additional heterogeneity may not be accounted for by such models.

3.2. Fixed Effects Negative Binomial

Hausman, et al. (1984) suggested fixed effects model is not a true fixed effects model and that it deals with the problem of overdispersion on the assumption that the $S_{it}$ has the negative binomial distribution (Allison and Waterman, 2002). The model of Hausman, et al. model is based on the density function given as:
Where $\Gamma$ represents a gamma function. $\theta_i$ is assumed to remain constant over time for each individual while $\lambda_{it}$ is dependent on the covariates given in the form of:

$$\ln(\lambda_{it}) = \beta x_{it}$$  \hspace{1cm} (5)

The decomposition decision of $\lambda_{it}$ in form of a function of covariates is surprising, since it is regarded as a parameter of overdispersion. The density function in (4) becomes Poisson density function as $\lambda \to \infty$.

Mean and variance of $S_{it}$ is given as:

$$E(S_{it}) = \theta_t \lambda_{it}$$

$$\text{var}(S_{it}) = (1 + \theta_t)\theta_t \lambda_{it}$$  \hspace{1cm} (6)

For any individual $i$, $S_{it}$ is assumed independent over time, implying that $\sum_t S_{it}$ has also a negative binomial distribution with parameters $\theta_t$ and $\sum_t \lambda_{it}$. Condition on the two parameters of total counts, the likelihood function for a single individual is given as:

$$\frac{\Gamma(\Sigma_t S_{it} + 1)\Gamma(\Sigma_t \lambda_{it})}{\Gamma(\Sigma_t S_{it} + \Sigma_t \lambda_{it})} \prod_t \frac{\Gamma(\lambda_{it} + S_{it})}{\Gamma(\lambda_{it})\Gamma(S_{it} + 1)}$$  \hspace{1cm} (7)

which indicates the elimination of $\theta_i$ parameters and the likelihood for the complete sample can be obtained from the multiplication of all individual terms as is in (7). Maximization of the likelihood can then be carried out with respect to $\beta$ parameters using traditional numerical approaches. The current paper reports results obtained from the use of Stata version 10.1 from the Stata Corp (www.stata.com). The computation of the above technique is not free from pitfalls as it does not really fits the fixed effects methods. Problem lies with the conditioning out of the $\theta_i$ parameters from the likelihood does not correspond to different intercepts in the following log linear decomposition of $\lambda_{it}$. Hausman et al. suggest to write the $\theta_i = \exp(\delta_i)$, where (5) and (6) implies

$$E(S_{it}) = \exp(\delta_i + \beta x_{it})$$

$$\text{var}(S_{it}) = (1 + e^{\delta_i})E(S_{it})$$

The model thus allow for an arbitrary intercept $\delta_i$ for each individual, where the approach has problem in that the $\delta_i$ plays a different role than $x_{it}$ and changes in $x_{it}$ affect mean variance directly and indirectly respectively through changes in mean, unless the $\delta_i$ is assumed omitted variable effect, then no compelling reason exists in the variables having a different sort of effect that from $x_{it}$. 
The use of Hausman et al. (1984) has a problem that such regression model can be estimating using both an intercept and time-invariant regressors, which is not permissible with conditional fixed effects models.

Alternative parameterization has been suggested in the literature with more generalization of the Poisson model. The probability mass function for such generalizations has been given as:

\[
f(S_{it}|\mu_{it}, \lambda_i) = \frac{\Gamma(\lambda_i+S_{it})}{\Gamma(\lambda_i)\Gamma(S_{it}+1)} \left( \frac{\mu_{it}}{\mu_{it}+\lambda_i} \right)^{S_{it}} \left( \frac{\lambda_i}{\mu_{it}+\lambda_i} \right)^{\lambda_i}
\]  

(8)

with corresponding mean and variance as:

\[
E(S_{it}) = \mu_{it} \\
var(S_{it}) = (1 + \frac{\mu_{it}}{\lambda_i})
\]  

