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Tobacco Use as Response to Economic Insecurity: Evidence from the National Longitudinal Survey of Youth*

Michael G. Barnes and Trenton G. Smith

Abstract

Emerging evidence from neuroscience and clinical research suggests a novel hypothesis about tobacco use: consumers may choose to smoke, in part, as a "self-medicating" response to the presence of economic insecurity. To test this hypothesis, we examine the effect of economic insecurity (roughly, the risk of catastrophic income loss) on the smoking behavior of a sample of male working-age smokers from the 1979 National Longitudinal Survey of Youth (NLSY79). Using instrumental variables to control for unobserved heterogeneity, we find that economic insecurity has a large and statistically significant positive effect on the decision to continue or resume smoking. Our results indicate, for example, that a 1 percent increase in the probability of becoming unemployed causes an individual to be 2.4 percent more likely to continue smoking. We find that the explanatory power of economic insecurity in predicting tobacco use is comparable to (but distinct from) household income, a more commonly used metric.

KEYWORDS: cigarettes, stress, self-medication, unemployment, poverty

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The believing we do something when we do nothing is the first illusion of tobacco.
--Ralph Waldo Emerson (1913, p. 251)

Introduction

In 1964, U.S. Surgeon General Luther Terry issued his landmark report, *Smoking and Health*, providing authoritative confirmation of the conclusion many public health experts had reached years before: that cigarette smoking is hazardous to your health (USPHS 1964). In the intervening decades, Terry's warning has been followed by a cascade of cultural and institutional changes that have combined to make smoking tobacco costly, inconvenient, and—in many circles—socially unacceptable (Brandt 2007). Yet 21% of American adults still smoke on a regular basis.[1]

To be sure, there is an important sense in which this observation is unsurprising. Smoking is for many people a pleasurable activity, and economic theory would predict that as the effective price of that activity rises, participation rates will fall—but not necessarily to zero. This point has been made repeatedly in the economics literature, much of which has focused on the habit-forming properties of tobacco, which would seem to imply (at a minimum) interesting dynamic properties of this particular consumer behavior.[2] But the dramatic drop in the incidence of smoking in the U.S. (relegating the practice, presumably, to individuals with strong personal or psychological motivation to smoke), together with advances in neuroscience (which are making it possible to reconcile the various biological, psychological, and economic aspects of tobacco use) present an important opportunity to delve a little deeper into a simple question: *why* do people smoke?

Our approach in this article is to focus on a particular hypothesis: that individuals faced with economic insecurity are more likely to smoke.[3] The main obstacle to empirical investigation of this question is the likely presence of confounding unobserved individual characteristics (such as peer group effects) that might affect both smoking behavior and socioeconomic outcomes. We address this problem in two ways: first, by excluding from our analysis all individuals who had not begun smoking prior to the beginning of our sample

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[1] See USDHHS (2007, Table 25). In contrast, approximately 47% of adults smoked cigarettes in 1955 (USPHS 1964).

[2] For a recent review, see Ciccarelli et al. (2007) and references therein.

[3] Though we will provide a brief sketch of some of the evidence that leads us to examine this question, a broader review of the related literature is provided in Smith (2009).

window (thus eliminating from consideration the "smoking initiation" decision likely to be heavily influenced by unobservables), and second, by exploiting geographic variation in local labor market conditions as a source of exogenous variation in experienced economic insecurity.

Background

Self-medication and subjective beliefs about economic insecurity

In a provocative article published more than a decade ago, Pomerleau (1997) reviewed evidence that as public health campaigns have decreased the incidence of cigarette smoking in the U.S., tobacco use has been increasingly concentrated in a number of specific populations, including those suffering from certain psychiatric disorders.[4] Noting that many of the afflictions suffered by these individuals are at least partially ameliorated by smoking, the author suggests that there might be an important sense in which these individuals were using cigarettes as a form of self-medication.[5]

The notion of tobacco use as self-medication is intriguing, but offers little in the way of *ex ante* behavioral hypotheses until it is placed in naturalistic perspective. Smoking, after all, triggers a cascade of physiological, psychological, and behavioral changes in the user, and neuroscience is shedding new light on the natural history of the affected molecular systems. In particular, it is often possible to interpret biochemical events in the brain (with the corroboration of physiological and psychological effects) as representing changes in what economists would call the consumer's *subjective beliefs*.[6] A full review of the effects of smoking on brain activity and behavior is beyond the scope of this article; however, a recent pharmaceutical innovation will serve to illustrate.

The form of depression known as *seasonal affective disorder* (SAD) is characterized by an increase in appetite, weight gain, and excessive sleep (Magnusson and Boivin 2003). Thought to be the human analogue of the winter fattening seen in many foraging animals, SAD represents—in a strictly behavioral sense—a clear-cut subjective belief: *food supplies will soon be scarce, so do what is needed to prepare*. While the leading medical treatment has long been

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[4] These include: depression, attention deficit-hyperactivity disorder, anxiety disorders, and bulimia. Pomerleau also notes the elevated use of tobacco by individuals of low socioeconomic status.

[5] The medical benefits of smoking have been noted elsewhere. Torrey (1830), for instance, declared in his classic compendium of moral advice, "We shall not refuse tobacco the credit of being sometimes medical, when used temperately, though an acknowledged poison" (p. 34).

[6] This argument is made most plainly in Smith (2009); but see also Smith and Tasnádi (2007).

exposure of the patient to carefully timed bursts of artificial light, an antidepressant drug—*bupropion*—has recently been identified as an effective pharmaceutical treatment. Bupropion is thought to influence the metabolism of the neurotransmitters dopamine and norepinephrine in the human brain, and its effects include appetite suppression, weight loss, and insomnia (Dhillon et al. 2008). In other words, bupropion can arguably be said to alter the patient's subjective beliefs as follows: under the influence of bupropion, patient behavior and physiology are consistent with the belief that food supplies are in fact *not* at risk in the coming months.

