Can higher cigarette taxes improve birth outcomes?

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Abstract

This study examines whether higher state cigarette taxes can be used to improve birth outcomes. Data on the outcomes of interest are taken from the 1989–1992 Natality Detail files, generating a sample of roughly 10.5 million births. The results suggest that smoking participation among pregnant women declines and average birth weights rise when excise taxes are increased. These results can be used to form an instrumental variables estimate of the impact of smoking on birth weight. This estimate is remarkably close to numbers from a random assignment clinical trial. The smoking participation price elasticity is estimated to be -0.5. © 1999 Elsevier Science S.A. All rights reserved.

1. Introduction

Low birth weight is an important public health concern.[1] Studies have shown that low birth weight infants face higher risks than other infants do for a variety of health and developmental disorders (Hack et al., 1995; Paneth, 1995). In addition, low birth weight significantly increases the risk of infant mortality. In order to address the problem of low birth weight, the factors that cause infants to be born too small must be identified. A baby may be too small at birth because it grew too slowly in utero, was born too soon, or some combination of the two. Despite

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[1] Low birth weight refers to infants born weighing less than 2500 grams (5.5 lbs).

extensive research, scientists do not have a sound understanding of the complex relationships between the various biological factors that cause slow fetal growth or preterm delivery. While the exact biological relationships may not be known, observational evidence indicate that three of the most important identifiable risk factors associated with low birth weight are low maternal pre-pregnancy weight, low maternal weight gain during pregnancy, and maternal smoking during pregnancy (Shiono and Behrman, 1995). It is interesting to note that all of these risk factors are to some extent self inflicted and as such could possibly be modified by public policy interventions.

The impact of smoking on birth weight is well documented. Studies have consistently found that smoking during pregnancy increases the risk of low birth weight by a factor of two and as a result, smoking accounts for approximately 20% of all low birth weight (U.S. Department of Health and Human Services, 1990). These results have lead some to conclude that smoking is the ''...single largest modifiable risk factor for low birth weight...'' (Shiono and Behrman, 1995, p. 11).

Low birth weight is a costly outcome. Estimates indicate that 35% of the total dollar amount spent in the United States on health care during the first year of life can be attributed to the incremental costs incurred by the 7% of infants that are low birth weight (Lewit et al., 1995). The costs of treating low birth weight infants attributed to smoking are also substantial. In the well-publicized results of Manning et al. (1991), the authors calculate that by excluding the costs of maternal smoking, the average per pack external cost of smoking is 29 cents (in 1991 dollars), which is roughly equal to the average excise tax on cigarettes. When the effects of maternal smoking are considered, the estimate of the optimal tax increases to 45 cents. This estimate does not take into consideration the long-term costs of low birth weight which include continued health care expenditures due to chronic conditions associated with low birth weight, increased schooling costs such as special education and grade repetition, or the increased chance of infant mortality. Hay (1991) estimates that when the long-term costs are included the average external cost of smoking increases to $4.80 per pack.

Much of the government policy aimed at improving birth outcomes has attempted to provide pregnant women with adequate nutrition and access to medical care. The most notable of such policies is the Medicaid expansions of the late 1980's.[2] Although health care providers may counsel against smoking during pregnancy, no public policy to date has attempted to deal directly with maternal smoking as a risk factor for low birth weight. One policy instrument that has been suggested but only indirectly studied is cigarette taxes. There is, however, little empirical evidence that pregnant women are sensitive to changes in the price of cigarettes. Most studies have focused on the population as a whole, not specifically on pregnant women.

In this study, we use birth record data to estimate reduced-form relationships

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[2] For an excellent description of the Medicaid expansions, see Currie and Gruber, 1996. For evaluations of their impact on birth outcomes, see Piper et al., 1990; Currie and Gruber, 1996.

between cigarette taxes and maternal smoking and between cigarette taxes and infant birth weight. Our estimates are the first to show that taxes do alter the smoking behavior of pregnant women and that increased cigarette taxes have a beneficial impact on infant birth weight. These reduced-form relationships are then used to construct an instrumental variable (IV) estimate of the impact of maternal smoking on infant birth weight. The IV estimate of the impact of maternal smoking on birth weight is remarkably close to estimates from a random assignment clinical trial.

The paper is organized as follows. Section 2 describes our statistical model. The birth record and tax data are discussed in Section 3. The main body of evidence is presented in Section 4 where we discuss the reduced-form estimates. In Section 5 we present the instrumental variable results and we compare these estimates to results from a randomized trial. Section 6 summarizes our findings and discusses what conclusions can be drawn from this work.

2. Statistical model

There is a large literature in economics that has examined whether smoking is correlated with taxes and prices. Despite a wide variety in the sources of data and the method of estimation, the results of these studies show that smoking declines in the face of higher taxes and that the demand elasticities typically range from -0.4 to -1.0 (Viscusi, 1992). These studies are not informative about the population we are interested in-pregnant women. In the only other paper to address this subject, Rosenzweig and Schultz (1983) estimate a birth production function with maternal smoking as a health input. In order to control for unobserved health heterogeneity, they use cigarette prices as an instrument for smoking behavior. They do not find a statistically significant relationship between either cigarette prices and maternal smoking or cigarette prices and birth weight.

In contrast, there has been a great deal of evidence that links smoking to birth weight. After reviewing the literature, the Surgeon General (U.S. Department of Health and Human Services, 1990) concluded that smoking during pregnancy decreases average birth weight by 200 g and doubles the chance of a low birth weight delivery. In theory, we could multiply estimates of the impact of taxes on smoking by pregnant women by these values to get a predicted impact of the relationship between taxes and outcomes. However, this average impact may not represent the impact of smoking on birth weight for those women who change their behavior in the face of higher taxes (Imbens and Angrist, 1994).

Consequently, our estimation strategy will be to estimate both steps in the process: the impact of taxes on maternal smoking and the impact of taxes on birth weight.

