QUANTILE REGRESSION ANALYSIS OF THE RATIONAL ADDICTION MODEL: INVESTIGATING HETEROGENEITY IN FORWARD-LOOKING BEHAVIOR

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SUMMARY

The time path of consumption from a rational addiction (RA) model contains information about an individual's tendency to be forward looking. In this paper, we use quantile regression (QR) techniques to investigate whether the tendency to be forward looking varies systematically with the level of consumption of cigarettes. Using panel data, we find that the forward-looking effect is strongest relative to the addiction effect in the lower quantiles of cigarette consumption, and that the forward-looking effect declines and the addiction effect increases as we move toward the upper quantiles. The results indicate that QR can be used to illuminate the heterogeneity in individuals' tendency to be forward looking even after controlling for factors such as education. QR also gives useful information about the differential impact of policy variables, most notably workplace smoking restrictions, on light and heavy smokers. Copyright © 2010 John Wiley & Sons, Ltd.

1. INTRODUCTION

The rational addiction (RA) model assumes that individual decisions about the consumption of harmful and addictive commodities are made on a rational basis (Becker and Murphy, 1988). In this context, a key element of rational behavior is a tendency to be forward looking, i.e. a tendency to take account of future consequences of current consumption decisions. Different individuals may well attach different weights to the present relative to the future while all still being fully rational.

In general, smokers tend to behave in a manner, which is consistent with discounting the future quite heavily. Indeed with respect to the relationship between education and smoking the debate in the literature deals with whether having less education makes individuals more likely to be smokers or whether the propensity to smoke and the propensity not to invest in educational capital are both consequences of a propensity to discount the future heavily (Farrell and Fuchs, 1982).

Many empirical efforts in this area have focused on looking for patterns of behavior, which are consistent with discounting the future more heavily. There is a literature that deals with smoker type which is defined in terms of these patterns of behavior: smokers tend to be less educated, have lower incomes and are less likely to engage in preventive health behaviors (on these

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points, see Ippolito, 2003; Evans and Montgomery, 1994; Munasinghe and Sicherman, 2000, for example).

An alternative approach, which we follow here, is to look for direct evidence on the strength of the forward-looking element in the individual's smoking behavior. This approach builds on the fact that the RA model is a model of inter-temporal optimization, meaning that, rather than making independent decisions about how much to smoke in each period the individual plots out an optimal lifetime smoking trajectory, conditional on future values of exogenous variables such as price. The optimal control problem which yields that trajectory incorporates the individual's attitudes to the harm smoking can do to her health and the rate at which she will trade the present against the future. This means that factors like the individual's degree of myopia are built into the trajectory of cigarette consumption which she will follow, and that consumption trajectory is what yields the forward-looking second order difference equation (SODE), which characterizes RA behavior. As we shall show below, the characteristic roots of the RA SODE can be interpreted as showing the strength of the forward and backward looking elements in the individual's consumption behavior.

Our use of this approach is similar to that of Jones and Labeaga (2003). We differ, however, in that where Jones and Labeaga estimated a single RA SODE for their entire data set and then on subsets defined by age and level of education, to see whether the forward and backward element of the consumption decision differed systematically according to values of these explanatory variables, we are interested in whether the strength of the forward and backward looking effects differs systematically across levels of cigarette consumption. Our approach is not to remove individual heterogeneity in forward-looking tendencies, as in the Dynamic Panel Data approach to estimating RA models, for example, but to investigate whether the distribution of consumption is systematically related to the distribution of those tendencies.

One possible approach would be to divide our sample into low, medium, and heavy smokers, as is sometimes done in the price elasticity literature. This would, however, require us to make arbitrary decisions about cutoff levels and would raise the possibility of econometric problems associated with truncation of the subsamples. Instead, we apply simultaneous quantile regression (QR), and investigate differences in strengths of forward and backward looking effects at various quantiles across the entire distribution of cigarette consumption. We use panel data to ensure that we are examining the behavior of individuals across time. Our hypothesis, then, is that in micro level data, differences in the time paths of cigarette consumption at different quantiles of the level of consumption will contain information about differences in the degree of forward-looking behavior.

2. THEORETICAL CONTEXT

The Becker–Murphy model of rational consumption of an addictive commodity is a model of individual inter-temporal optimization. At its core is the idea that when making consumption decisions about a commodity such as cigarettes, which are known to be harmful to health, the individual must weigh up the current satisfaction, or utility, which she derives from the act of smoking against the disutility associated with the damage to her health that is likely to occur if she smokes continually over a long period. When, as in the case of cigarettes, the commodity is also addictive, the consumer must factor into her utility calculations the likelihood that an increase in her current consumption will not only increase her risk of future harm, but will also tend to shift her preferences toward the addictive commodity. This would lead her to consume more of the addictive commodity in future than she would a non-addictive, but equally harmful commodity, thereby increasing the likelihood that her health will suffer. Formally, a forward-looking problem of this sort can be set up as an optimal control problem, the solution to which takes the form of an inter-temporal trajectory of consumption.

