The Efficacy of Local Cigarette Excise Taxes in Virginia

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ABSTRACT

Between the years 2004 and 2012 the smoking prevalence in Virginia declined by 3.43%. Over the same period, significant increases in federal, state, and local cigarette taxes occurred. This study first examines the extent to which smoking prevalence impacts smoking related hospitalizations in Virginia in 2004 and then provides analysis on the efficacy of local cigarette taxes in reducing smoking prevalence between the years 2004 and 2012. County-level econometric analyses determined that a one percentage point increase in total smoking prevalence is associated with a 0.0453% increase in COPD hospitalizations and about 27 more asthma hospitalizations per 100,000 persons. While multivariate regression analysis suggested increases in local cigarette taxes are associated with a decline in the total smoking prevalence, more rigorous first difference models suggested increases in local cigarette taxes are associated with an increase in total smoking prevalence. It remains unclear whether local cigarette taxes cause total smoking prevalence to increase. Further study should be done to assess whether increases in local cigarette taxes are conducive to the health of Virginians.

INTRODUCTION

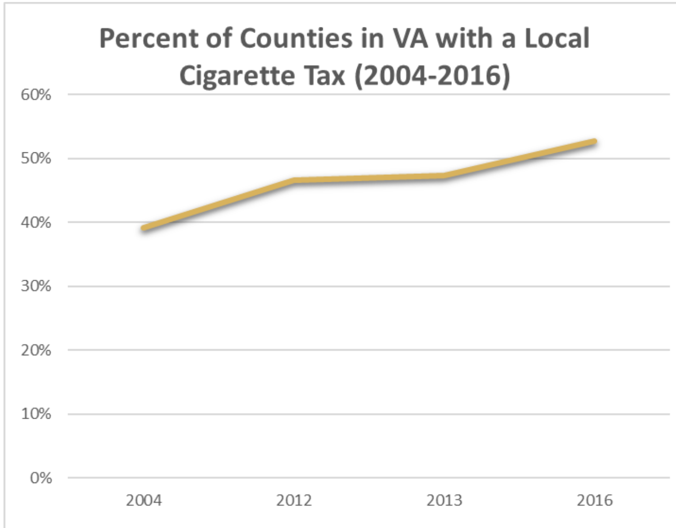
Current Cigarette Tax Policy in Virginia

The Department of Taxation in Virginia grants power to levy cigarette taxes to all towns and cities. Additionally, two counties, Fairfax and Arlington, have the power to levy cigarette taxes because they behave like cities in terms of the services they provide and their revenues. Over 85 localities in Virginia are subject to a cigarette tax. [1] All cigarette taxes are excise taxes. Excise taxes are an indirect per-unit tax paid by the distributor and then added on to the good's price prior to purchase. In addition to the excise tax, all cigarette packages sold in states with sales taxes, such as Virginia, are subject to the state's sales tax. All cigarette packages sold in Virginia are subject to both the state ($0.30) and federal ($1.01) excise taxes. Cigarette distributors are required by law to place a stamp on all packages prior to sale to prove the tax has been paid. Local cigarette taxes are added onto the state and federal taxes prior to sale.

Background

Between the years 2010 and 2013 over fifty localities in Virginia faced cigarette tax hikes. Over the same time period, tax revenues from cigarettes declined by 16.3% and were forecasted to decline even more once consumers adjusted to price increases. [2] Since 2013, local cigarette taxes in Virginia have been on the rise, and the proportion of counties in which there is some type of cigarette tax has been steadily increasing (see *Figure 1*). Dwindling revenues from cigarette taxes pose a perplexing question: If cigarette taxes are accomplishing, why do forecasted revenues continue to fall short? From a fiscal perspective, it may not be beneficial for Virginia localities to continue to raise cigarette taxes, especially if the taxes pose no health benefit to consumers or society. Therefore, it is important to investigate whether Virginia local cigarette taxes reduce smoking prevalence.

Figure 1



Counties' authority to levy cigarette taxes and cigarette tax legislation are salient policy issues in Virginia. In January 2018, Pulaski County lobbied the state legislature for a referendum to grant all counties in Virginia the authority to levy their own cigarette taxes. [3] Additionally, many localities are having debates on whether or not to levy cigarette taxes. In April 2018, Richmond City Council voted down a cigarette tax proposal. [4]

The mean smoking prevalence in Virginia decreased by 3.43% between the years 2004 and 2012 and has been steadily declining since then. The estimated cost of smoking to the United States is approximately $300 billion annually: $170 billion in direct medical care for adults and $156 billion in lost productivity due to premature death and secondhand smoke. [5] Hence it is in the interest of local, state, and federal governments, and individuals in reducing cigarette consumption. While there have been many federal and state-level policies discouraging people from smoking, cigarette taxes are thought to be the most effective local policy measure used to discourage smoking. [6]

Economic Underpinnings of Cigarette Taxation

Excise taxes act through basic economic principles to depress demand in cigarettes. Producers must purchase stamps from local, state, and federal governments. Assuming perfect competition, producers compensate for this additional cost by increasing the price of cigarettes to the base price of a package of cigarettes plus the tax. However, the cigarette industry is not perfectly competitive. Thus, the price of cigarette increases more than the base price plus the tax, posing a higher price hike to consumers. [7]

Consumers, subject to budget constraints, will respond to an increase in the price of cigarettes in one of two ways. Either consumers will decrease the quantity of cigarettes they purchase, depressing the demand for cigarettes, or consumers will exit the marketplace and purchase cigarettes elsewhere. The former is the mechanism by which cigarette taxes alter consumer behavior to produce a positive externality. The latter is typically accomplished by a consumer's entrance into the black market or entrance into another locality's or state's cigarette market.