The primary variables of interest in our models are measures of birth weight (Y), level of smoking during pregnancy (S) and the taxes faced by the women during her pregnancy (T). As we note below, the data set we use contains observations

that vary across individuals, states, and time. Since excise taxes on cigarettes vary across states, in principle, we can use the cross-state variation in taxes to identify the models of interest. We believe that this identification strategy has some potential shortcomings. If the level of taxation in a state is correlated with some underlying characteristics about the state (e.g., states with a small fraction of smokers are more likely to tax cigarettes heavily), then cross-sectional correlations may be subject to an omitted variables bias. As an alternative, we use a within-group estimator where we examine the changes in smoking and birth weights in a state before and after cigarette tax increases. The reduced-form within-group models we estimate can be characterized by the equations

$$S_{ist} = X_{ist}\gamma_1 + T_{st}\gamma_2 + u_{1s} + v_{1t} + \epsilon_{1ist} \tag{1}$$

and

$$Y_{ist} = X_{ist}\theta_1 + T_{st}\theta_2 + u_{2s} + v_{2t} + \epsilon_{2ist} \tag{2}$$

where i, s, t index individuals, states and time, respectively, X is a vector of demographic characteristics, u_j are state-effects, v_j are time effects, and ϵ_{jist} is a random error. In many cases, the outcome of interest is a discrete variable, such as when S measures whether a woman smokes or when Y measures whether a child is of low birth weight. In these cases, we will estimate probit models of the form

$$\text{Prob}(S_{ist} = 1) = \Phi(X_{ist}\gamma_3 + T_{st}\gamma_4 + u_{3s} + v_{3t}) \tag{3}$$

and

$$\text{Prob}(Y_{ist} = 1) = \Phi(X_{ist}\theta_3 + T_{st}\theta_4 + u_{4s} + v_{4t}) \tag{4}$$

where $\Phi()$ is the evaluation of the standard normal cdf. To translate the probit parameters into economically meaningful terms, we calculate the marginal effect of a tax change. For Eq. (3), the marginal effect is defined as

$$\partial \text{Prob}(S = 1)/\partial T = \gamma_4 \phi(\cdot)$$

where ϕ is the evaluation of the standard normal pdf. We evaluate the pdf at the value for a person with a probability of smoking equal to the sample mean $\bar{s}$, or $\phi = \phi(z)$ where $z = \Phi^{-1}(\bar{s})$.

   To facilitate comparisons of our estimates to those from other papers, we translate the estimate from Eqs. (1) and (3) into price elasticities of demand. Since retail prices (P) are a function of the taxes levied on cigarettes, the effect of taxes on smoking behavior can be expressed as $\partial S/\partial T = (\partial S/\partial P)(\partial P/\partial T)$ where $(\partial P/\partial T)$ is the change in price with respect to a change in tax rates. The price elasticity of demand is defined as

$$e_d = \frac{\dfrac{\partial S}{\partial T}}{\dfrac{\partial P}{\partial T}} \frac{\bar{p}}{\bar{s}} \tag{5}$$

where $\bar{p}$ and $\bar{s}$ are average values for price and smoking. Using state-level data on tax and price for the 1977–1992 time period, we regressed the average price of cigarettes on taxes plus state and year effects and obtained an estimate for SP/ST of 1.15, which is similar to estimates found by others (Harris, 1987; Sumner, 1981; Sullivan, 1985; Stern, 1987; Barnett et al., 1995; Keeler et al., 1996).

If taxes alter smoking and improve birth weights, we can potentially use the estimates from these two equations to obtain an estimate of the impact of smoking on birth weight. To see this, note that γ_2 is equal to $\partial S / \partial T$ and the coefficient θ_2 measures the joint product of the impact of taxes on smoking participation and the impact of smoking on birth weight, or $\theta_2 = \gamma_2(\partial Y / \partial S)$. Dividing θ_2 by γ_2 would then provide an estimate of the gradient $\partial Y / \partial S$. More specifically, in the birth weight production function

$$Y_{ist} = X_{ist}\beta_1 + S_{ist}\beta_2 + u_{3s} + v_{3t} + \epsilon_{3ist}, \tag{6}$$

the ratio θ_2 / γ_2 is just the indirect least-squares (instrumental variables) estimate of β_2 when tax is used as an instrument for smoking. One can argue that an OLS estimate of Eq. (6) may produce biased estimates of β_2 if women who smoke tend to have unobservable characteristics that would also adversely impact the growth of their child in utero. The IV estimate of β_2 will be unbiased so long as tax increases are uncorrelated with the unobservable determinants of birth weight, ϵ_{1ist}. This is probably a reasonable assumption. Changing birth weights are typically not given as a reason for changing state cigarette excise tax rates. In general, we can find little statistical evidence that states change taxes based on smoking levels or on changes in smoking rates. To demonstrate this hypothesis we regressed the nominal change in state tax rates over the 1989–1992 time period on the log per capita consumption in 1988. We found no evidence that states with higher levels of consumption in 1988 were more likely to raise taxes over the next 4 years. In addition, we regressed the tax change variable on the difference in log per capita consumption in the 1–5 years prior to 1988. Again, we found no statistically significant relationship between the cigarette tax changes and the per capita growth rate in tobacco consumption. From these results, we can conclude that states do not raise cigarette taxes based on year to year fluctuations in the level or growth rate of smoking in the state.[3]

Fortunately for our research, there is a random assignment clinical trial that allows us to gauge whether the IV estimates are reasonable. Sexton and Hebel (1984) conducted a fascinating experiment where pregnant women who smoked were randomized into either the treatment group where they received standard

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[3]There is another potential link between cigarette taxes and birth outcomes. One might think that cigarette taxes would be correlated with birth outcomes if the state designates some portion of the cigarette tax revenue to tobacco control or cancer control programs. During the time period of our study, only three states in our sample used any excise tax revenue for tobacco programs and only five used the revenue for cancer programs (NCI, State Cancer Legislative Database, Bethesda, MD: SCLD). No state changed their policy along this dimension over the time period of analysis. Subsequently, the state effects should capture the impact of any such program on smoking.

prenatal care and extensive smoking cessation counseling during their pregnancies, or a control group that received only standard prenatal care.[4] Sexton and Hebel found that the smoking cessation intervention was successful. After random assignment, the fraction of women that smoked in the treatment group was 23 percentage points lower than in the control group. Birth outcomes were also better in the treatment group, with birth weights being 92 g higher and low birth weight rates (those <2500 g) being 2.1 percentage points lower than values for the control group. Interestingly, the fraction of very low birth weight babies (<1500 g) increased by 1.1 percentage points.