Empirically, the deterministic part of the RA model is usually implemented as a forward-looking SODE:

$$C_t = \beta_0 + \alpha_1 \, C_{t-1} + \alpha_2 \, C_{t+1} + \beta X_t \tag{1}$$

where C refers to consumption of cigarettes and X stands for all of the exogenous variables which may determine consumption levels. The t subscripts refer to time, so in the RA SODE, current consumption is taken to depend on past and future consumption. Since this applies in each period, Equation (1) can be used to generate a time path for cigarette consumption, conditional on the values of the explanatory variables.

The easiest way to do this is to solve the SODE. There are in fact several ways we can look at the solution but to focus explicitly on the time path of consumption, we can write the solution to (1) as:

$$C_t = A_1 \lambda_1^t + A_2 \lambda_2^t + C^* \tag{2}$$

Here, $C^* = (\beta_0 + \beta X_t)/(1 - \alpha_2 - \alpha_2)$ is the equilibrium value of C, conditional on the explanatory variables so that $\partial C^*/\partial X = \beta/(1 - \alpha_1 - \alpha_2)$ is the long run effect of X on C. The A_i terms are constants depending on the initial and target terminal levels of consumption, and λ_1 and λ_2 are the roots of the SODE. The roots themselves are constant over time, but they are raised to the power t, so it is through the roots that the pure passage of time enters the solution expression. The roots in turn are functions of the coefficients (α_1 and α_2) on lead and lag consumption in equation (1) as $\lambda_1, \lambda_2 = [1 \pm \sqrt{1 - 4\alpha_1 \alpha_2}]/2\alpha_2$. In optimization problems, the solution will display saddlepoint dynamics, meaning that $\lambda_1 > 1$ and $0 < \lambda_2 < 1$, where λ_1 is referred to as the unstable root and λ_2 as the stable root.

An alternative approach to looking at the solution to (1), probably more familiar in macroeconomic dynamics, involves the use of the lag operator L, where $LC_t = C_{t-1}$ and $L^{-1}C_t = C_{t+1}$. Using operator notation, we can write (1) as

$$C_t = \beta_0 + \alpha_1 \, LC_t + \alpha_2 \, L^{-1} \, C_t + \beta X_t \tag{3}$$

which with some rearranging becomes

$$-\alpha_2 \, L^{-1} \left[1 - \frac{1}{\alpha_2} L + \frac{\alpha_1}{\alpha_2} L^2 \right] C_t = [\beta_0 + \beta X_t] \tag{4}$$

It can be shown that this can be written as

$$[1 - \lambda_1 L][1 - \lambda_2 L] \, C_t = -L \left[\frac{\beta_0}{\alpha_2} + \frac{\beta}{\alpha_2} X_t \right] \tag{5}$$

where the λs are defined as above. Some further manipulation (see Obstfeld and Rogoff, 1996) yields

$$C_t = \lambda_2 \, C_{t-1} + \frac{1}{\lambda_1} \sum_{i=0}^{i=\infty} \lambda_1^{-i} \, L^{-i} \left[\frac{\beta_0}{\alpha_2} + \frac{\beta}{\alpha_2} X_t \right] \tag{6}$$

From (6), we see that one way to look at the optimal current value of C is as a function of its immediate past value and (because of the L^{-i} term inside the summation sign) of the future values of the explanatory variables. From (6), we also see that the stable root can be interpreted as $\lambda_2 = \partial \, C_t/\partial \, C_{t-1}$, which is referred to as the strength of the addiction effect. In this notation, the short run effect of the explanatory variable X is $\partial C_t/\partial X_t = (1/(\lambda_1 - 1))\beta/\alpha_2$.

Returning to (5), it can be shown that an alternative way of writing the expression for C_t, using lag operator notation, is as

$$C_t = \frac{1}{\lambda_1} C_{t+1} + \frac{1}{\lambda_1} \sum_{i=0}^{i=\infty} \lambda_2^i \, L^i \left[\frac{\beta_0}{\alpha_2} + \frac{\beta}{\alpha_2} X_t \right] \tag{7}$$

Here, $1/\lambda_1 = \partial C_t/\partial C_{t+1}$, which is the strength of the forward-looking effect.[1]

In this paper, we consider whether differences in levels of consumption are associated with differences in the dynamics – the time path – of consumption. Specifically, we are interested in whether differences among individuals in the level of consumption, after controlling for exogenous factors such as age, sex, income, education, prices etc., seem still to be systematically associated with differences in the strength of the forward looking and addictive effects. The derivations presented above underlie the interpretations that we will put on the results from the empirical analysis to follow.

3. METHODOLOGICAL APPROACH

As we are interested in examining whether the dynamics of consumption vary systematically across levels of consumption, we have chosen to use simultaneous QR techniques, estimating a standard RA model across quantiles of consumption of cigarettes on individual panel data. Normally, this type of data would be analyzed using the dynamic panel data (DPD) econometric methodology (Arellano, 2003), but DPD cannot be used with QR as it requires differencing the data to remove unobserved heterogeneity and differences of quantiles are not the same as quantiles of differences. Simply using DPD on our entire data set would imply estimating a single pair of coefficients on lead and lag consumption for the entire population, which would defeat our purpose of investigating differences in the roots that are derived from those coefficients.