According to a study completed by Baltagi and Levin (1986) cigarettes have a price elasticity of -0.2, meaning a 1% increase in price is associated with a 0.2% decrease in quantity demanded. [8] Other literature are consistent with this result. [7] Therefore, strong evidence exists that cigarette taxes are successful in decreasing consumption, even when accounting for bootlegging and black-market sales.

While much research has been completed on the national and state-levels, very little research has examined the efficacy of cigarette taxes on the county-level. Federal and state-level cigarette taxes are very different in practice from locality-level taxes. Locality-level cigarette taxes are much easier to escape than state and federal taxes. [9] Some localities in Virginia are so small that consumers can cross the street and go to a different convenience store to dodge the tax. While bootlegging and black markets exist on all levels of taxation, the ease of dodging the tax on the local level is an important distinction worth studying.

This study accomplishes two main tasks: First, it demonstrates the link between county-level smoking related hospitalizations and smoking prevalence. Next, it analyzes whether local cigarette taxes cause smoking prevalence to decline in Virginia counties.

DATA AND SAMPLE

This study evaluates all 133 counties in Virginia during the years 2004 and 2012. A dataset for city, town, and county cigarette taxes was created using yearly reports on county, city, and town level tax rates in Virginia from the Weldon Cooper Center for Public Service at the University of Virginia. [10, 11] Since the tax report from the Weldon Cooper Center was not a fit for statistical analysis, information on local cigarette tax rates was manually entered into Microsoft Excel to create a dataset. County-level data on smoking prevalence for the years 2004 and 2012 was obtained from the Institute of Health Metrics and Evaluation. [12] Patient-level data for Chronic Obstructive Pulmonary Disease (COPD) and Asthma hospitalizations were obtained from Virginia Health Information (VHI). [13] County level population estimates for total population, race, ethnicity, sex, and age were obtained from the US Census Bureau's Population and Housing Unit Estimates datasets. Town and city-level estimates for total population were also obtained from the US Census Bureau's Population and Housing Unit Estimates datasets. [14] The US Census Bureau extrapolates the census estimates obtained every decade to create reliable yearly estimates. County-level median income and poverty rate estimates were obtained from the US Census Bureau Small Area Income and Poverty Estimates (SAIPE) Program's datasets. [15] All analysis was completed on the county-level.

METHODS

Smoking prevalence was defined as total number of persons in a county i who smoke divided by the total population in the county. Two additional measures of smoking prevalence were used in all regression models. The first was the total female daily smoking prevalence, measured by the total number of females who smoke on a daily basis in county i, divided by the total population in the county. The next was the total male daily smoking prevalence, measured by the total number of males who smoke on a daily basis in county i, divided by the total population in the county. Female and male daily smoking prevalences were used to account for frequency of smoking among adults who smoke.

In the smoking prevalence data, there were four cases in which independent cities residing within a county were treated as part of the county. Hence, one smoking rate existed for two observations in the sample. This problem occurred for the pairs of Fairfax County and Fairfax City, Augusta County and Waynesboro City, Prince William County and Manassas Park City, and

Southampton County and Franklin City. To correct for this issue, the smoking prevalence statistic was multiplied by the sum of the city and county's total populations to obtain the total number of persons within the city and county who smoke. Then, a city-county population allocation factor was multiplied by the total number of persons within the city and county who smoke. The city-county population allocation factor was obtained from Missouri Census Data Center's Geographic Correspondence Engine. [19] Two numbers were obtained from this process: one for the total number of persons in the respective city who smoke and the total number of persons in the respective county who smoke. Then, each of these numbers were divided by the total population in the respective city or county in the respective year. This process was completed for 2004 and 2012 smoking prevalence data.

All regression models estimated in this study used the same control variables. In models using 2004 data, control variables from the year 2004 are used. In models using 2012 data, control variables from the year 2012 are used. In models using both 2004 and 2012 data, control variables from both years are used. In all models listed below, X denotes the group of all control variables. Variables used as controls in this study include county-level measures of median income, poverty rate, percentage of females, percentage of young adults, percentage of middle age adults, percentage of elderly adults, percentage of Black residents, percentage of Asian residents, percentage of residents who report another race, and percentage of Hispanic residents. Percentage of male and white residents were omitted to prevent collinearity in the regression models.