Though manufacturer Glaxo Wellcome was presumably thrilled at the established efficacy of bupropion as an antidepressant, more good news was on the way. In addition to reporting relief from depression, patients in early trials reported an unexpected side effect: while taking the drug, they lost interest in smoking (Wilkes 2006). The effect was confirmed in later studies, and bupropion is now the leading non-nicotine smoking cessation drug (Hatsukami and Mooney 1999). It seems natural to conclude from these facts—together with the facts that smoking negatively affects weight and appetite,[7] that smoking is associated with "stress"[8] and poverty[9]—that the neurological "subjective belief" induced by smoking is similar to that of bupropion: all is well, and famine is not imminent. And if this conjecture—that smoking induces a specific subjective belief with respect to future material well-being—is correct, it may tell us something about *who* will be more likely to smoke. In particular, it leads us to hypothesize that individuals faced with financial or economic insecurity might react by "self-medicating" with tobacco.[10]

Relation to economic theories of cigarette demand

The question of the effect of economic insecurity—which we define, roughly speaking, as the subjective risk of catastrophic income loss—on household demand for cigarettes has not been directly addressed by previous economic studies. Rather, the literature has focused on the effects of variation in prices;

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[7] See Klesges et al. (1989), Wee et al. (2001), Honjo and Siegel (2003), Chou et al. (2004), Cawley et al. (2004), and Robb et al. (2008).

[8] See, for instance, Schachter et al. (1977), Mangan and Golding (1978), Ashton and Stepney (1982), Siahpush et al. 2005, and Morissette et al. (2007).

[9] See, for instance, Ashton and Stepney (1982), Ross and Wu (1995), Kirsch (1999), and Mulatu and Schooler (2002). The association with poverty does not necessarily imply a pure income effect—indeed, more careful analyses nearly always find that tobacco use increases with income (Gallet and List 2003)—but could reflect some other underlying factor. We argue that economic insecurity should be considered a leading candidate.

[10] It is possible, of course, to view weight gain in a similar light. See Smith et al. (2009) for an examination of the empirical relationship between economic insecurity and body weight.

income; and public policies such as excise taxes, restrictions on advertising, and indoor clean air regulations—often with special attention to the habit-forming nature of tobacco consumption (Gallet and List 2003, Goel and Nelson 2006). Nevertheless, the theory underlying more conventional approaches to the study of cigarette demand is not unrelated to our hypothesis. In the "rational addiction" view of tobacco use, for instance, the consumer's decision to initiate smoking represents a trade-off between the various present and future costs and benefits of adoption (Becker and Murphy 1988). Under rational addiction, it seems reasonable to expect that economic insecurity (interpreted as prospective income loss) might affect current consumption via pure income effects. That is, if cigarettes are a normal good (as suggested by the vast majority of empirical estimates; see Gallet and List 2003), then economic insecurity should *decrease* cigarette consumption—in contradiction to the "self-medication" hypothesis we propose.[11] While a considerable empirical literature has examined the hypothesis that smokers will adjust current consumption in response to information about future prices (Becker, Grossman, and Murphy 1994; Gruber and Köszegi 2001), we know of no explicit attempt to examine the impact of changes in expected future *income* on current smoking behavior.[12]

Relation to psychological aspects of nicotine addiction

Smoking is also often discussed in the context of the study of more explicitly psychological aspects of consumer behavior, such as hyperbolic discounting (Laibson 1997; see also Fuchs 1980), cue conditioning (Laibson 2001), and hot/cold emotional states (Sayette et al. 2008). We do not discount the importance or prevalence of these subjective phenomena, but because we cannot observe them directly in our data, we treat them as unobserved proximate mechanisms. The same holds true for mental illnesses such as depression, which are often discussed in the context of self-medication and tobacco use (Quattrocki et al. 2000). In other words: we aim to test the hypothesis that economic insecurity will cause tobacco use to increase. It may well be true that the mechanism(s) by which this occurs include depression, or time-inconsistent

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[11] A similar conclusion is reached if the insecurity effect is viewed as providing a savings motive: that is, prospective income loss might be expected to induce diversion of additional disposable income to savings, thus decreasing current consumption (including cigarettes).

[12] Partial exceptions are found in Ruhm (2000, 2005), which examine the effects of macroeconomic conditions on cigarette use, finding that cigarette use decreases during economic downturns. But these studies do not examine the effects of individual-level economic insecurity on smoking behavior, thus possibly confounding insecurity with pure income effects—not to mention the distinct effect of current (rather than prospective) unemployment on relative prices, including the opportunity cost of time.

behavior, or increased sensitivity to cues. But we observe only the behavior (smoking) and the economic circumstance in which the behavior occurs (employment & income history). In order to eliminate the possibility that these proximate "psychological" phenomena do not exert independent influences on the individuals in our sample, our empirical strategy aims to control for unobserved heterogeneity.

Empirical Model

We employ individual-level panel data from the National Longitudinal Survey of Youth (1979) to estimate the following linear model:

$$S_{1998,i} = ES_i\alpha + X_{j,i}\delta + \varepsilon_i$$

where $S_{1998,i}$ is a binary variable indicating whether an individual smokes daily in 1998, ES_i is a proxy for individual i's degree of economic security, $X_{j,i}$ is a vector of demographic, individual, state, and regional variables for individual i in year j, and ε_i is the disturbance term. Robust standard errors are adjusted for within-state correlation.

Two approaches are used to estimate this model. The first approach used is the linear probability model. The linear probability model is chosen over logit or probit for several reasons. First, like logit and probit, the estimated coefficients for the linear probability model are unbiased and consistent (Wooldridge 2002). Although predicted values from the linear probability model may lie outside the limits of probability, predicted values at the center of the distribution should not have this problem (Maddala 1983). Consequently, estimates of the partial effects at the center of the distribution are thought to be acceptable (Wooldridge 2002). In our model, approximately 90 percent of the predicted values fall within the unit interval [0,1], suggesting that there should not be a problem interpreting results at the mean. Furthermore, IV-logit approaches (Maddala 1983, Rivers and Vuong 1988) fail to generate consistent standard errors (Chen 2003 and Bollen et al. 1995), a problem that is avoided when using instrumental variables with the linear probability model.[13]

It is well-known that the linear probability model generates biased estimates in the presence of endogeneity stemming from reverse causality or unobserved personal characteristics. For example, we use information about a respondent's employment history as a proxy for his expectation about the future probability of job loss occurring. If (as seems likely) people who smoke are more likely to have

[13] As a test of robustness, we did re-estimate all regressions using the corresponding probit specifications. In nearly every case, the coefficients of interest had the same sign and were larger in magnitude when compared to the corresponding linear probability estimates, but the estimates were less precise. These results are available from the authors upon request.

lower wages[14] or to become unemployed—either because employers discriminate against smokers (reverse causality) or because certain personality traits are conducive to both smoking and negative employment outcomes (unobserved heterogeneity)—then the linear probability estimates of α will be biased.