We alluded earlier to the truncation issues that arise if we were to sub-set the sample into light and heavy smokers. QR allows us to avoid many of those issues by using the entire sample, and allows us to look at the evolution of the parameters of interest virtually continuously across levels of consumption. Another important advantage of this approach is that QR analyzes the way the shape of the entire distribution of consumption changes as values of explanatory variables change.

QR has been used by Manning *et al.* (1995) who investigate the price elasticity of demand across the distribution of alcohol consumption. In this paper, our interest is in using QR to estimate RA SODEs across the distribution of consumption. To control for differences in individual preferences other than the dynamics of consumption of cigarettes, we have also included individuals' chosen levels of consumption of certain other commodities (described below), as differences in individuals' general tastes and preferences are revealed in their choices about what particular bundle of commodities to consume. We are, therefore, estimating conditional quantile versions of Equation (1).

4. DATA

The data are drawn from several cycles of the Canadian National Population Health Survey (NPHS), a biennial longitudinal survey administered since 1994/1995. We start with only people who remained in the panel for all of the cycles, then remove never smokers, on the assumption that their individual preferences are fundamentally different from those of people who were at some time smokers. Although the smoking question was asked through all of the cycles of the survey, we were forced to reduce the time span, which we used quite significantly because many of the other questions which we used to derive explanatory variables i.e. about consumption of other commodities, were only asked in a few of the cycles. Ultimately we were able to use the 2002/2003 and 2004/2005 cycles as the core of our

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[1]Note that our expression for the roots is the inverse of the expression Becker, Grossman and Murphy use: we have written roots in the form common in the literature on theoretical dynamics while they have used notation common to econometric dynamics. We have also not imposed the restriction that the coefficient on future consumption equals that on past consumption multiplied by the discount factor.
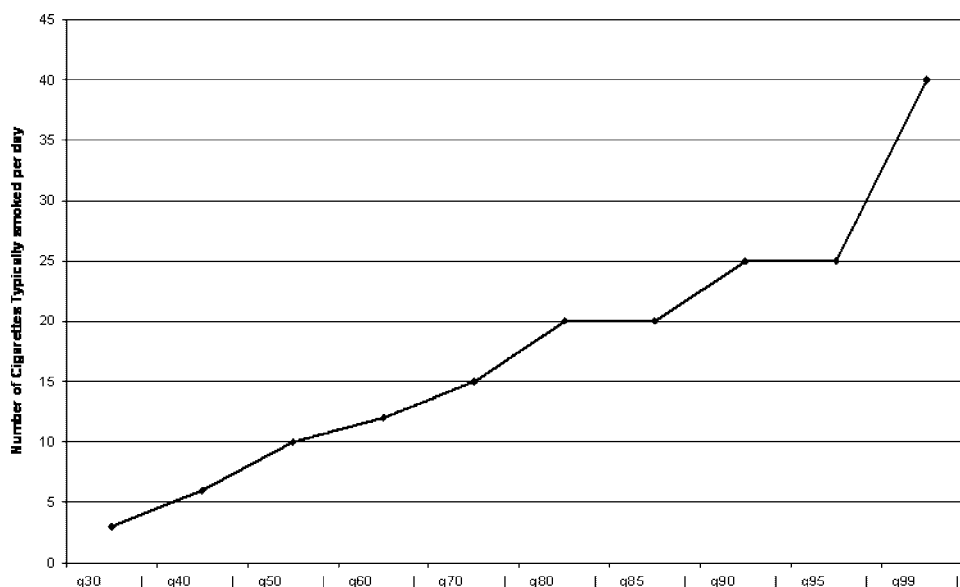
Figure 1. Unconditional quantiles of consumption

analysis (i.e. as sources for C_t data); however, C_{t-1} data were drawn from the 2000/2001 cycle and C_{t+1} data from the 2006/2007 cycle as well as the two intervening cycles. Our data, therefore, span 8 years for each individual.

Within this sample, we excluded anyone who reported zero consumption in all of the four cycles from 2000/2001 to 2006/2007, (i.e. reported smoking no cigarettes over eight years), leaving only individuals who reported positive consumption of cigarettes in at least one cycle. We recognize that by doing this we risk excluding people who smoked the occasional cigarette but reported their typical consumption to be zero. We return to this point in the discussion of our empirical results.

This left us with 4148 observations, two values of C_t on each individual, of which a significant number were still zero. As a consequence, we include dummy variables for whether the individual had attempted to quit within the last 6 months and whether they classified themselves as former daily or former occasional smokers. We include these last two to control for the effect of people who have chosen to go cold turkey, rather than follow a smooth inter-temporal consumption path. We also include a dummy variable for people who identify themselves as nonsmokers but who report positive consumption in any of the data periods which effectively identifies those who started smoking in our sample and controls for the fact that they are at the beginning of their smoking consumption trajectory.