(9)

Here the mean is allowed to vary but the parameter of overdispersion \( \delta_i \), is assumed to remain constant for each individual. Modelling dependence on covariates results:

\[
\ln(\mu_{it}) = \delta_i + \beta x_{it}
\]

It is the NB2 model of Cameron and Trivedi (1998) to be distinguished from previous NB1 in (6). If the event counts are assumed independent across time for each individual, then the above model is intractable for deriving conditional likelihood, because of \( \sum_t S_{it} \) which has not the negative binomial distribution. A complete and sufficient statistic is lacking in the current specification for the \( \delta_i \) that is a function of the data alone.

The paper discusses results obtained from the \textit{xtgee} and \textit{xtnbreg} commands of Stata and rest of the analysis is omitted to preserve space. Complete results can be obtained from the authors upon request. More details are presented in the following sections.

\section*{4. Data Description}

The British Household Panel Survey (BHPS) is being carried out by the Longitudinal Studies Centre of the Economic and Social Research Council, UK in collaboration with the Institute for Social and Economic Research (ISER) at the University of Essex. First wave was completed in 1991, and afterwards, it has been conducted annually with the latest completed wave 18 in 2009 and published in 2010. The main objective of the survey is to promote understanding of social and economic dynamics at the individual and household level in Britain, to identify, model and forecast social and economic changes, to evaluate their causes and consequences in relation to a range of socio-economic indicators. The paper utilizes data on smoking and socio-economic and health-related predictors from the British Household Panel Survey for the year 2002-2009 matching with corresponding waves 11 to 18 of the survey. The sample is an unbalanced panel of 6619 individuals observed from 1 to 9 years during the time period, 2002-2009 with total observations equal to 25181.
Given the panel nature of the data, it is observed that mean age of sampled individual is just above 39 years when excluding individuals of ages less than 16 years and exceeding 65 years respectively on the occasion that included individual will not be active labour market participants. Individuals are found to smoke about 15 cigarettes per week with variance 8.69 where variance is lower than the average number of smoked cigarette and making the data possibly under dispersed as a presumption. The underdispersion nature of the data will be formally checked using the suggested procedures by Hilbe (2011).

The sample includes 48% male and remaining 52% are female, as our analysis is based on fixed effect's analysis of the data, the inclusion of gender variable is seemingly inappropriate, but it will help to compare the sample pattern across the two groups.

<table>
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<tr>
<th>Table 1: Descriptive Statistics</th>
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<tr>
<td>variable</td>
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<td>Smoking</td>
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<td>Age</td>
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<td>Squared Age/100</td>
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<td>Financial Status 3</td>
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<td>Financial Status 4</td>
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<td>Financial Status 5</td>
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<td>male</td>
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<td>Likes Neighbourhood</td>
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<td>Children At Household</td>
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<td>Degree Level Qualification</td>
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<td>Anxious</td>
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<td>Feels Under Strain 4</td>
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<td>Feels Under Strain 5</td>
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<td>Feels Under Strain 6</td>
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<td>Feels Under Strain 7</td>
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<td>Private Sector Employee</td>
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<td>Fulltime Employee</td>
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<td>Work at Employer Premises</td>
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<td>Hospital Visits 2</td>
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<td>Financial Expectations 3</td>
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*Note: N is 25181, n is 6619 and T-bar is 3.80435*

Besides the above personal level characteristics, the analysis includes work-related determinants like income, education, full-time employment, management-level role and workplace as a proxy for checking the effects of public place smoking bans. The analysis includes indicators for social behaviour of the individuals. The indicators include neighbourhood, children at home, marital status and housing tenure. It has been observed that above 90% or more people like to dwell in the current neighbourhood with around 60% of them have their own houses or mortgaged. 25% of the sample has a child in the household with 12% of the individuals have the educational qualifications at a degree level. Table (1) summarizes results for the pooled sample and conditional fixed effects negative binomial (NB-2). Complete results are available with the author.