As noted above, we control for endogeneity bias in two ways. First, we exclude from our analysis all individuals who had not begun smoking daily prior to 1983. This isolates the "smoking initiation" decision (which is likely to be heavily influenced by permanent unobserved personal characteristics such as family background and peer effects) from the "smoking continuation" decision (which is perhaps more likely to be influenced by exogenous changes in economic circumstance).

We address remaining endogeneity with instrumental variables (IV) specifications (detailed below).[15] Because many of our equations are over-identified, we use the two-stage Generalized Method of Moments (GMM) estimator in the IV analyses, as described by White (1982) and Davidson and MacKinnon (1993, p. 599).

Data

Our primary data source is the *National Longitudinal Survey of Youth, 1979 Cohort* (NLSY79). Originally designed as a labor market survey, NLSY79 follows an initial cohort of 12,686 individuals born between 1957 and 1964. Our model specification covers a time period of sixteen years from 1983 to 1998. 1983 was chosen as the initial year of interest because in 1983 all the respondents are at least eighteen years old. This age is significant because it is the age at which subjects presumably assume a certain level of economic independence—including exposure to economic insecurity. The rich employment and income histories available in NLSY79 allow us to develop proxies for the beliefs individuals form from these experiences, and thus to estimate the effect of those beliefs on smoking behavior at the end of the period (1998). We exclude women from our analysis for three reasons. First, labor supply decisions for men are more uniform than those of women, particularly as our sample is composed of individuals aged 18-40, prime childbearing years. Second, smoking in women may be partly related to fertility decisions, and these decisions are also likely to be related to economic variables. Third, the economic security of women in the

[14] Levine et al. (1997) find some evidence that—after controlling for unobserved heterogeneity—smoking reduces wages by 4-8%.

[15] Another way to get at unobserved heterogeneity would be to allow for individual fixed effects in a panel specification. Unfortunately, questions about respondent tobacco use are sporadic and inconsistent in NLSY79, making such a specification infeasible.

NLSY79 cohort is more dependent on spousal income than it is for men, and spouse-level indicators of economic insecurity are not reported as comprehensively in NLSY79 as the individual-level indicators we utilize.

Several demographic and individual-level variables that are expected to play a role in determining smoking behavior are included in our empirical analysis. They include: family income, age, race, weight, height in 1985, a dummy variable indicating whether the respondent lives in a metropolitan area, marital status, family size, years of schooling, and the years of schooling their mother completed. Unless otherwise specified, each variable is as reported for the year 1998. The means and standard deviations for all the variables used in the regression analysis are reported in Tables 1a-1d.[16]

Several state and regional variables are included in our analysis. They include state cigarette prices (in cents), clean indoor-air laws,[17] state median home income, local unemployment rates from 1983-1998, a regional dummy variable, and state averages and median values (generated from the NLSY79 sample) for the number of drops in real income and the probability that a family's income falls below the poverty threshold.

Because economic insecurity is inherently difficult to measure,[18] and because no consensus measure of insecurity has emerged in the literature, we construct three alternative measures of economic insecurity. The first proxy for economic insecurity is an individual's posterior probability of unemployment. This measure is formed by using a Bayesian updating process on unemployment history and is effectively called the Bayesian posterior probability of unemployment. The posterior probability is calculated using a five-year (1994-1998) history of weekly data on employment status available in NLSY79 with prior distributions generated from the full sample of NLSY79 men (see Data Appendix for details).[19] The average posterior probability of unemployment is 0.050 for smokers and 0.028 for former smokers.

The second proxy for economic insecurity measures the probability that an individual's family income falls beneath the specified poverty threshold. This

[16] A complete description of variables that were calculated or obtained from a source other than NLSY79 is found in the Data Appendix.

[17] An index of state clean-indoor air laws similar to that discussed by Chaloupka and Grossman (1996) is used. Higher values indicate greater restrictions on smoking in the state.

[18] The difficulty arises because we view "economic insecurity" as a subjective belief about the risk of income loss. Conventional measures such as current poverty or employment status are poor proxies for this because they i) lack information about the subject's life experience, and ii) are necessarily confounded by contemporaneous changes in income and time constraints.

[19] The sample median tenure with a given employer in the NLSY79 sample is four years, with the mean being six.

Table 1a: Means and Standard Deviations of Individual and State Characteristics NLSY79 Male Smokers and Former Smokers in 1998

Characteristic	Mean	Standard Deviation
Smoke daily in 1998	0.5193	0.4999
Family income (in $1000) in 1998	51.908	46.671
Posterior probability of unemployment	0.0393	0.0949
Probability of being below the poverty level	0.0480	0.1410
Number of Drops greater than 10% in Real Family Income, 1983-1998	2.9801	1.4269
State clean air regulations in 1998	3.3190	2.3200
Avg. state price of cigarettes (in dollars) in 1998	2.3407	0.2811
Years of education completed in 1998	12.516	2.2923
Years of education respondent's mother completed, 1979	10.953	3.0512
Family size in 1998	3.0352	1.6682
Age in 1998	37.019	2.2714
Weight in 1998 (in pounds)	191.24	37.012
Height in 1985 (in inches)	67.794	3.1643
Black	0.2497	0.4331
Hispanic	0.1536	0.3608
White	0.5967	0.4908
Married	0.5686	0.4956
Never Married	0.2227	0.4163
Divorce or separated	0.2028	0.4023
Widowed	0.0059	0.0764
Live in Metropolitan Area	0.7022	0.4575

N=853
Sources: See Data Appendix.

variable was generated as follows (see Data Appendix for details): First, each individual's history of annual family income is regressed on a time trend for the 16-year period of interest. Then, assuming a Gaussian error structure, we calculate the probability of falling below the poverty line. This variable captures income volatility faced by the individual due to employment history, changes in hourly wages, and changes in household composition that might result from exogenous shocks to the local economy, but are not captured by our other measures of insecurity. The average probability of falling into poverty is 0.052 for smokers, and 0.044 for former smokers.