Even after our exclusions, our data set contains a large number of zeroes, to the extent that the 25th percentile of the unweighted distribution of cigarette consumption in the data set was one cigarette. Figure 1 below shows the number of daily cigarettes associated with various quantiles of the distribution of consumption.

The NPHS is not a diary survey; hence individuals were not asked to report actual consumption of cigarettes on any particular day. Rather they were asked how many cigarettes they would smoke on a typical day. In essence, their answer is their expected daily cigarette consumption.

The dynamic structure of the empirical model is represented by the presence of lead and lag cigarette consumption. The RA model suggests that future consumption, C_{t+1}, should be treated as an endogenous variable because people will respond to random deviations of current consumption from the optimal path by trying to return to the optimal trajectory in the future. A Hausman test for the

endogeneity of C_{t+1} was not significant at the 5% level.[2] It seems likely that this was due to the 2-year gap between observations; any correction to a random shock in a period t had probably been completed before the next observation in our data set was taken.

Price data (P_t) were based on the price in each province of a carton of 200 cigarettes including taxes, drawn from the Non-Smokers Rights Association of Canada[3], combined with province-specific data on the Consumer Price Index for cigarettes, as nominal price data were not available for all of the periods in the sample.

Among other explanatory variables, we included dummy variables for level of education attained (high school, postsecondary, and university/college), age group (age1519, age2039, age4059 (base), age6079, age80pl), and ranges of income (less than $20 000, $20 000–$30 000, $40 000–$79 000(base), greater than $80 000). We also included data on family circumstances – married and the presence of children younger than 12 years in the household – and a dummy for the sex of the respondent (male). We included dummies for a number of indicators of health status – whether the respondent uses asthma medication, whether they are on blood pressure medication, whether they have had a heart attack, whether they have diabetes and whether they find life stressful, and a variable indicating whether, overall, their self-assessed health status is poor. We include a dummy variable for whether they attempted to quit smoking within the last 6 months, another for whether they face restrictions on smoking in the workplace and one for whether any member of their household smokes in the house.

Among other consumption variables, we include weekly consumption of fruits, juice, salad, potatoes, carrots, and vegetables generally, and a variable indicating whether the respondent assesses her dietary habits to be poor. We also include a variable for the quantity of alcohol, which the individual consumes in a week[4].

5. RESULTS

The results of QR are usually presented in graphical form because it yields an estimating equation, and standard errors, for each quantile. Because the bottom 20% of the distribution of consumption is zero (the 25th percentile is one cigarette), we report results from the 25th percentile up.

The estimated intercepts for the quantile equations are shown in Figure 2. In this figure, as in the other coefficient graphs, the solid center line shows the coefficient estimates, whereas the dashed lines on either side of the center line show the 95% confidence interval for the estimates. As expected, the estimated intercepts rise from the lowest to the highest quantiles. The horizontal scale of the diagram is slightly misleading as we generally work in increments of ten percentiles, but after the 80th percentile report the 85th, 90th, 95th, and 99th percentiles. In addition, Figure 2 includes a horizontal dotted line, which shows the single intercept estimated by OLS. As we would expect, the OLS intercept is above those for the lower quantiles and below those for the upper quantiles.

The health variables proved unexpectedly weak in the regressions, and income had a non-significant effect throughout. Although the individual fruit and vegetable variables did not do much in any of the equations, the self-assessed poor diet variable was associated with higher cigarette consumption, with an effect that was roughly constant across quantiles (Figure 3). It is possible that this variable is more informative about people's general dietary habits than are variables that relate to a few specific items (e.g. carrots).

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[2]We used lead price and other lead variables to instrument lead consumption.

3 http://www.nsra-adnf.ca/cms/file/pdf/cigarette_prices_Canada_17_April_2009.pdf.