5. **Econometric Results:**

The analysis begins with testing the presence of over or underdispersion in the data. Following Hilbe (2011), first unconditional negative binomial regression is estimated to obtain the value of alpha (0.261), which is used to control for the dispersion. The dispersion parameters obtained from the product of (1/df) and Deviance or Pearson coefficient is 1.04 or 0.81, indicating the dispersion has been controlled to an acceptable extent, that around 5% above the dispersion equal to 1 (Hilbe, 2011). It is notable that from the summary statistics, it seemed that the data might be underdispersed but proper follow-up tests indicated that it is actually overdispersed, and the dispersion has been controlled with including the value to of alpha into the GLM model. The results indicate using Negative Binomial is the appropriate technique that can be used to investigate the determinants of smoking.
Literature reveals various versions of the negative binomial regression models. Most commonly applied version in panel data literature is the conditional fixed effects negative binomial (NB-2) a common choice of the econometrician and GLM version of negative binomial (NB-1) is the choice of statisticians (Cameron & Travedi, 1986, 1998 and Greene, 2008). Greene (2008) further notes that Cameron and Travedi (1986 & 1998) have no preference for the NB-1 or NB-2 models as these models are non-nested, no parametric test exists to suggest the more preferred model from the NB-1 or NB-2. Moreover, Greene (2008) suggest using NB-P model, which has superiority over the NB-2 model but there is only little effects on the coefficient estimates using NB-P model, hence the choice depends on the computational ease. Furthermore, as the current study is aimed only to identify some important socio-economic and health-related indicators, which affect individual’s decisions to smoke in terms of incidence rates, the study employs population averaged and conditional fixed effects negative binomial (NB-2) as the appropriate and computationally easy model.

Table 2 indicates the effect of age is quadratic on the smoking decisions in terms of incidence rates, which change non-linearly with increasing age. It is observed that the incidence rate is first increasing rapidly and then declines with higher ages, which confirm the results that smoking is less prevalent among the elder portions of populations. One aspect of such evidence might be that older people are more mature, and they care more about factors that might negatively affect their health. Another significant finding is that anxiety causes more smoking prevalence in terms of incidence rate. One explanation that is present in case of higher smoking among anxious people that they are more likely feeling depressed, and they relax themselves while smoking, which is usually preferred among those who want to relieve depression. To enforce this finding the study incorporates strain as a proxy for the depression parameter of smoking. Strained individuals are found smoking more than those who are less strained.

| Table 2: Population Averaged and Fixed Effects Negative Binomial Regression Results |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                 | PA\(^a\) Poisson | FE\(^b\) Poisson | PA Negative Binomial | FE Negative Binomial |
| Male                            | 1.128*** (8.91)  | 1.122*** (8.56)  |                  |                  |
| Age                             | 1.052*** (17.92) | 1.077* (2.56)    | 1.050*** (17.66) | 1.082*** (13.26) |
| Squared Age/100                 | 0.951*** (-14.36)| 0.961*** (-10.50)| 0.953*** (-13.97)| 0.961*** (-9.46) |
| Financial Status                | 0.992 (-1.34)    | 1.000 (-0.09)    | 0.990 (-1.77)    | 1.001 (0.16)     |
| Financial Expectations          | 0.998 1.001      | 0.999 1.001      |                  |                  |
The two indicators indicate that more depressed persons are usually found more smoking as compared to less depressed. Further research will provide evidence on what are the social or economic factors causing more depression? The results are confirming the evidence from Ikard, Green and Horn (1969) stating that cigarettes are either pleasurable or relieving. The
results further confirm the finding that smoking changes the mode of smokers and calms the smokers by reducing the anger of smokers (Warburton, 1992, p. 57).

