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Has Suburbanization Caused Obesity? Evidence Across Gender, Race, and Income

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ABSTRACT

Has Suburbanization Caused Obesity? Evidence Across Gender, Race, and Income[1]

In this paper, we examine the effect of suburbanization on obesity rates. Our study is an improvement over the existing literature because we will use county level data for our analysis, enabling us to look at the effect of moving from the central city to the suburbs. Previous research has only had health data at the MSA level, and therefore could not look at the effect of urban growth on obesity rates within an MSA, particularly the suburbs versus the central city. To estimate the relationship between obesity and urban sprawl, we will use county-level data on obesity rates from the Behavioral Risk Factor Surveillance System (BRFSS). Because there are likely unobserved selection issues regarding obesity and urban sprawl, we instrument for population density using the 1947 Interstate Highway Program. We find that counties that are less sprawled, defined by a higher population density, have lower obesity rates.

JEL Classification: I12, I14, O18

Keywords: obesity, health, suburbanization

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I. Introduction

The population in central cities in the United States has declined dramatically since the 1950s. Despite the decline in the city center, there has been a growth in metropolitan areas as a whole, suggesting that individuals are still living in metropolitan areas but are moving into the suburbs. Baum-Snow (2007) examined this phenomenon and found that approximately one third of the decrease in aggregate central city population relative to the metropolitan area population overall can be explained by the expansion of the interstate highway system. This finding is consistent with the findings from the standard Alonso (1964) model, which predicts that as commuting times decrease, the cost of traveling to work will decrease, and individuals will migrate into the suburbs.

At the same time as the increase in suburbanization, the obesity rate in the U.S. increased dramatically. Between 1960 and 2006, the obesity rate increased from 13% to 34% (NCHS, 2008). Obesity is a concern for policy makers, as this health issue has been linked to numerous health conditions, including diabetes, heart disease, and stroke. Given the timing of this increase and the migration from the central city, researchers have begun to ask if there a relationship between suburbanization and obesity. As individuals move from the central city to the suburbs, people tend to rely more on cars instead of walking. Therefore, individuals who reside in the central city will tend to get more exercise than their suburban counterparts. Also, the presence of big box stores in the suburbs reduces the price of food. Previous research has found that lower food prices cause increases in food consumption (French, 2005). However, while big grocery stores may lower the price of food, it lowers the price of all types of food, including healthy alternatives (Jetter & Cassidy, 2006). Therefore, the overall effect of the movement to the suburbs is theoretically ambiguous. In this paper, we examine this relationship between suburbanization and obesity, and look at the impact of urban sprawl on the rates of obesity within a metropolitan area.

Previous research has examined the relationship between sprawl and obesity. Early papers were limited in their ability to provide causal estimates, as there is an endogenous selection problem given that residents choose which neighborhoods to reside within. Later research attempted to address these selection issues by using fixed effects methods to control for unobserved individual attributes (Eid et al., 2008; Ewing et al., 2006; Plantinga & Bernell, 2007). One issue with these studies is that they used data from the National Longitudinal Survey of Youth. While the fixed effects do control for unobserved individual attributes, it is likely that the individual preferences of the survey participants vary over time as individuals get older, form families, and other life changes that could affect preferences. Therefore, the individual-level fixed effects may not be controlling for all unobserved attributes. Later work by Zhao & Kaestner (2010) utilized an instrumental variable strategy to address the concern regarding the endogenous selection of neighborhoods. They found that increases in the degree of urban sprawl in a metropolitan area caused an increase in the obesity rates in that MSA. We build upon this literature on urban sprawl and obesity by using an instrumental variables strategy to look not just at obesity rates across cities, but how changes in urban sprawl within an MSA affect obesity within a city. Future work will also examine how these effects vary across the gender, race, and income level of individuals.

To conduct our analysis, we compiled two data sets. For our instrument, we used the Interstate Highway Act of 1947. This plan was the beginning of a series of planned highways across the United States that were primarily funded by the federal government. The Eisenhower Highway Plan has been shown to be correlated with rates of suburbanization, but is likely to be uncorrelated with obesity rates decades later. Therefore, Eisenhower Highway Plan meets the criteria necessary for a valid instrument.[2] In addition to this data on the number of miles of highways, we obtained data on individual characteristics including body mass index (BMI), age, gender, race, education, and income from the annual survey of Behavioral Risk Factor Surveillance System (BRFSS) from 1997 to 2003[3]. Use utilized Census data to calculate the total population in a given county, as well as the total land area of the county. From this, we were able to calculate the population density of all counties in our sample.