Permutt and Hebel (1989) used the data from this trial to estimate the impact of maternal smoking on birth outcomes by using the random assignment into treatment as an instrument for smoking behavior. Consider the bivariate regression model

$$y_i = \alpha + \beta x_i + \epsilon_i \tag{7}$$

where y_i is birth weight and x_i is a measure of smoking. Let z_i denote the binary instrument, which is equal to one if the woman received smoking cessation counseling (was a member of the treatment group). The instrumental variable estimate of the effect of smoking in this model is given by

$$\beta_{IV} = [(\bar{y}|z_i = 1) - (\bar{y}|z_i = 0)]/[(\bar{x}|z_i = 1) - (\bar{x}|z_i = 0)] \tag{8}$$

where $(\bar{y}|z_i = 1)$ is the mean of y_i for those observations where $z_i = 1$ and the other terms are similarly defined. This is the now famous Wald estimate that was introduced into evaluation research by Angrist (1990). All terms in the Wald estimate are easily calculated with the data from the random trial. The IV estimates (standard errors) of smoking participation on birth weight, low birth weight, and very low birth weights from the controlled experiment are -400 g (177), 0.091 (0.074), and -0.034 (0.034) respectively. These estimates will provide a useful benchmark for our analysis.

3. Data

3.1. Birth record data

To estimate the models outlined above, data is needed on birth outcomes, maternal smoking, demographic and socioeconomic characteristics of the mother, and the state in which the birth occurred. The data set that we use, The Natality Detail File (National Center for Health Statistics, 1992a,b, 1993, 1994), is a census of births in the United States in a given year. The Natality data are taken directly

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[4] We wish to thank Joshua Angrist for referring us to this article.

from birth records and contain information regarding birth outcomes, demographic characteristics, and maternal smoking, as well as other information.

In choosing the Natality Detail files, we are limited to data from the years 1989 through 1992. Prior to 1989, the smoking information was not reported in the public use tapes and when we began this study, data after 1992 was not yet available. In our sample period, smoking data is not reported in a consistent manner by several states.[5] Births in these states comprise about 24% of all births.

Studies have shown that approximately 20% of women who smoke before pregnancy quit smoking as soon as they learn they are pregnant (National Center for Health Statistics, 1988; Prager et al., 1984). This group of quitters represents nearly 70% of all women who quit smoking during pregnancy (Fingerhut et al., 1990). For the vast majority of women, the decision whether to continue to smoke is made early on in the pregnancy. Therefore, the tax rate that is relevant to the decision is one that is measured near the beginning of pregnancy. We use the tax measured during the month of conception. We estimate the month of conception from data on the month of birth and the clinical estimate of gestation.

Organizing the data by the month of conception illustrates that there is a potential sample selection problem at the beginning and end of the sample. The problem stems from the fact that not all babies conceived in the same month will make it into the sample. For example, most children conceived in April of 1988 will be born in January of 1989, the first month in our sample. Some children, however, will be born before the ninth month of pregnancy and thus, will not be included in our sample. Subsequently, the first few months of the sample contain higher than average birth weights. Likewise, babies born in December of 1992 were conceived at some point between February and August of 1992. The only observations included in the sample for babies conceived in August of 1992 are for those infants that were born preterm. Babies conceived late in our sample have lower than average birth weight. For these reasons, we limit the analysis to the interior months of the sample starting with conceptions in of June 1988 and ending with babies conceived in February of 1992, a total of 45 months. We impose two final restrictions on the data. We restrict the sample to singleton births and births to women 15–44 years of age. Excluding those observations with missing smoking data and imposing the sample restrictions discussed above, the final data contains approximately 10.5 million birth records out of a possible 16 million births over this time period.[6]

The potential covariates included in the Natality data can be broken down into

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[5]States not reporting smoking status (years not reporting) are California, New York, Indiana, and South Dakota (1989–92), Oklahoma (1989–90), Louisiana and Nebraska (1989).

[6]The Natality Detail data contains information on all live births. A small fraction (less than 0.1%) of the observations record birth weights of less than 500 grams. We suspect that some of these values may be recording errors. We have experimented with deleting these observations. The results are virtually identical whether we include these observations or not.

three categories: demographic variables, proxies for socioeconomic status, and other health behaviors. The demographic variables include the age and race of the mother and the sex of the infant. The proxies for socioeconomic status are educational level, marital status, and parity of the birth. The health outcomes include a measure of the adequacy of prenatal care called the Kessner index and a measure of weight gain during pregnancy. There are a number of other covariates that ideally should be included, such as income level or maternal drinking. The Natality data, however, does not provide information on income and the quality of the maternal drinking data is very poor. We will show below that a large number of observations are necessary to identify the impact of taxes on birth outcomes. As such, we are willing to trade off some control variables in order to have an extremely large data set.

The outcome of interest in this study is infant birth weight. We use a variety of measures of this outcome, including a continuous measure in grams and two low birth weight indicators. While we will present results for all three of these measures, we focus primarily on the continuous measure, total birth weight in grams.

Two measures of smoking behavior are reported in the Natality Detail files. The woman's smoking status is obtained from her medical record. If she reports being a smoker, she is then asked to indicate the average number of cigarettes smoked per day during pregnancy. As in any survey that uses self-reported smoking data, there is the possibility that smokers understate cigarette consumption. By chemically testing adults for cotinine, a by product of nicotine, researchers have found that adults tend to accurately report smoking participation (Pojer et al., 1984; Pierce et al., 1987). However, aggregating national surveys of cigarette consumption generates only 60% of cigarette sales indicating that individuals tend to underreport their cigarette consumption (Evans and Farrelly, 1998). Women may underreport their cigarette consumption for a variety of reasons. One possibility is that the negative public sentiment toward smoking in general causes women to lie about their cigarette consumption (Lapham et al., 1991). A second possibility is that some women may be unable to recall accurately how much they smoked on average, especially if they quit smoking during the early months of their pregnancy. Systematic under reporting, such as this, would bias the estimate of the effect of smoking on birth weight. Since smoking participation appears to be more accurately reported in adults, possibly more weight should be given to results from models that use this variable.