Our final proxy for economic insecurity is the number of drops in annual real income greater than 10 percent over the 16-year study period. In accordance with our economic insecurity hypothesis, we expect that individuals with more drops in

Table 1b: Means and Standard Deviations of Individual and State Characteristics NLSY79 Male Smokers in 1998

Characteristic	Mean	Standard Deviation
Family income (in $1000) in 1998	47.421	44.232
Posterior probability of unemployment	0.0496	0.1055
Probability of being below the poverty level	0.0515	0.1352
Number of Drops greater than 10% in Real Family Income, 1983-1998	3.1196	1.4432
State clean air regulations in 1998	3.2938	2.2782
Avg. state price of cigarettes (in dollars) in 1998	2.3449	0.2872
Years of education completed in 1998	12.036	1.9329
Years of education respondent's mother completed, 1979	10.853	2.7692
Family size in 1998	2.8307	1.6589
Age in 1998	36.941	2.2932
Weight in 1998 (in pounds)	186.37	37.562
Height in 1985 (in inches)	67.754	3.2315
Black	0.2551	0.4364
Hispanic	0.1309	0.3377
White	0.6140	0.4874
Married	0.4853	0.5003
Never Married	0.2777	0.4483
Divorce or separated	0.2325	0.4229
Widowed	0.0045	0.0671
Live in Metropolitan Area	0.6817	0.4663

N=443
Sources: See Data Appendix.

real income will be more likely to smoke. This variable can be viewed as a cruder measure of income volatility that is independent of income level. The average number of such drops is 3.12 for smokers and 2.83 for former smokers.

Instruments

In order to generate unbiased estimates with instrumental variables, it is vital to use valid instruments. For an instrument to be valid it must be uncorrelated with the error term (and thus correctly excluded from the model) while still being sufficiently correlated with the endogenous variable of interest. The series of annual BLS unemployment rates from 1983-1998 in the geographical area where the respondent resided are used to identify the effect of each of our measures of economic insecurity on smoking. We believe these variables are appropriate instruments because official unemployment rates are presumably correlated with

Table 1c: Means and Standard Deviations of Individual and State Characteristics NLSY79 Male Former Smokers in 1998

Characteristic	Mean	Standard Deviation
Family income (in $1000) in 1998	56.757	48.762
Posterior probability of unemployment	0.0282	0.0807
Probability of being below the poverty level	0.0442	0.1470
Number of Drops greater than 10% in Real Family Income, 1983-1998	2.8293	1.3951
State clean air regulations in 1998	3.3462	2.3669
Avg. state price of cigarettes (in dollars) in 1998	2.3362	0.2747
Years of education completed in 1998	13.034	2.5279
Years of education respondent's mother completed, 1979	11.061	3.3293
Family size in 1998	3.2561	1.6519
Age in 1998	37.102	2.2474
Weight in 1998 (in pounds)	196.51	35.714
Height in 1985 (in inches)	67.838	3.0934
Black	0.2439	0.4300
Hispanic	0.1780	0.3830
White	0.5780	0.4945
Married	0.6585	0.4748
Never Married	0.1634	0.3702
Divorce or separated	0.1707	0.3767
Widowed	0.0073	0.0853
Live in Metropolitan Area	0.7244	0.4474

N=410
Sources: See Data Appendix.

the respondent's employment and income histories, but are arguably unrelated to unobserved individual characteristics—such as peer group effects, family background, and childbirth—that might be correlated with both smoking behavior and our measures of economic insecurity). In addition, we rely on NLSY-generated state means and medians (men and women pooled together) to instrument for the probability of falling below the poverty level and the number of drops in real income. Because these instruments are formed directly from the data, it should be noted that they are arguably not as exogenous as other state-level instruments. The instrument for family income is state median household income in 1998.

Table 1d: Means and Standard Deviations of State and Local Characteristics

Characteristic	Mean	Standard Deviation
Unemployment rate in local labor market, 1983	11.989	3.9826
Unemployment rate in local labor market, 1984	8.9433	3.3502
Unemployment rate in local labor market, 1985	8.3177	3.1857
Unemployment rate in local labor market, 1986	7.9712	3.0194
Unemployment rate in local labor market, 1987	7.2618	2.6831
Unemployment rate in local labor market, 1988	6.3420	2.5930
Unemployment rate in local labor market, 1989	5.5415	2.0682
Unemployment rate in local labor market, 1990	5.7073	1.9034
Unemployment rate in local labor market, 1991	7.4485	2.7301
Unemployment rate in local labor market, 1992	8.0328	2.4794
Unemployment rate in local labor market, 1993	7.5392	2.4968
Unemployment rate in local labor market, 1994	7.1149	2.5565
Unemployment rate in local labor market, 1996	6.7845	2.9745
Unemployment rate in local labor market, 1998	5.0722	2.4490
State median household income (in $1000), 1998	39.210	4.6922
Average State Probability of being below the poverty level	0.0764	0.0191
Median State Probability of being below the poverty level	0.0010	0.0010
Average State Number of Drops greater than 10% in Real Family Income, 1983-1998	2.2441	0.1941
Median State Number of Drops greater than 10% in Real Family Income, 1983-1998	2.0434	0.2595

N=853
Sources: See Data Appendix

Results

Estimation results are tabulated in Tables 2 and 3. Table 2 presents the OLS estimates for four alternative specifications, while Table 3 presents the corresponding IV estimates. A dummy variable representing smoking in 1998 is the dependent variable in each specification. First stage results from the IV procedure are presented in Tables 4a-4c. Because the OLS specifications produce biased estimates, the discussion in this section focuses on the IV estimates. It is worth noting, however, that the direction of bias (relative to IV) in our OLS specifications is toward zero for each measure of income and economic insecurity. This is consistent with our expectation that unobserved personal characteristics cause individuals in our sample, on balance, to choose both smoking and low-wage (but also low-risk) jobs.