We find evidence that a lower population density causes an increase in obesity rates. This finding supports the arguments that suburbanization is contributing to rising obesity rates in the United States. Some reasons that this may be occurring is that individuals are exercising less as they are driving more instead of walking. In addition, as highways develop and big box stores become more prevalent, the cost of food decreases and therefore individuals may consume more calories than they did previously. Our future research will continue to examine these mechanisms of how suburbanization may be causing obesity, as well as heterogeneity in the effects of highways across gender, race, and income levels.

The rest of the paper will proceed as follows. Section 2 will outline the existing research on the relationship between obesity and suburbanization. Section 3 will discuss the instrumental variables strategy that we will use to obtain causal estimates. Section 4 will discuss the data sets used in our analysis. Results are presented in Section 5, and a discussion of conclusions and future work are in Section 6.

[2] See Baum-Snow (2007) for more information on the 1947 Highway Plan and its relationship with rates of suburbanization.
[3] We are currently working to add more years of data to our analysis.

II. Previous Research

Rising obesity rates have become a major public health concern and economists have entered the debate on what may be the cause of the increase. Changes in obesity rates are interesting to economists as the choices associated with overeating are based on weighing the costs and benefits of consuming different amounts of calories (Courtemanche & Carden, 2011). Reasons for the increase in obesity can be traced to various changes in the opportunity costs of individuals. For example, Cutler et al. (2003) argue that rising obesity rates can be attributed to technology making the food preparation process easier. If it takes less time to prepare food, then individuals are more likely to over eat. In addition to cooking within the home, technology to prepare food outside the home has also improved, which can cause the price of food to decrease in the market and individuals to consume more as portion sizes have increased (Philipson & Posner, 2003; Lakdawalla & Philipson, 2002; Chou et al., 2004). Both of these effects would cause individuals to eat out more, as well as to overeat when dining in restaurants.

Courtemanche and Carden (2011) look at the impact of opening a new Wal-Mart supercenter in a local jurisdiction on obesity rates. Using an instrumental variables approach, where the instrument exploits the geographical pattern of expansion around the headquarters in Arkansas, the authors find that the proliferation of Wal-Mart explains 10.5% of the rise in obesity since the 1950's. In other words, as more individuals move into the suburbs near these big box stores, which have lower prices, individuals will end up consuming more calories and obesity rates will increase. This would suggest that our analysis will find that increases in urban sprawl will cause increases in county obesity rates.

Alternatively, some researchers argue that obesity rates have increased as we have become more suburbanized because individuals walk less. Christian (2011) found that increased commuting times have led to decreases in time spent doing other health related activities, such as exercising and preparing healthy meals. In addition, as individuals move out of the central city, they are more likely to drive to work than to walk, which further decreases the activity level of individuals.

More recent work has acknowledged that there is an endogeneity issue present that must be corrected for when examining the relationship between obesity and population density. Eid et al. (2008) looked at the literature examining the relationship between urban sprawl and obesity and argued that there is a selection process that these papers failed to deal with that is likely to bias the estimates. To address these problems, the authors used data that tracks individuals over time to control for unobservable individual attributes. They did not find the positive effect that existed in the literature, suggesting that obesity was not caused by suburbanization but was a matter of individuals who had a propensity to be overweight choosing to live in those areas. Plantinga and Bernell (2007) used a similar identification strategy of tracking individuals and found additional evidence that there was a selection issue present that is causing researchers to obtain biased estimates of sprawl on obesity. Alternatively, more recent work by Zhao & Kaestner (2010) utilized an instrumental variable strategy to address the concern regarding selection bias and found that increases in urban sprawl in an MSA resulted in higher obesity rates at the MSA level.

We build upon this literature on urban sprawl and obesity by looking not just at obesity rates across cities, but how changes in the highway system affect obesity within a city. Our paper contributes to the literature by looking within MSAs because changes in the highway system are likely to have larger effects within a given city than across cities. Also, future work will look at the possible heterogenous effects of suburbanization on obesity rates, as it is possible that the effect of the move to the suburbs on individuals varies across gender, race, and income groups.