3.2. State level tax data

The covariate of interest is the tax on cigarettes during the month the mother conceived. This data is taken from *The Tax Burden on Tobacco* (The Tobacco Institute, 1995). Using the specific date at which the tax rate changed, we can compute monthly observations on excise taxes (state and Federal). In addition,

monthly values of the consumer price index are used to adjust for inflation. The individual level data is merged together with the tax data based on the state where the birth occurred and the month the infant was conceived.[7]

   Table 1 defines the main variables used and reports their sample means and standard deviations. The average birth weight in the sample is 3363 g (7 lbs 6 oz). Approximately 6% of the births are moderately low birth weight (<2500 g) and 1% are extremely low birth weight (<1500 g).[8] Roughly, 17% of mothers report being a smoker with the average number of cigarettes smoked per day is 2.2. This mean, however, includes zeros for all non-smokers. Among smokers, the average number of cigarettes smoked per day is approximately 13.

3.3. A note about sample sizes

   Until very recently there have been modest year-to-year changes in state tax rates on cigarettes. Subsequently, detecting a statistically significant link between taxes and birth weights requires an incredibly large sample. To see this, consider the following simple thought experiment. Suppose taxes are increased for a certain

Table 1
Descriptive statistics, natality detail data, 1989–1992

Variable	Definition	Mean (standard deviation)
Birth weight	Birth weight in grams	3363 (580)
Low birth weight	Indicator variable, =1 if birth weight <2500 grams	0.0595 (0.2366)
Very low birth weight	Indicator variable, =1 if birth weight <1500 grams	0.0102 (0.1005)
Smoker	Indicator variable, =1 if mother smoked during pregnancy	0.1710 (0.3765)
Cigarettes/day	Average cigarettes smoked per day during pregnancy (non-smokers equal 0)	2.2 (5.9)
Cigarettes/day (smokers only)	Average cigarettes smoked per day during pregnancy (excludes non-smokers)	12.8 (8.1)
Cigarette tax	Real state tax per pack (State+Federal) in cents (1982–84 dollars)	30.5 (7.8)

Note: There are 10,571,642 observations in the data set.

[7]The Natality data reports both the state of occurrence of the birth and the state of residence of the mother. In the vast majority of cases, the state of residence and state of occurrence are the same and thus, it does not matter which is used as the basis of the data merge. For those women whose birth does not occur in their state of residence, however, it is difficult to determine the relevant tax rate. We have chosen to use the tax rate from the state of occurrence because it is the only state that we know for certain that the woman was in during the pregnancy.

[8]These numbers are lower than published figures because we delete multiple births.

population by ΔT cents per pack. Let the indicator $t_i = 1$ if woman i was subject to a tax increase and 0 otherwise. The change in birth weight brought about by the tax increase is given by the difference in means $\hat{d}_n = [(\bar{y}|t_i = 1) - (\bar{y}|t_i = 0)]$ and if the number of observations in both the treatment and control samples is equal to n, a consistent estimate of the variance of this estimate is defined as

$$\text{Var}(\hat{d}_n) = \frac{\hat{\sigma}_1^2}{n} + \frac{\hat{\sigma}_0^2}{n} \qquad (9)$$

where σ_t^2, is the variance in birth weight for $t = 0$ or 1. For simplicity, assume $\hat{\sigma}^2 = \hat{\sigma}_1^2 = \hat{\sigma}_0^2$. The magnitude of $\hat{d}_n$ will be a function of (i) the size of the tax change, (ii) the impact if taxes on smoking, and (iii) the impact of smoking on birth weight. Using the notation from the estimation equations outlined previously, $\hat{d}_n = \Delta T \gamma_2 \beta_2$. Noting from Eq. (5) that $\gamma_2 = e_d(\partial P/\partial T)(\bar{s}/\bar{p})$, we can write $\hat{d}_n$ as $\Delta T \beta e_d(\partial P/\partial T)(\bar{s}/\bar{p})$. For the estimate of $\hat{d}_n$ to be statistically significant, it must be the case that $|\hat{d}_n/(2\hat{\sigma}^2/n)^{.5}| > 1.96$ which implies that $n > 2(1.96)^2\hat{\sigma}^2/\hat{d}_n^2$ or $n > 2(1.96)^2\hat{\sigma}^2/[\Delta T \beta_2 e_d(\partial P/\partial T)(\bar{s}/\bar{p})]^2$. Based on our estimates, we set $\partial P/\partial T = 1.15$, ($\bar{p}$) in real 1982–4 dollars is 120 cents, and from Table 1, $\hat{\sigma} = 580$ and $\bar{s} = 0.17$. Among those states that experienced nominal changes in the tax on cigarettes during the 1989 to 1992 period, the average difference in real tax rates (ΔT) between the beginning and end of the sample period is about five cents. A mid-range estimate of the participation elasticity of demand (e_d) is -0.3, and the average of estimates from observational studies and the random assignment clinical trial suggest that smoking reduces birth weight by 300 g (p_2). These numbers would suggest that we would need 4.8 million observations in both the treatment and control group, or 9.6 million observations in all to detect a statistically significant relationship between taxes and birth weight.

While the number of observations from the Natality data appears adequate to detect an impact of taxes on birth weight, the data set is too small to detect a significant impact of taxes on low birth weight frequencies. Suppose smoking increases the probability of a low birth weight birth by 0.06 percentage points which is roughly equal to the sample mean. From Table 1, we note that $\hat{\sigma} = 0.2366$. Holding all other parameters constant, our estimates suggest that given the modest tax changes that occurred over the 1989–1992 time period, we would need 20 million observations in each of the treatment and control groups, or 40 million observations in total to detect a statistically significant impact of taxes on low birth weight rates. Although we do not expect to detect an impact of taxes on low birth weight rate, we still generate estimates for this outcome.

4. The effect of cigarette taxes on maternal smoking behavior

In this section, we present evidence of the impact of cigarette taxes on maternal smoking. We estimate nine variations of the general model. The first three models

use the smoking participation indicator as the dependent variable but vary the covariates. In model (1), we include indicators for age and race of the mother, an indicator for the sex of the child, state and time effects, and the real tax rate. This is a ''basic'' model in that it includes purely exogenous variables. In model (2), we add some socioeconomic variables that have been shown to be correlated with birth weight, including a dummy for whether the mother is married, a set of indicators for years of education, parity of birth fixed-effects, and indicators for the Kessner index of adequacy of prenatal care.[9] These variables, while fixed at the time of the birth, may be correlated with the errors in Eqs. (1) and (2) and therefore, the coefficients on these variables may be subject to an omitted variables bias. Finally, we would like to control for some other health habits of the women. We include a set of indicators for maternal weight gain (the categories are <10 lbs, ≥ 10 and <20, ≥ 20 and <30, ≥ 30 and <40, ≥ 40 and <50, ≥ 60, and weight gain not reported). Although these variables control for the health habits of the mother, it is not clear whether these variables should be included in these models, especially the birth outcome regression. For example, one typical impact of smoking cessation is increased weight gain. If taxes reduce smoking, we may be adding an endogenous variable to the right-hand-side of the outcome equation.