Table 2: Effect of Economic Insecurity on Daily Cigarette Smoking for Men, 1998 (OLS)

Variables	(1)	(2)	(3)
Family income (in \$1000)	-0.00026 (0.00036	-0.00036 (0.00036)	-0.00022 (0.00039)
Posterior probability of unemployment	0.2990** (0.148)		
Probability of being below poverty level		-0.2227** (0.110)	
Number of drops in family income, 83-98			0.0112 (0.011)
Weight (in pounds)	-0.0017*** (0.00043)	-0.0017*** (0.00044)	-0.0017*** (0.00043)
Height (in inches)	0.0044 (0.006)	0.0040 (0.006)	0.0048 (0.006)
State clean air regulations	0.0043 (0.008)	0.0049 (0.008)	0.0047 (0.008)
State cigarette price (in dollars)	-0.0071 (0.075)	0.0077 (0.075)	-0.0072 (0.076)
Years of education	-0.0479*** (0.008)	-0.0516*** (0.008)	-0.0492*** (0.008)
Mother's education (1979)	0.0074 (0.007)	0.0088 (0.007)	0.0077 (0.007)
Family Size	-0.0134 (0.011)	-0.0134 (0.011)	-0.0134 (0.011)
Age	-0.0023 (0.007)	-0.0024 (0.007)	-0.0015 (0.007)
Black	-0.0827* (0.043)	-0.0627 (0.043)	-0.0670 (0.043)
Hispanic	-0.0597 (0.052)	-0.0628 (0.054)	-0.0559 (0.052)
Married	0.0442 (0.183)	0.0158 (0.159)	0.0458 (0.182)
Never Married	0.2009 (0.196)	0.2002 (0.174)	0.2081 (0.197)
Divorced or Separated	0.1100 (0.203)	0.0919 (0.180)	0.1135 (0.204)
Live within a city	-0.0612 (0.037)	-0.0582 (0.037)	-0.0584 (0.037)
N	853	853	853
R^2	0.087	0.087	0.085

Sources: See Data Appendix; Variables are for the year 1998, unless otherwise specified; Robust standard errors (adjusted for within-state clustering) in parentheses; * significant at 10%, ** significant at 5%, *** significant at 1%

Table 3: Effect of Economic Insecurity on Daily Cigarette Smoking for Men, 1998 (IV)

Variables	(1)	(2)	(3)
Family income	0.0039	0.0045***	0.0043**
(in $1000)	(0.0028)	(0.0016)	(0.0018)
Posterior probability	2.4425***		
of unemployment	(0.705)		
Probability of being		1.0928**	
below poverty level		(0.494)	
Number of drops in			0.1728***
family income, 83-98			(0.052)
Weight (in pounds)	-0.0009*	-0.0011***	-0.0015***
	(0.00094)	(0.00039)	(0.00045)
Height (in inches)	0.0040	0.0096**	0.0062
	(0.004)	(0.004)	(0.004)
State clean air	0.0015	0.0111*	0.0139**
regulations	(0.007)	(0.006)	(0.007)
State cigarette price	-0.0049	-0.0984	-0.0651*
(in dollars)	(0.048)	(0.060)	(0.037)
Years of education	-0.0442***	-0.0550***	-0.0534***
	(0.016)	(0.008)	(0.011)
Mother’s education	-0.0119*	-0.0074	-0.0017
(1979)	(0.007)	(0.005)	(0.006)
Family Size	-0.0094	-0.0036	-0.0007
	(0.010)	(0.010)	(0.010)
Age	-0.0177***	-0.0060	-0.0005
	(0.006)	(0.006)	(0.006)
Black	-0.1585***	-0.0416	0.0030
	(0.061)	(0.035)	(0.031)
Hispanic	-0.0930***	-0.0449	-0.0261
	(0.034)	(0.044)	(0.035)
Married	-0.1097	0.3779*	-0.0639
	(0.181)	(0.206)	(0.137)
Never Married	0.0953	0.5740**	0.2129
	(0.155)	(0.232)	(0.131)
Divorced or Separated	0.0316	0.5665***	0.0813
	(0.157)	(0.217)	(0.131)
Live within a city	-0.0824***	-0.0798***	-0.0466*
	(0.029)	(0.023)	(0.025)
N	853	853	853
R^2	-0.180	-0.185	-0.197

Sources: See Data Appendix; Variables are for the year 1998, unless otherwise specified; Robust standard errors (adjusted for within-state clustering) in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%

Table 4a

First Stage Results for Posterior Probability of Unemployment Regression

Instruments	**Endogenous Variables**	
	Family Income	Posterior Probability
Cigarette Prices	7.6516	-0.0024
	(7.713)	(0.015)
Clean Indoor Air Laws	-0.8280	0.0007
	(0.854)	(0.001)
Years of School	3.6418**	-0.0083***
	(1.125)	(0.002)
Mother's Education	1.3249*	0.0019
	(0.576)	(0.002)
Age	1.5228*	0.0025
	(0.746)	(0.002)
Family Size	-0.2448	-0.0014
	(1.213)	(0.002)
Weight	-0.1127*	0.0001
	(0.053)	(0.000)
Height	0.4938	0.0007
	(0.552)	(0.001)
Black	-8.8989*	0.0469***
	(3.617)	(0.008)
Hispanic	6.4886	0.0044
	(7.367)	(0.007)
Married	29.9980***	0.0267*
	(5.563)	(0.015)
Never Married	7.6298	0.0541***
	(4.878)	(0.017)
Divorced/Separated	4.5129	0.0450***
	(5.379)	(0.013)
Live in a City	1.6477	0.0080*
	(2.993)	(0.004)
State Median Household	0.2163	-0.0002
Income	(0.578)	(0.001)
Unemployment rate in	-1.1201	-0.0019
local labor market, 1983	(0.689)	(0.001)
Unemployment rate in	0.8393	0.0005
local labor market, 1984	(0.866)	(0.002)
Unemployment rate in	0.4140	0.0006
local labor market, 1985	(0.860)	(0.002)
Unemployment rate in	0.4492	0.0041**
local labor market, 1986	(0.876)	(0.002)
Unemployment rate in	0.7130	0.0005
local labor market, 1987	(1.647)	(0.002)
Unemployment rate in	1.0435	-0.0026
local labor market, 1988	(1.204)	(0.002)
Unemployment rate in	-1.6461	-0.0013
local labor market, 1989	(1.598)	(0.002)
Unemployment rate in	-3.4300*	0.0006
local labor market, 1990	(1.480)	(0.004)

(continued on next page)

Table 4a, Continued

Instruments	**Endogenous Variables** Family Income	Posterior Probability
Unemployment rate in local labor market, 1991	0.9705 (1.600)	-0.0017 (0.002)
Unemployment rate in local labor market, 1992	1.6289 (1.858)	0.0047* (0.003)
Unemployment rate in local labor market, 1993	-0.8576 (1.277)	0.0005 (0.003)
Unemployment rate in local labor market, 1994	-0.7378 (1.524)	-0.0054* (0.003)
Unemployment rate in local labor market, 1996	1.9775** (0.640)	0.0027* (0.001)
Unemployment rate in local labor market, 1998	-0.6106 (0.723)	0.0036** (0.002)
N	853	853
R^2	0.183	0.152
Adj. R^2	0.152	0.119