III. Empirical Strategy

The goal of this paper is to examine the relationship between suburbanization in the United States and obesity rates. To estimate such a relationship, one could start by considering the following OLS regression:

$$〚Obesity〛\_it = \beta\_1 \quad 〚popdensity〛\_ct + \beta X\_it + \gamma\_t + \delta\_s + \varepsilon\_it \qquad (1)$$

The subscript i indicates the individual responding to the survey, t indicates the year, and c indicates the county the individual resides within. To proxy for suburbanization, we use a measure of population density, counties that are more suburbanized will be more sprawled and will have a lower population density.[4] X_it includes a variety of socio-economic attributes of the individual, including age, gender, race, education, and income variables. We also include controls for marital status and smoking behavior. In addition to the individual control variables, we use state fixed effects, δ_s, to control for unobserved characteristic within each state and year fixed effects, γ_t, to control for unobserved attributes that are present in a given year. ε_it is an idiosyncratic error term.

In order for OLS to produce unbiased estimates, it must be the case that the idiosyncratic error term is uncorrelated with any unobserved attributes not controlled for in the model. This is

[4] Population density is defined as the total population in a county divided by the total land area of that county.

unlikely to be true when considering obesity rates and urban sprawl for a variety of reasons. For example, it is possible that individuals who are overweight self-select into different areas within an MSA than individuals who do not have higher BMI. One such situation would occur if overweight individuals choose to live in an area where walking is not as prevalent. Therefore, in order to obtain causal estimates, we instrument for population density in Equation (1) using a measure of the number of planned highway miles from the 1947 Eisenhower Highway Plan as our first stage regression:

$$〖popdensity〗\_it = \theta\_1 \quad 〖highway\_miles〗\_it + \theta X\_it + \gamma\_t + \delta\_s + \epsilon\_it.. \qquad (2)$$

$〖highway\_miles〗\_it$ is the number of highway miles proposed in the 1947 Eisenhower Highway Plan.[5] We believe that the highway mileage proposed in 1947 is a valid instrument for a variety of reasons. First, the number of highways planned in 1947 was determined long before obesity was a problem in the United States. Therefore, it is unlikely that the number of highways proposed in the 1940s is correlated with obesity rates in the 1990s and 2000s. Furthermore, previous research has shown that highways have led to suburbanization (Baum-Snow, 2007). Therefore, it is plausible that the number of highway rays proposed is uncorrelated with obesity rates in 1990-2000 but is correlated with the population density in a given county, causing this to be a valid instrument for our analysis.

[5] We thank Nate Baum-Snow for giving us this data set on highway mileage.

IV. Data

Data at the individual level was obtained from the Behavioral Risk Factor Surveillance System (BRFSS), which is a survey conducted annually by the Center for Disease Control (CDC).[6] This data set contains a wealth of information on individual's health behavior, including questions about the general health of individuals, level of physical activity, health insurance information, smoking behavior, and a variety of other health related issues. In this paper, we focus on the information on the Body Mass Index (BMI) of each individual when considering obesity rates. BMI uses information on an individual's weight, height, and gender to determine if that person is underweight, average, overweight, or obese. While this measure is not a perfect indicator of health, as it does not account for muscle mass or bone density, it is generally the measure used to determine rates of obesity.[7]

As indicated in our above models, we for a variety of individual attributes. We created indicators for the level of education of the individual - elementary education only, some high school, high school graduate, some college, and college graduate. In addition to these education measures, we include a variable that includes different levels of income. Level 1, includes those individuals with less than 10000 dollars annual income. Levels 2, 3, 4, 5, 6, and 7 indicate whether the individual has an annual household income of 10000 to 14999, 15000 to 19999, 20000 to 24999, 25000 to 34999, 35000 to 49999, and 50000 to 74999 respectively. The income variable is 8 for those with annual income of 75000 or more. We also include an indicator variable for if the person female, racial indicators (black, white, Asian, and other), and marital status indicators (married, divorced, widowed, and single). We also control for smoking the

[6] Note that the same individuals are not surveyed ever year, so the data set we use is a repeated cross section versus panel data.