As we noted above, one variable that is in the Natality Detail data is a measure of alcohol consumption during pregnancy. In the 1991 Natality Detail File approximately 1% of women report having consumed alcohol during pregnancy. We believe that this significantly understates the incidence of alcohol consumption. As evidence, calculations using data from the 1991 Behavioral Risk Factor Surveillance System indicate that 12.4% of pregnant women consumed some alcohol during their pregnancy. Subsequently, we have not included the alcohol information into the models.

The first stage estimates indicate that pregnant women are responsive to changes in cigarette taxes. In the first row of Table 2, we report probit estimates of the smoking participation equation. As you move across row 1 of Table 2, it is evident that the effect of the cigarette tax on smoking participation is robust to model specification. As more covariates are added, the absolute value of the marginal effect of taxes increases from 0.00081 to 0.00085. These estimates indicate that a one-cent real tax increase would lead to approximately a 0.08 percentage point reduction in the mean rate of smoking participation. The price elasticity of participation ranges between -0.49 and -0.52 depending on the model specification. The second row of Table 2 reports the estimates from the linear probability model of smoking participation. The linear probability estimates are needed to construct the instrumental variables estimate associated with Eq. (4).

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[9]The Kessner index is a three-point scale that is based on the timing of the initiation of care as well as the number of visits given the length of the pregnancy. Prenatal care usage is coded into three categories: adequate, intermediate, and inadequate. In our estimates we also include an indicator for missing data on adequacy of care.

Table 2
OLS and probit estimates of first-stage equations, natality detail data, 1989–1992

Dependent variable	Estimation method	Independent variable	Probit marginal effects or OLS Estimates		
			Model (1)	Model (2)	Model (3)
Smoker	Probit	*Cigarette tax*	−0.00085	−0.00085	−0.00085
			(−14.68)	(−14.71)	(−14.68)
		Elasticity of demand	−0.49	−0.52	−0.52
Smoker	OLS	*Cigarette tax*	−0.00045	−0.00036	−0.00035
			(−8.95)	(−7.50)	(−7.36)
		Elasticity of demand	−0.27	−0.22	−0.21
		R^2	0.032	0.121	0.126
Cigarettes/day	OLS	*Cigarette tax*	−0.0028	−0.0019	−0.0017
			(−3.64)	(−2.47)	(−2.29)
		Elasticity of demand	−0.14	−0.09	−0.08
		R^2	0.028	0.104	0.106
Cigarettes/day (smokers only)	OLS	*Cigarette tax*	−0.0015	−0.0049	−0.0045
			(−0.55)	(−1.75)	(−1.63)
		Elasticity of demand	−0.01	−0.04	−0.04
		R^2	0.061	0.091	0.094

Note: *t*-statistics in parenthesis. Covariates in model (1) are state, month of conception effects, age, race, Ethnicity, and sex of child effects. Model (2) adds indicators for parity, marital status, education, and adequacy of prenatal care. Model (3) adds indicators for weight gain.

Again, the coefficient estimates of the effect of taxes are robust to the addition of the socioeconomic and health behavior covariates. The linear probability estimates, however, are approximately one half the size of the probit marginal effects. The participation elasticity from the linear probability models ranges between −0.21 to −0.27. This is one case where the linear probability estimates differ in a meaningful way from probit results.

The estimates of the effect of excise taxes on the average number of cigarettes smoked per day are consistent with the finding that pregnant women are responsive to changes in cigarette prices. One puzzling result, however, does arise. The price elasticities of demand that are indicated by this model are smaller than the participation elasticities. It should be the case that the elasticities of demand from the quantity of cigarettes smoked model encompass both the participation effect and the quantity effect. The expected result would thus be that the participation elasticities are smaller than the quantity elasticities. One explanation for the results in this study is that the effect of taxes on smoking works solely through participation. If this is the case, then the two sets of elasticities should be the same. This phenomenon can be investigated by estimating the price elasticity

of demand for cigarettes for a sample that includes only those women who are smokers. The results of this estimation indicate that for those that continue to smoke, taxes do not affect the quantity smoked. As seen in Table 2, we find that for smokers the price elasticity of demand for cigarettes is only -0.01 and is not statistically significant. The reduction in smoking that is found in the full sample appears to be driven entirely by women who quit smoking.

There are two potential problems with our estimates of the impact of cigarette taxes on the smoking participation of pregnant women. First, some authors have noted that the impacts of state taxes may be mitigated by cross-border purchases (Batalgi and Levin, 1986; Coats, 1995). Second, if other state policies related to tobacco are changing at the same time our excise tax coefficient may be picking up the effects of those changes in regulations. We are able to investigate both of these possibilities in our sample.

4.1. Considering the impact of lower taxes in border state

By exploiting the rich geographic information in the Natality Detail data, we can test whether cross-border shopping significantly alters the first-stage estimates reported in Table 2. The data files identify a mother's county of residence for counties with more than 100,000 residents. Restricting the sample to people in these larger counties, we use Bureau of the Census data on the longitudes and latitudes for the geographic centers of counties and calculate the great circle distance to the nearest county in another state. We use the tax in this county as the border tax and let this value be $T_{st}{}^{c}$. The border tax is irrelevant if people live far away from borders or if the tax in the neighboring state is higher than the in-state rate. To capture both of these instances, we constructed two indicators. The first is labeled as C_{ist} and it equals 1 if the geographic center of a county is within 100 kilometers of the geographic center of a county in another state. The second variable D_{ist} equals 1 if $T_{st} - T_{stc} > 0$. Because one of the covariates of interest changes at the county level, the econometric model must now take into considera- tion these county effects. Because of the number of county effects, we are unable to estimate a probit model and instead, focus on linear probability estimates. Controlling for border effects, the basic first-stage relationship is now