Table 4b

First Stage Results for Probability of Being in Poverty Regression

Instruments	**Endogenous Variables** Family Income	Probability of Poverty
Cigarette Prices	5.3159	0.0900***
	(6.571)	(0.022)
Clean Indoor Air Laws	-0.1796	0.0011
	(0.921)	(0.002)
Years of School	3.6107***	-0.0068***
	(1.139)	(0.002)
Mother's Education	1.4746**	0.0025
	(0.572)	(0.002)
Age	1.4770*	-0.0036
	(0.736)	(0.002)
Family Size	-0.2467	0.0020
	(1.195)	(0.003)
Weight	-0.1138**	-0.0000
	(0.050)	(0.000)
Height	0.5841	-0.0028
	(0.554)	(0.002)
Black	-8.3830**	0.0277**
	(3.718)	(0.013)
Hispanic	8.2123	-0.0279
	(7.169)	(0.020)
Married	30.6388***	-0.1548
	(3.227)	(0.117)
Never Married	8.9161***	-0.0539
	(2.966)	(0.125)

(continued on next page)

Table 4b, Continued

Instruments	**Endogenous Variables**	
	Family Income	Probability of Poverty
Divorced/Separated	4.8379	-0.1237
	(3.827)	(0.114)
Live in a City	1.9027	0.0024
	(3.128)	(0.013)
State Median Household	0.0792	-0.0031***
Income	(0.544)	(0.001)
Unemployment rate in	-1.3321*	0.0015
local labor market, 1983	(0.719)	(0.003)
Unemployment rate in	0.6097	-0.0017
local labor market, 1984	(0.831)	(0.001)
Unemployment rate in	0.7972	-0.0020
local labor market, 1985	(0.864)	(0.005)
Unemployment rate in	0.4706	-0.0008
local labor market, 1986	(0.810)	(0.004)
Unemployment rate in	0.3387	0.0011
local labor market, 1987	(1.704)	(0.006)
Unemployment rate in	1.3778	0.0062
local labor market, 1988	(1.287)	(0.005)
Unemployment rate in	-1.2923	-0.0072*
local labor market, 1989	(1.672)	(0.004)
Unemployment rate in	-3.6336**	0.0042
local labor market, 1990	(1.400)	(0.004)
Unemployment rate in	0.8937	-0.0017
local labor market, 1991	(1.519)	(0.004)
Unemployment rate in	1.7480	-0.0009
local labor market, 1992	(1.691)	(0.004)
Unemployment rate in	-1.2419	0.0102***
local labor market, 1993	(1.148)	(0.004)
Unemployment rate in	-0.2635	-0.0093*
local labor market, 1994	(1.364)	(0.005)
Unemployment rate in	2.0378***	0.0012
local labor market, 1996	(0.604)	(0.002)
Unemployment rate in	-0.8184	-0.0016
local labor market, 1998	(0.678)	(0.002)
State Average Probability	-257.0505***	0.4641
of Poverty	(92.123)	(0.279)
State Median Probability	245.8635	3.2484
of Poverty	(710.721)	(3.488)
N	853	853
R^2	0.192	0.186
Adj. R^2	0.159	0.152

Table 4c

First Stage Results for Number of Drops in Real Income Regression

Instruments	**Endogenous Variables**	
	Family Income	Number of Drops
Cigarette Prices	6.4493	0.2244
	(6.964)	(0.162)
Clean Indoor Air Laws	-0.9013	0.0023
	(0.819)	(0.026)
Years of School	3.4733***	-0.1216***
	(1.112)	(0.026)
Mother's Education	1.4044**	0.0152
	(0.576)	(0.018)
Age	1.5689**	-0.0173
	(0.747)	(0.014)
Family Size	-0.4070	-0.0158
	(1.193)	(0.042)
Weight	-0.1133**	0.0005
	(0.051)	(0.002)
Height	0.5120	-0.0189
	(0.551)	(0.018)
Black	-9.5306**	-0.1708
	(3.609)	(0.135)
Hispanic	7.0880	-0.1986
	(7.189)	(0.249)
Married	28.7145***	0.2226
	(5.393)	(0.378)
Never Married	6.6239	0.5522
	(4.731)	(0.386)
Divorced/Separated	2.9240	0.7076*
	(5.345)	(0.405)
Live in a City	2.0100	-0.1074
	(2.939)	(0.112)
State Median Household	0.5885	-0.0272**
Income	(0.445)	(0.011)
Unemployment rate in	-1.1502*	-0.0492*
local labor market, 1983	(0.674)	(0.025)
Unemployment rate in	0.6394	0.0709*
local labor market, 1984	(0.824)	(0.040)
Unemployment rate in	0.3646	-0.0743*
local labor market, 1985	(0.870)	(0.042)
Unemployment rate in	0.7808	0.0666
local labor market, 1986	(0.802)	(0.041)
Unemployment rate in	0.6144	0.0023
local labor market, 1987	(1.733)	(0.051)
Unemployment rate in	0.8263	0.0166
local labor market, 1988	(1.211)	(0.041)
Unemployment rate in	-1.8090	-0.0664*
local labor market, 1989	(1.659)	(0.039)

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Table 4c, Continued

Instruments	**Endogenous Variables**	
	Family Income	Number of Drops
Unemployment rate in	-3.5801**	0.0400
local labor market, 1990	(1.341)	(0.049)
Unemployment rate in	0.8858	0.0359
local labor market, 1991	(1.652)	(0.048)
Unemployment rate in	1.9709	-0.0306
local labor market, 1992	(1.628)	(0.053)
Unemployment rate in	-1.1791	0.0136
local labor market, 1993	(1.191)	(0.043)
Unemployment rate in	-0.5036	-0.0460
local labor market, 1994	(1.367)	(0.060)
Unemployment rate in	1.9336***	-0.0183
local labor market, 1996	(0.608)	(0.022)
Unemployment rate in	-0.5987	-0.0198
local labor market, 1998	(0.735)	(0.032)
State Average Number	2.5125	0.7209*
of Drops	(7.292)	(0.360)
State Median Number	17.0578**	-0.1551
of Drops	(7.871)	(0.219)
N	853	853
R^2	0.192	0.090
Adj. R^2	0.158	0.053

We briefly discuss general results before analyzing our proxies for economic insecurity. In each specification, the number of years of education has a statistically significant negative effect on smoking (though because education—an individual choice—is treated as exogenous, these results should be interpreted with caution). Weight has a small but statistically significant negative effect on smoking (though again, because smoking can induce weight loss, the direction of causation is unclear), and individuals who live in a city are 5-8 percent less likely to smoke than individuals who do not live in a city.