[7] In future work, we will experiment with cutting the BMI at different levels. For example, individuals who are just overweight are frequently athletes, who have more muscle mass which is heavier than fat. We will look at the percentage that are overweight relative to those that are underweight to address issues such as this.

behavior to account for underlying health factors of the individual. We include an indicator variable for if the individual is currently a smoker, an indicator for if the individual is a former smoker, and an indicator for if the individual never smoked. Summary statistics of all these variables are presented in Table 1.

We obtained the data on planned and completed highways from Baum-Snow (2007). This data set created by Baum-Snow contains the mileage of highways that are completed and open in each country in each year. In addition, this data set has information on what was planned in terms of highway construction from the 1947 Eisenhower Highway Plan. Information on the highway mileage data is also presented in the summary statistics in Table 1.

V. Results

As discussed above, we use an instrumental variables approach to estimate the effect of suburbanization on obesity, measured through calculating an individual's BMI. The instrument that will be used in our analysis is the number of highway miles proposed in the 1947 Eisenhower Highway Plan. Table 2 presents the results from our first stage regression, given in Equation (2) above. The first column contains a model with controls for an individual's age, gender, education level, income, and racial group. The second column adds controls for marital status, as research has shown there is a systematic relationship between obesity rates and whether or not an individual is married (Mukhopadhyay, 2008). The final column includes measures of smoking behavior, as individuals who smoke, those who are quitting, and those who have never smoked have differences in obesity rates (Chou et al., 2004).

As can be seen in Table 2, we find that additional highway miles have a negative and statistically significant effect on population density for all models. This means that additional highway miles cause the population density in a county to decrease. This finding is not surprising based on the standard urban model, because highways will decrease commuting costs and allow individuals to live further from the central city. For all models, the F-stats are above the standard cutoff of 10, suggesting that our instrument is strong. Table 3 presents the results from the reduced form regressions, where we estimate the effect of the length of planned highways on obesity. We find a positive and statistically significant relationship between the highway miles and obesity for all models.

Table 4 contains our primary results. We begin by looking first at a standard OLS model estimating the effect of population density on BMI, presented in columns 1-3 of Table 4. We find that a lower population density is associated with a higher BMI, suggesting that suburbanization is causing individuals to weigh more. However, this result is likely to be biased as there are unobservable individual attributes that are likely to be correlated with how suburbanized of a city an individual chooses to live in. As discussed earlier in the paper, the sign of this bias is also ambiguous. For example, supermarkets and other big box stores have decreased the price of food. This could cause individuals to overeat because food is more expensive – suggesting the bias would be upwards. Alternatively, the cost of all foods are lower as a result of these big box stores, which includes lower prices for healthy foods. This would suggest that individuals may now be able to eat healthier – suggesting the bias would be downwards. Therefore, the OLS results are likely to be biased, and the sign of that bias is theoretically ambiguous.

We then look at our results using our instrumental variable, which are presented in columns 4-6 of Table 4. In the fourth column of Table 4, we include controls for age, gender, race, income, and education.[8] In the second column, we add controls for the marital status of individuals, as previous research has suggested that there are differences in obesity rates between married and single individuals. The last column includes all these controls, as well as controls for if the individual is currently a smoker, has never smoked, or is a former smoker. Overall, we still find the expected negative relationship, and find evidence that OLS is biased as our results from the IV regressions are an order of magnitude larger. This effect is consistent across the different types of controls included in the model. We will focus on the last column for the rest of the discussion, as this includes the most complete set of controls.

In terms of the effects among the different control variables, we find results that are generally consistent with the literature. Older individuals tend to have a higher BMI, which makes sense given the sample only includes individuals age 18-65. We find that on average, women tend to have a higher BMI and more educated individuals tend to have a lower BMI. Married individuals are more likely to be obese, which is consistent with a literature that suggests individuals still actively looking for a mate are less likely to be overweight. We also find smokers have lower BMI, again consistent with research that suggest smoking kills an individual's appetite.