$$S_{ist} = X_{ist}\gamma_1 + T_{st}\gamma_2 + (T_{st} - T_{st}^{c})C_{ist}D_{ist}\gamma_3 + u_{1cs} + v_{1t} + \epsilon_{1ist} \qquad (10)$$

where u_{1cs} are the county of residence effects. In this model, if $(T_{st} - T_{st}{}^{c}) < 0$ or $C_{ist} = O$ then $\partial S/\partial T = \gamma_2$ as before. If $(T_{st} - T_{st}{}^{c}) \geq 0$ and $C_{ist} = 1$ then the impact of a tax change is a function of whether it is a state or Federal tax change. In the case of a state tax, the difference between T_{st} and $T_{st}{}^{c}$ will increase and therefore $\partial S/\partial T = \gamma_2 + \gamma_3$. With a Federal tax change since $\partial(T_{st} - T_{st}{}^{c}) = 0$, $\partial S/\partial T = \gamma_2$. To estimate this model, we must make two additional sample selection restrictions. First, we reduce the sample to people who live and give birth in the same county

and we delete people for whom county of residence is not identified. This generates a sample of roughly 7.04 million observations. Most observations were deleted because county of residence was not identified.

Estimating a model identical to model (3) in Table 2 using *Smoker* as the dependent variable, we estimate a coefficient (t-statistic) on the tax variable of -0.00030 (-5.5) which is slightly lower than the estimate of -0.00036 for the full sample. Adding the composite variable $(T_{st} - T_{st}^c) C_{ist} D_{ist}$ and county effects to the model, the coefficients (*t*-statistics) on γ_1 and γ_2 are -0.00034 (-5.7) and 0.00011 (1.3), respectively. Adding these numbers together, the tax gradient on smoking participation falls from -0.00034 to -0.00023 when $C = 1$ and $D = 1$, although we cannot reject the null hypothesis that the presence of lower taxes in nearby counties has no impact on the estimated tax coefficient. Overall, not controlling for border effects does not qualitatively alter the estimates of Eq. (1).

4.2. Considering the impact of changing state tobacco restrictions

Using data from the National Cancer Institute State Cancer Legislative Database we are able to identify changes in state clean indoor air laws that took place during the period of study. Each new law was coded based on the types of restrictions it imposed. The four major categories of clean indoor air restrictions are on government work sites, private work sites, restaurants and malls, and public transportation. An indicator variable was created for each category of restrictions. The indicator is equal to 1 if the state policy regarding smoking in that category of place had changed since the beginning of the period. We estimate a model similar to model (3) in the first row of Table 2 and including the state restriction indicator variables. The marginal effect (*t*-statistic) of the cigarette tax on smoking participation is -0.00081 (-13.9) as compared to -0.00085 (-14.7) in the model that does not control for the changes in state smoking restrictions. The tax coefficient is not simply picking up the impact of changing state regulations.

4.3. The effects of excise taxes on birth weight

Estimates from Table 2 indicate that higher excise taxes will reduce maternal smoking. In this section, we examine whether these tax increases actually translate into better birth outcomes. Such a result can be seen in the reduced-form estimates in Table 3. In the first row of the table, we report nine OLS models using the three different dependent variables and the three model specifications from Table 2. For the discrete outcomes, we also report probit estimates in row 2.

As expected, the reduced-form estimates indicate that taxes have a positive effect on birth weight. In moving from column one to column three in the first row in Table 3, the effect of taxes on birth weight increases slightly. In the first model, a one-cent increase in the state tax rate on cigarettes increases average birth weight

Table 3
OLS estimates of reduced-forms and OLS/IV/sample selection correction estimates of birth outcome equations, natality detail data, 1989–1992

Covariate	Estimation method	Dependent variable is Birth weight			Dependent variable is Low birth weight			Dependent variable is Very low birth weight		
		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Cigarette tax	OLS	0.159 (2.10)	0.203 (2.70)	0.208 (2.83)	4.5E−5 (−1.41)	−5.9E−5 (−1.89)	−4.5E−5 (−1.45)	2.1E−5 (1.54)	3.0E−6 (0.22)	1.3E−5 (0.99)
Cigarette tax	Probit	–	–	–	−4.8E−5 (−1.46)	−5.5E−5 (−1.66)	−4.7E−5 (−1.39)	2.2E−5 (1.56)	1.2E−5 (0.86)	2.3E−5 (1.54)
Smoker	IV	−353 (−2.04)	−564 (−2.54)	−594 (−2.65)	0.098 (1.39)	0.164 (1.83)	0.129 (1.42)	−0.047 (−1.52)	−0.008 (−0.22)	−0.038 (−0.98)
Smoker	OLS	−254 (−550)	−235 (−491)	−233 (−500)	0.055 (281)	0.047 (233)	0.046 (230)	0.0057 (68)	0.0045 (52)	0.0041 (47)
Smoker (Permutt and Hebel)	IV		−400 (−2.26)			0.091 (1.23)			−0.034 (−1.00)	

Note: t-statistics are in parentheses. Covariates in model (1) are state, month of conception effects, age race, Ethnicity and sex of child effects. Model (2) adds indicators for parity, marital status, education, and adequacy of prenatal care. Model (3) adds indicators for weight gain.

by 0.16 g. When the socioeconomic and health behavior covariates are added to the model, the birth weight increase is approximately 0.21 g per one-cent increase in the tax. All of these results are statistically significant.

The results in Table 3 also suggest that higher cigarette taxes decrease the fraction of low birth weight infants, but this estimate is not statistically distinguishable from zero. As we noted above, the lack of statistical significance is expected. The results, however, are of plausible magnitude. Interestingly, comparing the first and second rows of Table 3, the marginal effects from the probit estimation and the linear probability estimates are quite similar.

The impact of taxes on the fraction of extremely low birth weight infants is quite interesting. The estimates in the final three columns of Table 3 suggest that higher taxes actually increase the fraction of these infants. A cynical interpretation of this result would be that smoking actually improves prospects for very low birth weight infants. However, we believe the exact opposite is possibly indicated. Studies have shown that smoking during pregnancy increases the risk of fetal loss (Stein et al., 1981; Ahlborg and Bodin, 1991; Armstrong et al., 1992). This result suggests that if higher taxes reduce maternal smoking then the higher taxes may also change the composition of babies that make it into our sample. The Natality data tapes only include live births. If smoking reduces the chance that a baby is born alive and if these babies are small relative to the population, a tax increase may actually increase the fraction of extremely low birth weight babies by having more infants survive until birth. Since this is a small fraction of children, the changing sample composition may contaminate the very low birth weight results.