[4]Had the NPHS been a diary survey, we would have faced issues of endogeneity involving expenditure (and hence quantity) of alcohol and the various food items. The cigarette consumption question asked about typical, rather than precise daily, consumption, so it seemed unlikely that there would be a statistical endogeneity problem with regard to the food and drink questions, and as a consequence these variables were not instrumented.
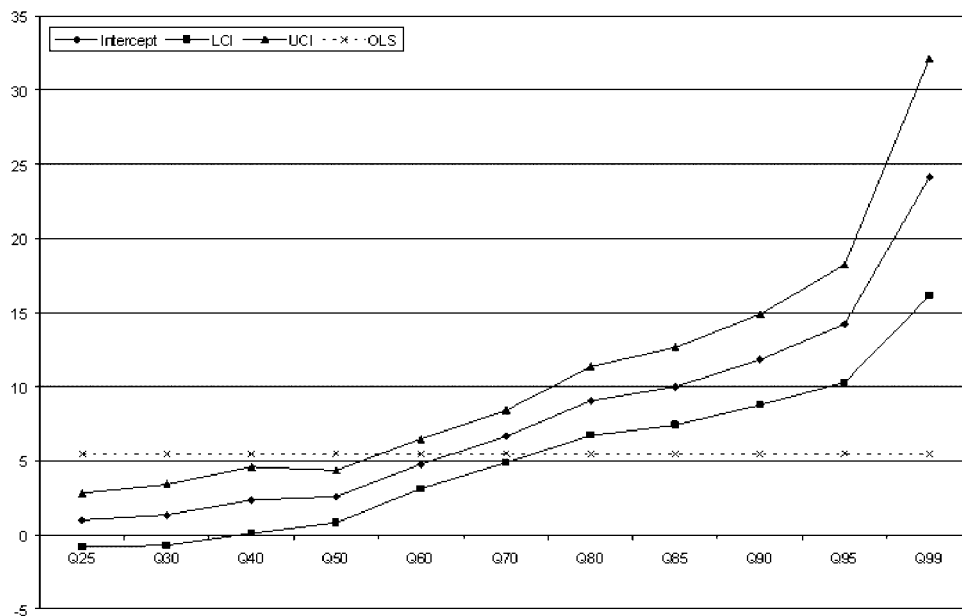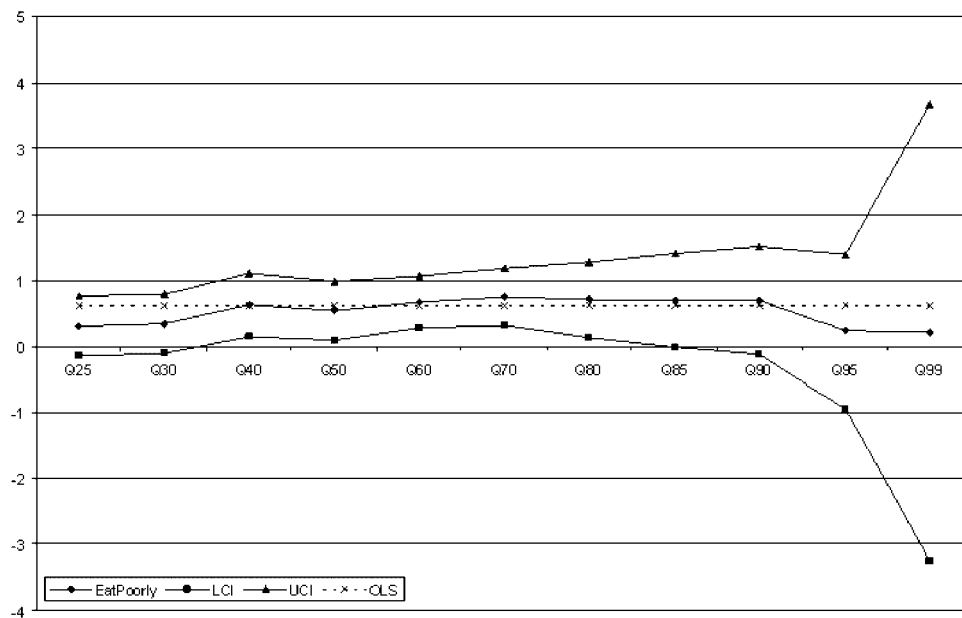
Figure 2. Intercepts

Figure 3. Self-assessed poor diet

Figure 4 shows that the effect of being male is non-significant at the bottom quantiles, but that it is significantly greater as we move to the higher quantiles of cigarette consumption, indicating a stretching out of the top of the distribution of male compared with female consumption.