Moreover it is clear from the Table (2) that individuals who have more frequent visits to hospitals or health centres are found less smoking and main reason for their less smoking prevalence is that doctors usually prohibits from smoking whenever one has to complete a medical course for treatment. Also the rate is less among those visitors, and they are usually more sensitive when they have some medical issue and it is one of the main reasons that they are smoking less than their usual smoking habits.

One last significant finding from the analysis appears to be the effect of ban on smoking in public premises as indicated from the proxy for the determinant. The study includes working in an employers’ premises and there is ruling in the UK that smoking free work environment should be provided. The people who usually work at the employers’ premises are found fewer frequent smokers as they have to spend more time at work premises. This is usually because of the reason that employers have to maintain smoking free work environment, and they do not allow smokers to smoke frequently with breaks from the job.

Although the effect of financial variable on smoking is not statistically significant but the results are economically viable, better financial status has a negative effect on individual preferences to smoke and those who have no better financial expectations from the future are found more frequent smoking, possibly due to expected hardships in the future. It would be interesting if research identifies the relationship between future expectations, depression and anxiety and smoking. All this is logically viable and the results indicate importance of economic conditions on the individuals’ preferences to smoke or not to smoke. The incidence rate increases if one has worst expected future and the incidence rate increases if they have better financial status. It is further evident of the results that if a person has a better financial condition, it is expected that they would have their own houses and the effect of house ownership is clearly negative on smoking prevalence in terms of fewer incidence rate of smoking.

6. Conclusion

The count nature of the data requires careful application of econometric techniques for the prediction of the effects of included determinants on dependent variables. It is clear from the results that aged persons have less prevalent smoking and smoking prevalence decreases in terms of a lower incidence rate ratio when they are less depressed as indicated by the
significant effect of anxiety and stain on smoking. Moreover, the results indicate that individuals who have frequent visits to hospitals are found less frequently smoking as they usually are sensitive when they have some medical problems and visit hospitals for treatment. The study has implications for health policy effectiveness to prevent smoking and the related diseases not only prevailing in the smokers but also on the passive smokers, those who are present in the surrounding of the smokers and can inhale the smoke.

References:


Duncan, C., Jones, K. and Moon, G., 1999, Smoking and deprivation: are there
eighbourhood effects?, Social Science and Medicine 48, pp. 497-505

Evans, W., Farrelly, M. and Montgomery, E., 1999. ‘Do Workplace Smoking Bans Reduce
Smoking?’, American Economic Review 894: 728-47

Smoking And Cigarette Pack Sizes,” Department of Economics - Working Papers Series 887,
The University of Melbourne.

Greene, W. H., 1994. "Accounting for Excess Zeros and Sample Selection in Poisson and
Negative Binomial Regression Models," Working Papers 94-10, Leonard N. Stern School of
Business, Department of Economics, New York University

Greene, W., 2008. “Functional forms for the negative binomial model for count data,”


Cambridge, UK.

Horn, D. 1979. "Psychological Analysis of Establishment and Maintenance of the Smoking
Habit." Pp. 24-29 in Cigarette Smoking as a Dependence, Process edited by N.A. Krasnegor

Huba, G.J., and Bentler, P.M., 1982. "A Developmental Theory of Drug Use: Derivation and
Assessment of a Causal Modeling Approach." Pp. 147-203 in Life-Span Development and

Goodstadt, Y. Israel, H. Kalant, E. M. Sellers, and J. Vingilis Eds., Research advances in

Ikard , F. F. , Green , D. E. , and Horn , D.  1969 . A scale to differentiate between types of
smoking as related to the management of affect . International Journal of the Addictions , 4 ,


Racial/Ethnic Subgroups: Findings from the National Education Longitudinal Study, Journal
of Health and Social Behaviour, Vol. 41, No. 4, pp. 392-407


Schachter, S., 1978, Pharmacological and physchological determinants of smoking, Annals of Internal Medicine, vol. 88 no. 1, pp. 104-114