5. Two stage least squares – the impact of smoking on birth weight

There is clear scientific evidence of a negative correlation between maternal smoking during pregnancy and infant birth weight. Whether the single-equation estimate of this relationship is an unbiased estimate of the impact of smoking on birth weight is not so clear. It has been argued that smokers have different discount rates than non-smokers (Farrell and Fuchs, 1982; Evans and Montgomery, 1994). If smokers put less value on the future, they may be more likely to have other bad habits that will affect their long-term health. If the smoking participation indicator is a proxy for the discount rate, the single equation estimate will overstate the effect of smoking on birth weight. It is also possible that the unobserved health habits may modify the effects of smoking on birth weight. In this case, the direction of the bias of the single equation estimate will be ambiguous because the relationship between smoking participation and the unobserved characteristics is unknown. In this section, we use the reduced-form estimates from the previous section to isolate the effect of maternal smoking on birth weight. In this case, we use the variation in smoking generated by changes in state excise taxes as an instrument for smoking in a birth weight production function. Since the model is exactly identified, the IV estimates are simply the ratio of the tax coefficients in the

birth outcomes and smoking participation linear probability models. The *t*-statistics for the IV estimates are calculated using the delta method.

The instrumental variable (IV) estimates of Eq. (6) are presented in the third row of Table 3. The first three columns present the IV estimates from the birth weight equations. The estimates of the moderately and extremely low birth weight indicator equations are presented in the following six columns. The effect of smoking participation on infant birth weight from model (1) indicates that smoking during pregnancy causes mean birth weight to decrease by approximately 356 g (13 ounces). The estimates from models (2) and (3) find even larger reductions in birth weight due to maternal smoking. It is interesting to note that the IV estimates are larger in magnitude than what has typically been found in single equation studies. As a basis of comparison, we estimate a single equation model of the effect of smoking participation on birth outcomes. These single equation estimates (*t*-statistics) are found in the fourth row of Table 3 and range between −233 (−500) and −254 (−550) g in the birth weight equations. A possible explanation for the relative magnitudes of the estimate is that an increase in cigarette taxes leads those with the highest marginal benefit of reducing cigarette consumption to quit. As a result, the instrumental variable estimate would be larger than the ordinary least squares estimate. We note; however, that because the OLS estimate of taxes on smoking participation is small relative to the probit model, then the IV estimates may be overstated. In the end, we cannot reject the null hypothesis that the OLS estimates are an accurate estimate of the impact of smoking on birth weight.

Although the precision of the instrumental variable estimates seems low based on the number of observations used in the study, recall the earlier simulation. The simulation indicated that approximately 10 million observations would be needed in order to identify an effect of the magnitude we found. After imposing the necessary sample restrictions, the data set used contains more than 10.5 million observations. Thus, absolute values of *t*-statistics in the 2 to 3 range on the coefficient of smoking participation in the birth weight equation is about as high as we can reasonably expect to obtain.

In the final row of Table 3, we report the IV estimates of the impact on smoking on the outcomes from the random assignment trial as discussed by Permutt and Hebel. Two results are of interest. First, note that in most cases the results we generate using taxes as an instrument are close to the estimates in Permutt and Hebel. The IV estimates for model (1) for the three outcomes are quite close to the Permutt and Hebel estimates. As we add more controls, however, this difference increases in absolute value. For example, the results in columns (1) and (2) differ from the Permutt and Hebel estimates by −12 and 41% respectively. Second, the surprising result of a negative relationship between smoking and very low birth weight is replicated in the random assignment trial as well.

We should caution that there is however, no reason why the IV estimates should be the same across the two data sets since the instrument is very different. Angrist et al. (1996) show that the IV estimate can be thought of as the average treatment

effect for those whose behavior was changed as a result of receiving the instrument. In the case of the random trial, women were encouraged to quit through the actions of health care providers. One may surmise that the women who would quit smoking because of a small change in price may be similar to those who would quit based on the recommendation of a doctor or nurse. We do however, believe that the similarity in the magnitude of these results is encouraging.

6. Summary and conclusions

In this paper, we estimate the causal relationships between cigarette taxes, maternal smoking behavior, and birth outcomes. We are the first to show that pregnant women are responsive to changes in cigarette tax rates. The smoking participation price elasticity is roughly -0.50. This estimate appears to be robust to the inclusion of detailed controls for mother's characteristics as well as health habits, plus controls for cross-border shopping and state clean indoor air restrictions. We are also able to show that increases in cigarette tax rates have a beneficial impact on mean birth weight. Using these two reduced-form relationships, we construct an instrumental variable estimate of the impact of smoking during pregnancy on birth weight. Our estimates are larger in magnitude than estimates from other observational studies, however, they are quite similar to estimates from a randomized controlled trial.

To put these results into perspective, consider the impact on maternal smoking from a recent bill proposed by Senator John McCain of Arizona that would raise cigarette taxes by $1.10 over a period of years. To simplify the problem, we will assume the tax hike happens in 1 year. In 1982–4 dollars, the $1.10 tax hike would increase taxes by $(110/1.622) = 67.8$ cents per pack. Using the results from model (3) from the smoking participation probit, a 67.8 cent tax hike would reduce maternal smoking by about 5.5 percentage points, which is a 32% reduction in smoking. Using the results from model (3) in the low birth weight probits from Table 3, the tax hike will reduce low birth rates by.32 percentage points which is a 5% reduction. The smaller size of the impact of taxes on birth outcomes is not surprising given the fact that taxes can only alter the behavior of the 17% of pregnant women who smoke.

Acknowledgements

References

Ahlborg, G., Bodin, L., 1991. Tobacco smoke exposure and pregnancy outcome among working women. American Journal of Epidemiology 133, 338–347.

Angrist, J.D., 1990. Lifetime earnings and the Vietnam-era draft lottery: evidence from Social Security administrative records. American Economic Review 80, 313–336.

Angrist, J.D., Imbens, G.W., Rubin, D.B., 1996. Identification of causal effects using instrumental variables. Journal of the American Statistical Association 91, 444–455.