Figure 5 shows that the workplace restrictions variable, which has a negative and significant coefficient in the OLS regression, is in fact statistically significant only from the 70th percentile up.
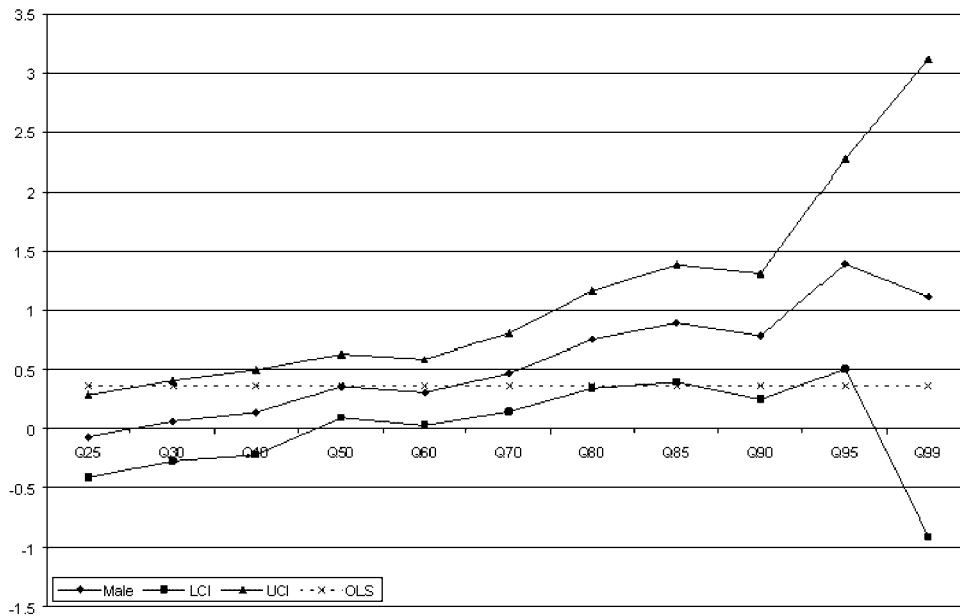
Figure 4. Male
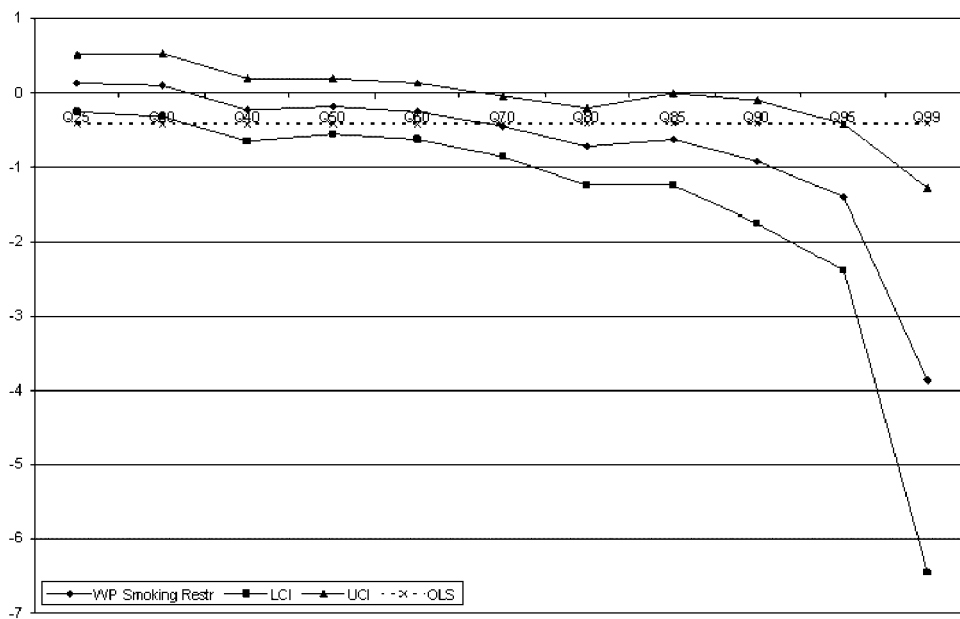
Figure 5. Faces workplace smoking restrictions

The QR results suggest that workplace smoking restrictions are a binding constraint for heavy smokers.

As we noted above, we included in our equations dummy variables for individuals who made discrete jumps from being daily or occasional smokers to zero consumption. The coefficients on these variables were, not surprisingly, consistently negative and statistically significant. We did this on the assumption

that an individual who went cold turkey was different from one who followed a smooth trajectory, even a trajectory which was heading toward zero consumption. Such an individual might, for example, have discovered that they had unexpected health problems and gone cold turkey on their doctor's advice. We included dummies for these individuals because we wanted the coefficients on lead and lag consumption, and therefore the roots of the SODE characterizing their behavior, to reflect the behavior of individuals who were following a trajectory which represented the solution to their forward looking optimal control problem – the type of trajectory which the cold turkey individuals might have followed had they not, for example, had a health shock.[5] We investigated the relation between the cold turkey dummies and our health status variables, and found that there was indeed a correlation, and that when we dropped these dummies from the equations, several of the health variables became significant. Our preferred specification, however, includes the cold turkey dummies, so the health variables lose significance in it.

The price variable had a persistent tendency to have the wrong sign and to be non-significant. This is, of course, inconsistent with market level studies, which generally find price to have a strong negative effect on cigarette consumption. One possible explanation for this is the lack of variability in the price series. We were forced to assume that everyone living in one of Canada's ten provinces in a given year faced the same price, which, especially if true, means that there is not much variation in the price series within the data set.[6]

We also found less effect from the education variables than might have been expected. Having a university or college education has a negative but weak effect across the quantiles, despite having been significant in the OLS equation. One possible explanation is that education has its effect on the decision whether or not to be a non-smoker, which we have not modeled here. An alternative possibility is that, as some of the smoking literature has suggested that education has only a weak effect on smoking behavior (Farrell and Fuchs, 1982), and that the observed negative association between smoking and education is a result of the smoking decision and the education decision both being functions of the degree to which an individual is forward looking. In a regression that estimates only one set of roots for the entire sample, variations in education might proxy for differences in individual forward-looking propensities from the average. The QR approach allows the propensity to be forward looking to vary across equations, which may leave the education variables to reflect only their (weaker) direct effect.