We provide a battery of instrument validity tests in Tables 5a-5c. The exogeneity of the instruments can be evaluated by analyzing the Hansen *J*-Statistic obtained by evaluating the GMM criterion function at the efficient GMM estimate (Hansen 1978, 1982). By this criterion, our instruments are exogenous and correctly excluded from the model at the 5% level in each case. Several approaches are suggested by Baum et al. (2003, 2007) for evaluating the strength of instruments when there is more than one endogenous variable.[20] A formal test for weak instruments is achieved by evaluating the Kleibergen-Paap rank LM

[20] Instruments with little explanatory power can result in bias in the IV estimates (Haun and Hausman 2002). We therefore suggest caution when interpreting estimates in regressions that do not pass the weak instruments test.

Instrument Validity Tests

Table 5a

Test of Over-Identification (Instrument Exogeneity) Null: Over-identifying restrictions are valid (implies instruments are exogenous) (Note that "Fail to Reject the Null" implies *valid* instruments)			
	(1)	(2)	(3)
Hansen J statistic (over-identification test of all instruments)	20.97	23.18	20.54
χ^2 distribution *p*-value	0.074	0.080	0.152

Table 5b

Test of Under-Identification (Instrument Relevance) Null: Equations are under-identified (implies instruments are not related to endogenous variables) (Note that "Fail to Reject the Null" implies *invalid* instruments)			
	(1)	(2)	(3)
Kleibergen-Paap (2006) rk LM statistic	9.72	17.56	21.17
χ^2 distribution *p*-value	0.782	0.351	0.172

Table 5c

Additional Tests of Instrument Relevance						
Specifications	(1)		(2)		(3)	
	Posterior Probability	Family Income	Probability of Poverty	Family Income	Number of Drops	Family Income
Shea Partial R^2	0.0221	0.0156	0.0238	0.0296	0.0248	0.0297
Partial R^2	0.0269	0.0189	0.0255	0.0316	0.0241	0.0289
Difference Between R^2s	0.0048	0.0033	0.0017	0.0020	0.0007	0.0008
Stock-Wright *S* statistic (*p*-value)	23.32 (0.077)		24.02 (0.119)		23.38 (0.137)	

statistic (Kleibergen and Paap 2006), where the null hypothesis is that the model is under-identified, or that the smallest canonical correlation between the linear combinations of the independent variables and the instruments is zero. Rejection of the null implies that the instrumental process has full rank, or that the instruments pass the weak instruments test (i.e., they are highly correlated with the endogenous variables). Because none of our instruments pass the Kleibergen-Paap rank LM weak instruments test at the 5% level,[22] we discuss evidence from other statistics that suggest our instruments are sufficiently correlated with the endogenous variables to produce unbiased estimates. In particular, we compare the Shea Partial R^2 (Shea 1997) to the Partial R^2 in each of the first stage

[22] This is likely due to the fact that we exploit geographic (rather than individual-level) variation to identify causal effects.

regressions. If the two values are "close" then the instruments are strong enough to explain the endogenous regressors. We also report Stock-Wright *S* statistics (Stock and Wright 2000), which test the null hypothesis that the coefficients of the endogenous variables are jointly equal to zero; this test is robust to the presence of weak instruments.

IV results indicate that increases in income have a positive causal effect on smoking. A $1,000 increase in family income increases the probability of smoking by approximately 0.4 percent across all specifications.[23] This result suggests that although smoking is often correlated with poverty, marginal increases in income have a positive effect on smoking.

Our first measure of insecurity, the posterior probability of unemployment, positively affects smoking. The IV results suggest that an increase of one percent (0.01) in the probability of future unemployment increases the probability of smoking by 2.4 percent. It should be noted that the instruments do not pass the weak instruments test using the Kleibergen-Paap LM test statistic, with a *p*-value of 0.78. The differences between the Shea Partial R^2 and the Partial R^2, however, are quite small for the first stage regressions (0.005 and 0.003), indicating that the instruments do have some explanatory power. Moreover, the Stock-Wright *S* statistic is at least marginally significant, with a *p*-value of 0.077.

The next insecurity proxy is the probability that the respondent's predicted family income in 1998 falls below the poverty level threshold. An increase of one percent in the probability of falling below the poverty level increases the probability of smoking by 1.1 percent. The instruments once again fail to pass the weak instruments test using the Kleibergen-Paap LM test statistic, with a *p*-value of 0.35. The differences between the Shea Partial R^2 and the Partial R^2, however, are again quite small for the first stage regressions (0.002 and 0.002), and again the Stock-Wright test provides (somewhat weaker) evidence of instrument strength, with $p = 0.119$.

Our last proxy for economic insecurity is the number of drops in real income greater than 10 percent that the respondent faced over the 16-year study period. IV estimates indicate that an increase of one such drop increases the probability of smoking by over seventeen percent. In this specification the Kleibergen-Paap test statistic has a *p*-value of 0.17, but once again the difference between the Shea Partial R^2 and the Partial R^2 is small (0.0007 and 0.0008), and $p = 0.137$ in the Stock-Wright test.

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[23] These findings are consistent with Ruhm (2000), who finds that a $1000 increase in state median family income increases the number of predicted smokers by 0.3 percent. Our coefficient estimates also imply income elasticities of around 0.4 at the sample mean, well within the range of published estimates for tobacco and cigarette demand (see Gallet and List 2003).