Armstrong, B.G., McDonald, A.D., Sloan, M., 1992. Cigarette, alcohol, and coffee consumption and spontaneous abortion. American Journal of Public Health 82, 85–90.

Batalgi, B.H., Levin, D., 1986. Estimating dynamic demand for cigarettes using panel data: the effects of bootlegging, taxation and advertising reconsidered. Review of Economic and Statistics 68, 148–155.

Barnett, P.G., Keeler, T.E., Hu, T., 1995. Oligopoly structure and the incidence of cigarette excise taxes. Journal of Public Economics 57, 457–470.

Coats, R.M., 1995. A note on estimating cross-border effects of state cigarette taxes. National Tax Journal 48, 573–584.

Curie, J., Gruber, J., 1996. Saving babies: the efficacy and cost of recent changes in the Medicaid eligibility of pregnant women. Journal of Political Economy 104, 1263–1296.

Evans, W.N., Farrelly, M., 1998. The compensating behavior of smokers: taxes, tar and nicotine. RAND Journal of Economics 29, 578–595.

Evans, W.N., Montgomery, E., 1994. Education and health: where there's smoke there's an instrument. National Bureau of Economic Research, Working Paper Number 4949.

Farrell, P., Fuchs, V.R., 1982. Schooling and health: the cigarette connection. Journal of Health Economics 1, 217–230.

Fingerhut, L.A., Kleinman, J.E., Kendrick, J.S., 1990. Smoking before, after, and during pregnancy. American Journal of Public Health 80, 541–544.

Hack, M., Klein, N.K., Taylor, G., 1995. Long-term developmental outcomes of low birth weight infants. The Future of Children 5, 19–34.

Harris, J.E., 1987. The 1983 increase in the federal cigarette excise tax. In: Summers, L.H. (Ed.), Tax Policy and the Economy. Vol. 1. MIT Press, Cambridge, MA.

Hay, J., 1991. The harm they do to others: A primer of the external costs of drug abuse. In: Kraus, M.B., Lazear, E.P. (Eds.), Searching for alternatives: Drug control policy in the United States. Hoover Institution Press, Stanford, CA, pp. 200–225.

Imbens, G., Angrist, J.D., 1994. Identification and estimation of local average treatment effects. Econometrica 62, 467–476.

Keeler, T.E., Hu, T., Barnett, P.G., Manning, W.G., Sung, H.Y., 1996. Do cigarette producers price-discriminate by state? An empirical analysis of local cigarette pricing and taxation. Journal of Health Economics 15, 499–512.

Lapham, S.C., Kring, M.K., Skipper, B., 1991. Prenatal behavioral risk screening by computer in a health maintenance organization-based prenatal clinic. Journal of Obstetrics and Gynecology 165, 506–514.

Lewit, E.M., Baker, L.S., Corman, H., Shiono, P.H., 1995. The direct costs of low birth weight. The Future of Children 5, 35–51.

Manning, W.G. et al., 1991. The costs of poor health habits. Harvard University Press, Cambridge, MA.

National Center for Health Statistics, 1992a. Natality Detail File, 1989. National Center for Health Statistics, Hyattsville, MD.

National Center for Health Statistics, 1992b. Natality Detail File, 1990. National Center for Health Statistics, Hyattsville, MD.

National Center for Health Statistics, 1993. Natality Detail File, 1991. National Center for Health Statistics, Hyattsville, MD.

National Center for Health Statistics, 1994. Natality Detail File, 1992. National Center for Health Statistics, Hyattsville, MD.

National Center for Health Statistics, 1988. Health promotion and disease prevention, 1985. Vital and Health Statistics, Series 10., No. 163, Public Health Service. DHHS Publication No. (PHS) 88-1591. National Center for Health Statistics, Hyattsville, MD.

Paneth, N.S., 1995. The problem of low birth weight. The Future of Children 5, 19–34.

Permutt, T., Hebel, J.R., 1989. Simultaneous equation estimation in a clinical trial of the effect of smoking on birth weight. Biometrics 45, 619–622.

Pierce, J.F., Dwyer, T., DiGiusto, E., et al., 1987. Cotinine validation of self-reported smoking in commercially run community surveys. Journal of Chronic Diseases 40, 689–695.

Piper, J., Ray, W.A., Griffin, M.R., 1990. Effects of Medicaid eligibility expansion: prenatal care and pregnancy outcome in Tennessee. J Am Med Assoc 264, 2219–2224.

Pojer, R., Whitfield, J.B., Poulos, V., Eckhardt, I.F., Richmond, R., Hensley, W., 1984. Carboxyhemoglobin, cotinine, and thiocyanate assay compared for distinguishing smokers from nonsmokers. Clinical Chemistry 30, 1377–1380.

Prager, K., et al., 1984. Smoking and drinking behavior before and during pregnancy of married mothers of live-born infants and stillborn infants. Public Health Reports 99, 117–127.

Rosenzweig, M.R., Schultz, T.P., 1983. Estimating a household production function heterogeneity, the demand for health inputs, and their effects on birth weight. Journal of Political Economy 95, 723–746.

Sexton, M., Hebel, J.R., 1984. A clinical trial of change in maternal smoking and its effects on birth weight. J Am Med Assoc 251, 911–915.

Shiono, P.H., Behrman, R.E., 1995. Low birth weight: analysis and recommendations. The Future of Children 5, 4–18.

Stein, Z., Kline, J., Levin, B., 1981. Epidemiology in human reproduction. In: Berg, G.G., Maille, H.D. (Eds.), Measurement of Risks. Plenum Press, New York, pp. 163–183.

Stern, N., 1987. The effects of taxation, price control, and government contracts in oligopoly and monopolistic competition. Journal of Public Economics 32, 133–158.

Sullivan, D., 1985. Testing hypotheses about firm behavior in the cigarette industry. Journal of Political Economy 93, 586–598.

Sumner, D.A., 1981. Measurement of monopoly behavior: an application to the cigarette industry. Journal of Political Economy 89, 1010–1019.

Tobacco Institute, 1995. Tax burden on tobacco, vol. 30, Tobacco Institute, Washington, DC.

US Department of Health and Human Services, 1990. The Health Benefits of Smoking Cessation. DHHS Publication (CDC) 90-8416. Office of Smoking and Health, Department of Health and Human Services, Rockville MD.

Viscusi, W.K., 1992. Smoking: Making the Risky Decision. Oxford University Press, New York.