Figures 6 and 7 depict the coefficients on lag and lead consumption. We note that the coefficient on lagged consumption tends to increase over the quantiles while that on lead consumption tends to decrease as we move to higher quantiles. Figure 8 shows the smaller root (addiction effect) and the inverse of the larger root (forward-looking effect). The forward-looking effect is stronger in the lower quantiles of cigarette consumption and decreases as we move to higher quantiles, while the addiction effect is weaker in the lower quantiles, becoming stronger as we move to higher quantiles. This would mean that the dynamics described by the SODE derived from the RA model are consistent with intuition, suggesting that heavier smokers are less forward looking than are lighter smokers.

As noted above however, we have excluded people who reported zero consumption in all four cycles, across 8 years, even though by doing so we risk excluding infrequent consumers who regard their 'typical' consumption as zero.[7] These may, for example, be people who smoke occasionally to relieve stress, but are at the same time extremely sensitive to the possibilities of addiction and of future damage to their health and deliberately reduce their smoking to zero in what they regard as normal, or typical

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[5]Our objective was to estimate the consumption trajectory, which a rational smoker follows, a trajectory which is based on their rate of time preference and their subjective probability of experiencing a health shock. What we have referred to as the cold turkey dummies, capturing downward jumps, are taken to signal that the individuals have had to re-optimize their consumption as a result of a health shock, meaning that their consumption before the drop reflects the solution to a different optimization problem than does their consumption after the drop.

[6]This is a common problem in Canadian micro-econometric cigarette studies. See, for example, Beatty (2008).

[7]We note again that our dependent variable is typical cigarette consumption, not expenditure on cigarettes. The infrequency problem would be expected to be more significant for purchase than for consumption data.
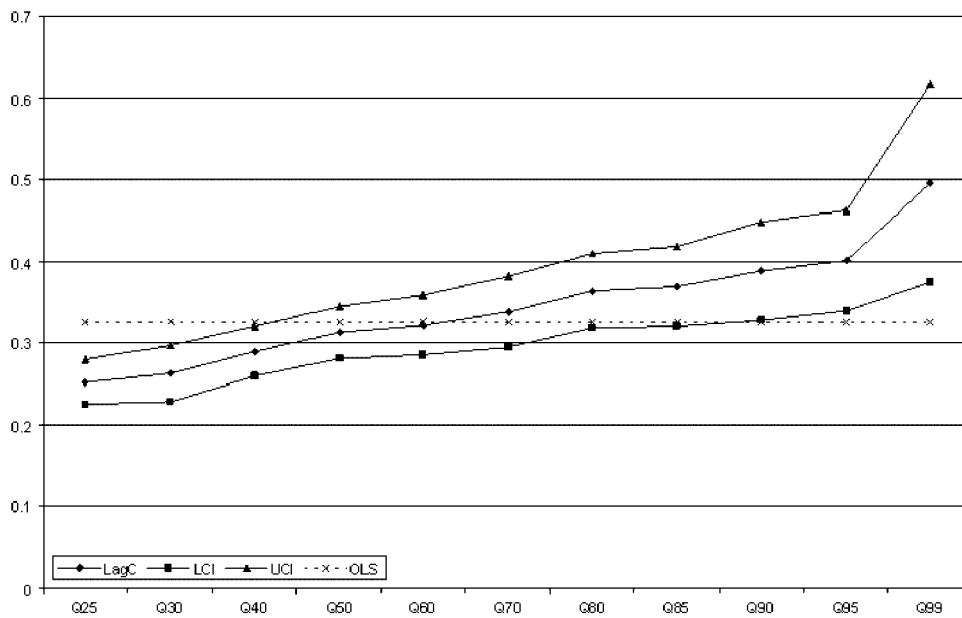
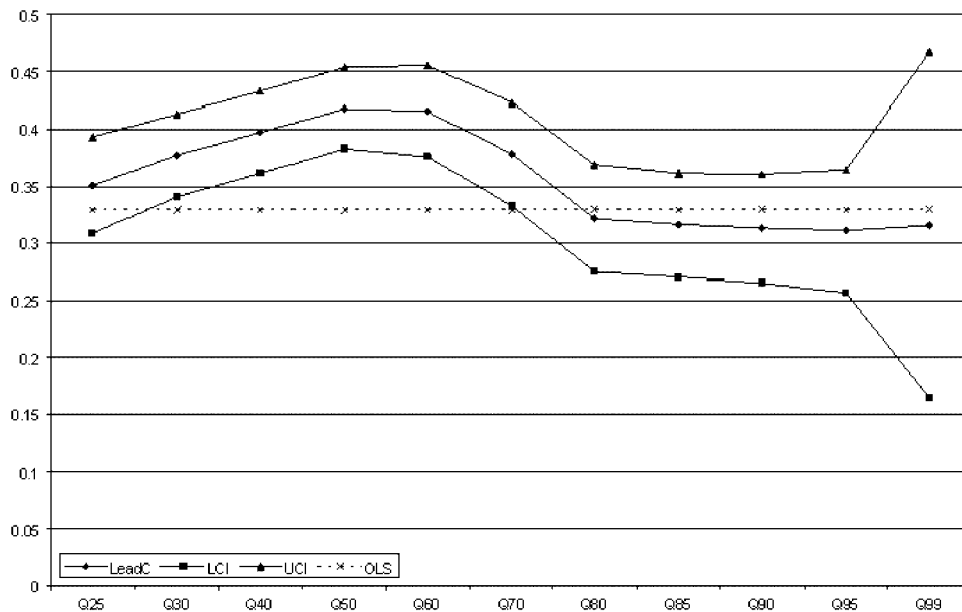Figure 6. Full RA lag C coefficient