VI. Conclusions and Future Research

Based on the results of this paper, we find that an increase in population density is associated with a lower BMI in a given county. To do this, we utilize an instrumental variables approach and IV for the population density in a county with the number of highway miles proposed in the 1947 Eisenhower Highway Plan. Existing literature has found that highways are correlated with

[8] In the interest of space, we do not show all the controls included in the model. Income in particular is excluded because it is coded based on cutoff levels, which makes it hard to interpret exactly what the coefficient is measuring.

suburbanization, but the 1947 Highway Plan is unlikely to be correlated with obesity rates decades later. Overall, our findings are consistent with the previous literature examining the relationship between obesity and urban sprawl. The two main mechanisms discussed that are likely to cause this positive effect is the decrease in the price of food as a result of suburbanization, as well as a decrease in activity level as individuals drive more and walk less.

We have several steps we plan to pursue with this research area. First, the current results use just the overall BMI level as the measure of obesity. BMI is not a perfect measure, as it does not account in particular for muscle mass and general body type. This could be problematic for a variety of reasons. For example, athletes tend to have a BMI that classifies them as borderline overweight because athletes have more muscle mass and muscle weighs more than fat. We plan to exploit cutoffs in the BMI classifications to compare individuals who are normal weight and underweight to those that are overweight and obese. This would allow us to look at the percentage of the population that appears to be overweight or obese to test the robustness of our findings based on how we set these cutoffs to account for athletes.

In addition, we plan to explore how these effects vary across racial groups, gender, and income levels. Our control measures indicate that individuals of different genders, racial groups, and income levels have different tendencies towards obesity. Future work will examine how highways may be affecting these different patterns. For example, whites have migrated to the suburbs at a faster rate than blacks and Hispanics – so is this causing the effect of highways to have different effects on the two groups? Similarly, are the effects varying based on gender, as now women are choosing different jobs in the suburbs?

References

Chou, S., M. Grossman, and H. Saffer (2004). "An Economic Analysis of Adult Obesity: Results from the Behavioral Risk Factor Surveillance System," *Journal of Health Economics*, 23, 565-587.

Christian, T. (2011). "Trade-Offs between Commuting Time and Health Related Activities," *Journal of Urban Health*, 89(5), 746-757.

Courtemanche, C. and A. Carden (2011). "Supersizing Supercenters? The Impact of Wal-Mart Supercenters on Body Mass Index and Obesity," *Journal of Urban Economics*, 69(2), 165-181.

Cutler, D., E. Glaeser, and J. Shapiro (2003). "Why have Americans become More Obese?" *Journal of Economic Perspectives*, 17, 93-118.

Eid, J., H. Overman, D. Puga, and M. Turner (2008). "Fat City: The Relationship between Urban Sprawl and Obesity," *Journal of Urban Economics*, 63, 385-404.

Lakdawalla, D. and T. Philipson (2002). "The Growth of Obesity and Technological Change: A Theoretical and Empirical Investigation," National Bureau of Economic Research Working Paper 8965.

Mukhopadhyay, S. (2008). "Do Women Value Marriage More? The Effect of Obesity on Cohabitation and Marriage in the US," *Review of Economics of the Household*, 6, 111-126.

National Center of Health Statistics (2008). "Prevalence of Overweight, Obesity, and Extreme Obesity among Adults: United States, Trends 1976-1980 through 2005-2006."

Philipson, T. and R. Posner (2003). "The Long-Run Growth of Obesity as a Function of Technological Change," *Perspectives in Biology and Medicine*, 46, S87-S108.

Plantinga, A. and S. Bernell (2007a). "The Association between Urban Sprawl and Obesity: Is it a Two-Way Street?" *Journal of Regional Science*, 47(5), 857-879.

Plantinga, A. and S. Bernell (2007b). "Can Urban Planning Reduce Obesity? The Role of Self-Selection in Explaining the Link between Weight and Urban Sprawl," *Review of Agricultural Economics*, 29(3), 557-563.

Zhao, Z. and R. Kaestner (2010). "Effects of Urban Sprawl on Obesity," *Journal of Health Economics*, 29, 779-787.