Conclusion

This paper represents a first attempt to test a novel hypothesis about the relationship between smoking and household income. Motivated by recent findings in neuroscience, we ask whether smoking can be viewed as a form of self-medication that individuals turn to when exposed to economic insecurity. Using individual level data (including richly detailed contemporaneous household economic histories) and instrumental variables, we find evidence of an independent effect of economic insecurity on smoking. The magnitudes of our estimates are not trivial: an increase of one standard deviation in our various measures of economic insecurity increases the probability of smoking at the end of our sample period by 15-25%, whereas by way of comparison, the corresponding effects of an increase in income are 18-21%. Needless to say, if this "insecurity effect" on cigarette demand extends beyond our relatively small sample (male NLSY79 smokers for whom comprehensive employment and income histories are available), it could represent a critical factor in explaining population-level persistence of smoking behavior.

Though additional research is needed to corroborate our findings, the implications of this research for clinical practice and public policy are potentially far-reaching. Current tobacco preventative and rehabilitative programs, for example, pay little attention specifically to economic insecurity, which our results suggest could be an important underlying causal factor. Such programs might benefit from a shift toward more "holistic" approaches aimed at bolstering the economic situation of those at risk of nicotine addiction by, for instance, facilitating improved access to health insurance, or perhaps providing counseling in financial and career planning.

More broadly, while it is sometimes argued that smoking should be viewed as an economic decision best left to the consumer, our findings suggest that consumer preferences for tobacco may be endogenous to the economic environment in a manner heretofore unexplored. This view has benefit of lending credence to the rational choice model of tobacco use while validating the abundant evidence of "psychological" effects among users. But our findings suggest—to push the "self-medication" metaphor a bit further—that nicotine addiction may be more productively viewed as a symptom than a disease.

Data Appendix

Description of constructed NLSY and non-NLSY variables

Median household income. This variable represents the median household income in the respondent's state of residence in 1998 and comes from the *Statistical Abstract of the United States*.

Number of drops in real family income greater than 10 percent, 1983-1998. Family annual income in each survey year is reported in NLSY79. This variable is a count of the number of times family income (adjusted for inflation) was less than 10 percent of the most recently reported previous income.

Posterior probability of unemployment. NLSY79 includes weekly data on employment status (working, unemployed, out of labor force, etc.) for each subject. From this information we derive an approximation of each respondent's subjective beliefs about the probability of experiencing involuntary job loss at the time of the 1998 survey. If one is willing to posit that this probability is fixed but unknown (to the worker) at the beginning of the worker's current career, and that workers adjust their beliefs in a Bayesian manner as time goes on, it is possible to calculate the worker's belief (i.e., his posterior probability) directly. We calculate posterior probability as follows:

We assume the worker has a fixed, but unknown probability π of being unemployed in any given week. He knows that there are k possible values of π, denoted π_i for i = 1, 2, …, k and prior probabilities $P(\pi = \pi_i)$. After n weeks the worker observes that he has been unemployed for $x \leq n$ weeks. The probability that he will be unemployed in week n + 1 is given by

$$\sum_{i=1}^{k} \pi_i P(\pi = \pi_i | x) \qquad (1)$$

where

$$P(\pi = \pi_i | x) = \frac{P(x | \pi = \pi_i) P(\pi = \pi_i)}{\sum_{j=1}^{k} P(x | \pi = \pi_j) P(\pi = \pi_j)} \qquad (2)$$

and because for any given value π_i, x is realized from a binomially distributed random variable,

$$P(x \mid \pi = \pi_i) = \frac{n!}{x!(n-x)!} (\pi_i)^x (1-\pi_i)^{n-x} \qquad (3)$$

(1) is computed by generating values for π_i (job-loss hazard) and $P(\pi = \pi_i)$ (prior probability of a given hazard level) from the sample of 4625 male NLSY79 respondents for whom we have comprehensive weekly employment data from 1994-1998. Observations were sorted into 30 "bins," with approximately 49 observations per bin, with the exception of the first bin, which represents the 3200

observations with prior probability of 0. π_i is then calculated as the mean hazard (number of weeks unemployed divided by total number of weeks) for the each individuals in the same bin, and the prior probability $P(\pi = \pi_i)$ is given by the number of observations in bin *i* divided by the total number of observations.

Probability of falling below the poverty level. This variable is formed by finding the probability that individual *i*'s predicted family income in 1998 is below the poverty level. Poverty levels are obtained from the Department of Health and Human Services website, the poverty levels are specified by the *HHS Poverty Guidelines*. They are dependent on the number of family members living in the home, family income, and the state. In order to find the probability of being below the poverty level, we first apply separate regressions for each individual who has at least three annual income levels reported from 1983-1998. We regress annual family income (as reported in NLSY79 each year) on year for each individual, by applying ordinary least squares regression formulas. These formulas yield estimated coefficients for the slope, or rate of change and intercept for the linear time trend in family income. The slope is calculated by:

$$\frac{n\sum_{t=83}^{98} t y_t - \sum_{t=83}^{98} t \sum_{t=83}^{98} y_t}{n\sum_{t=83}^{98} t^2 - \left(\sum_{t=83}^{98} t\right)^2}$$

where t = two-digit year (t = 83, 84, 85, …, 98), y = income in year t, n = number of years when income is reported (i.e., data is not missing), and in years where data is missing (i.e., no income reported in year t) neither t nor y_t exist.

The intercept is calculated by:

$$\frac{\sum_{t=83}^{98} y_t}{n} - (slope)\frac{\sum_{t=83}^{98} t}{n}$$

Then, the predicted value of family income in 1998 is computed:

$\hat{Y}_{98}$=(*intercept*) + (*slope*)(98)

Finally, a confidence interval is calculated, with the poverty level as the lower confidence limit:

$$\hat{Y}_{98} - t(1-\alpha/2; n-2)\sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-2}\left(\frac{1}{n} + \frac{(x_h - \bar{x})^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right)} = poverty\ level$$

We then solve for *t* and using the *ttail* command in Stata compute the probability of having a value below the poverty level.

Self reported weight and height corrections. Reporting bias are corrected for in self-reported weight and height using the method described in Cawley (2000). Matched data on reported and actual heights and weights from the NHANES III survey were used for this purpose. Separate OLS regressions were performed for each sex and race/ethnic group.

To estimate the actual weight in pounds of an individual, actual weight of the subset of NHANES III respondents between the ages of 26 and 45 was regressed on reported weight (in lbs.), reported weight squared, and the respondent's age in years. Estimated coefficients were then used to correct for the bias.

State cigarette tax data. Data on cigarette taxes for each state in 1998 is from *The Tax Burden on Tobacco*, by Orzechowski and Walker.

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