Figure 7. Full RA lead C coefficient

times. By excluding them, we may be excluding the most forward looking individuals in our sample and hence underestimating the strength of the forward-looking effect in the bottom quantiles of the distribution of consumption of cigarettes.
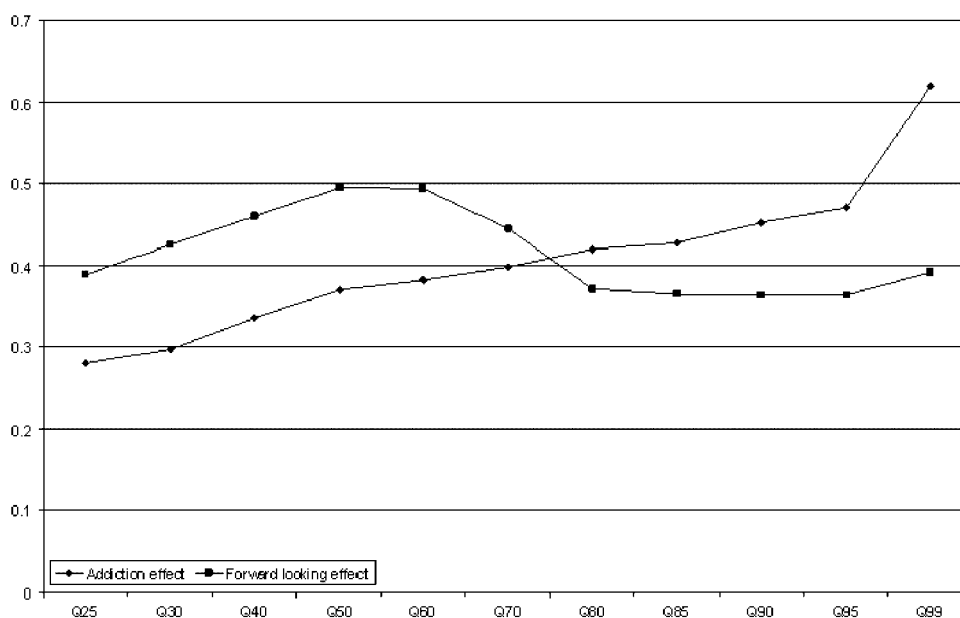
Figure 8. Full RA addictive and forward-looking effects

6. CONCLUSIONS

In this paper, we have estimated trajectories of consumption of cigarettes across the distribution of levels of consumption of cigarettes, to investigate whether differences in levels are systematically associated with differences in forward-looking behavior, the alternative being that the fundamental dynamics of consumption are the same across levels.

The results point to a number of interesting conclusions. Perhaps, most important is that the strength of the forward looking and addictive effects do differ systematically across levels of consumption (controlling for observable individual characteristics). Thus, empirical methods which yield a single average estimated value for each of these effects can be seriously misleading at both the high and low levels of cigarette consumption.

Our results also come down on the side of the literature that suggests that much of the estimated effect of education on smoking is in fact proxying differences in forward and addictive effects. It appears that heavy smokers are systematically less forward looking than lighter smokers independent of factors like education and income.

From a policy point of view, in this exercise, the use of QR proves particularly revealing with respect to the results for the impact of workplace restrictions. They show that while the policy had a significant effect on heavy smokers, its impact on lighter smokers tends to be non-significant. This sets a limit on the effectiveness of workplace restriction policies.

Individual heterogeneity is a matter that has received considerable attention in the literature on the consumption of addictive goods. The focus of this paper has been heterogeneity in the weight that individuals place on the future relative to the present and on the relationship between these differences and levels of consumption. What the theoretical model makes clear, and what we have attempted to highlight in our analytic approach, is that current consumption ought to be thought of as emerging from the relative strengths of the addictive and forward-looking effects. Taken together, the results suggest that in RA models it is well worth going beyond looking at average effects, and that this particular aspect of individual heterogeneity can be made observable. We found this to be true even

after we had excluded never smokers and worked with a sample of smokers. If we are going to estimate a model with lead and lag values of the dependent variable as explanatory variables, we should extract all the information contained in that structure. Our results indicate that evidence about one key aspect of the hypothesis is that there exists a smoking type that can be derived from the RA model if we think of it as an exercise in economic dynamics and analyze it accordingly.

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