Table 1: Summary Statistics	
	Mean
BMI	27.15
Length of planned highway	39.26
Population Density	1449.80
Income Indicator	5.76
Age	50.72
Percent Female	58.96%
Percent White	79.91%
Percent Black	11.72%
Percent Hispanic	8.66%
Percent Married	47.09%
Percent Widowed	3.48%
Percent Divorced	21.67%
Percent Single	23.94%
Percent Only Elementary School	2.12%
Percent Some High School	6.26%
Percent High School Graduate	31.8%
Percent Some College	30.96%
Percent College Graduate	28.52%
Percent Smoke Now	27.86%
Percent Former Smoker	21.67%
Percent Never Smoked	50.30%

Table 2: First Stage

	Population Density	Population Density	Population Density
Length of planned highway	-2.894	-2.761	-2.767
	(0.191)	(0.190)	(0.190)
F-Statistic	13.62	14.50	14.54
Observations	406,882	406,882	406,882
R^2	0.3877	0.3895	0.3896

Table 3: Reduced Form Models

	BMI	BMI	BMI
Length of planned highway	0.012618*	0.015739**	0.014990**
	(0.007)	(0.007)	(0.007)
Age	0.726392***	0.743918***	0.711291***
	(0.016)	(0.017)	(0.017)
Female	10.906233***	11.097182***	10.383539***
	(0.397)	(0.399)	(0.400)
White	-20.156858***	-20.035418***	-19.324654***
	(1.371)	(1.370)	(1.368)
Black	-3.877756**	-3.242406**	-3.940553**
	(1.606)	(1.607)	(1.604)
Some HS	-48.231219***	-47.381438***	-44.838329***
	(5.727)	(5.724)	(5.714)
HS Grad	-51.931000***	-50.629225***	-49.920828***
	(5.687)	(5.685)	(5.675)
Some College	-53.918580***	-52.017113***	-52.344655***
	(5.689)	(5.686)	(5.677)
College Grad	-63.266029***	-60.975911***	-63.092376***
	(5.692)	(5.691)	(5.681)
Married		7.119995***	5.438497***
		(0.788)	(0.788)
Single		1.222828	0.27202
		(0.850)	(0.849)
Current Smoker			-20.195560***
			(4.584)
Never Smoked			-3.499646
			(4.577)
Observations	406,882	406,882	406,882
R^2	0.035	0.037	0.04

Table 4: Impact of Urban Sprawl on Obesity

	OLS			Instrumental Variables		
	BMI	BMI	BMI	BMI	BMI	BMI
Population Density	-0.000105*	-0.000105*	-0.000125**	-0.005701**	-0.005701**	-0.005417**
	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Age	0.743807***	0.743807***	0.711231***	0.743476***	0.743476***	0.711541***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Female	11.103432***	11.103432***	10.389036***	11.270327***	11.270327***	10.517701***
	(0.399)	(0.399)	(0.400)	(0.410)	(0.410)	(0.408)
White	-20.121716***	-20.121716***	-19.422335***	-23.823054***	-23.823054***	-22.898637***
	(1.370)	(1.370)	(1.368)	(2.188)	(2.188)	(2.170)
Black	-3.152045**	-3.152045**	-3.849242**	-1.73194	-1.73194	-2.53203
	(1.606)	(1.606)	(1.604)	(1.750)	(1.750)	(1.740)
Some HS	-47.403974***	-47.403974***	-44.868661***	-50.009092***	-50.009092***	-47.258669***
	(5.724)	(5.724)	(5.714)	(5.911)	(5.911)	(5.887)
HS Grad	-50.681009***	-50.681009***	-49.984850***	-54.247706***	-54.247706***	-53.330569***
	(5.685)	(5.685)	(5.675)	(5.977)	(5.977)	(5.955)
Some College	-52.062018***	-52.062018***	-52.401687***	-55.345361***	-55.345361***	-55.504348***
	(5.687)	(5.687)	(5.677)	(5.945)	(5.945)	(5.927)
College Grad	-60.991210***	-60.991210***	-63.117091***	-62.916126***	-62.916126***	-64.987548***
	(5.691)	(5.691)	(5.681)	(5.823)	(5.823)	(5.810)
Married		7.066831***	5.379624***		5.542659***	3.894704***
		(0.788)	(0.788)		(1.059)	(1.069)
Single		1.251767	0.304028		2.517898**	1.470648
		(0.850)	(0.849)		(1.036)	(1.025)
Current Smoker			-20.216298***			-21.334002***
			(4.584)			(4.663)
Former Smoker			-3.50506			-4.17979
			(4.577)			(4.636)
N	406,882	406,882	406,882	406,882	406,882	406,882
adj. R^2	0.037	0.037	0.04	0.014	0.014	0.02