Poverty rate was defined as the number of persons below the federal poverty line in county i divided by total population in the county. Percentage of females was defined as the total number of females in county i divided by the total population in the county. Young adults were defined to be all persons between the ages of 20-44. Middle age adults were defined to be all persons between the ages of 45-64. Elderly adults were defined to be all persons ages 65 and above. Percentage young adult, middle age, and elderly, were defined by the number of persons in the respective age category in county i divided by the total population in the county. Black residents were defined to be residents whose only race is Black. Asian residents were defined to be residents whose only race is Asian. Residents who reported another race were defined to be residents who were one or more race or did not fall into the category of being Black, Asian, or white. Percentage Black, Asian, and Other were defined by the number of persons in the respective race category in a county i divided by the total population in the county. Hispanic residents were defined to be any resident of Hispanic origin. Percentage Hispanic was defined to be the total number of Hispanic persons in a county i divided by the total population in county i.

Population-weighted standard errors were used to correct for heteroscedasticity in all models. In all models u refers to unobserved error.

Smoking-Related Hospitalizations

Smoking-related hospitalizations were defined to be all hospitalizations occurring in short term or critical care hospitals of patients 20 years or older with a primary or secondary diagnosis of COPD or asthma. [17, 18] Codes from the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) were used to identify primary and secondary diagnoses of COPD and asthma. The following ICD-9-CM codes were used to identify patients diagnosed with COPD: 490, 491.0, 491.1, 491.2, 491.20, 491.21, 491.22, 491.8, 491.9, 492.0, 492.8, 494, 494.0, 494.1, and 496. The following ICD-9-CM codes were used to identify patients diagnosed with asthma: 493.00, 493.01, 493.02, 493.10, 493.11, 493.12, 493.20, 493.21, 493.22, 493.81, 493.82, 493.90, 493.91, and 493.92. Two variables indicating the presence of a primary or secondary diagnosis of COPD or asthma were created. The first, $COPDhosp$, took a value of "1" if the patient had a primary or secondary diagnosis of COPD, and zero otherwise. The second, $ASTHMAhosp$, took a value of "1" if the patient had a primary or secondary diagnosis of asthma, and zero otherwise. Once patients with a diagnosis of COPD and asthma were identified, the patient-level dataset was collapsed to the county-level. In the county-level dataset, the $COPDhosp$ variable consisted of the total number of hospitalizations of COPD in a county i in the year 2012. Likewise, the $ASTHMAhosp$ variable consisted of the total number of hospitalizations of asthma in a county i in the year 2012. Both $COPDhosp$ and $ASTHMAhosp$ were then divided by 100,000 to obtain total COPD and asthma hospitalizations per 100,000 persons. Multivariate cross-sectional regressions were then used to obtain population estimates.

The first analysis explored the relationship between smoking-related hospitalizations and smoking prevalence on the county-level in 2012.

$$(1)\ \ln(COPDhosp12_i) = \beta_0 + \beta_1 smoke12_i + \beta_2 X_i + u_i$$

$$(2)\ \text{ASTHMA}hosp12_i = \beta_0 + \beta_1 smoke12_i + \beta_2 X_i + u_i$$

Equations (1) and (2) exploit between county variation in smoking prevalence and COPD and asthma hospitalizations in 2012. Using equations (1) and (2) population estimates capturing the extent to which smoking prevalence impacted COPD and asthma hospitalizations in 2012 were obtained. The natural log of $COPDhosp$ was taken to correct for multiplicative errors.

In equations (1) and (2) $smoke12$ takes three definitions in three separate iterations of each model: total smoking prevalence, total female daily smoking prevalence, and total male daily smoking prevalence.

Measuring Cigarette Tax Efficacy

Tax variables in all models below refer to the population adjusted county-level nominal cigarette rate tax. Tax variables were constructed by weighting town-level cigarette tax rates by the proportion of a county's residents that reside within the town limits in the respective year. Independent cities were treated as county-units in this study. In cases where a town existed in two or more counties, a population allocation factor was used to allocate the town's population in its corresponding county. [19] Once the town-level cigarette taxes were properly weighted, tax data was collapsed to the county-level. In cases where there were multiple towns and cities within a county, the population-weighted town taxes were added together to generate an estimation of the total tax to which residents in a county are subjected. The Fairfax County cigarette tax did not apply in the towns of Clintwood, Herndon, and Vienna in Fairfax County. Instead, Clintwood, Herndon, and Vienna levied their own cigarette taxes. Hence the Fairfax County population-adjusted tax consisted of the weighted cigarette taxes for Fairfax County, Clintwood, Herndon, and Vienna.

The first model used to assess the efficacy of local cigarette taxes in Virginia was a cross sectional regression. This model uses between-county variation in 2004 data on nominal cigarette tax rates and smoking prevalence to estimate the relationship between cigarette taxes and smoking prevalence.

$$(3)\ smoke04_i = \beta_0 + \beta_1 TAX04_i + \beta_2 X_i + u_i$$

In equation (3) $smoke04$ takes three definitions in three separate iterations of the model: total smoking prevalence, total female daily smoking prevalence, and total male daily smoking prevalence.

Next, a first difference model was used to assess the relationship between cigarette taxes and smoking prevalence between the years 2004 and 2012. The first difference model is able to estimate regression coefficients with greater rigor because it is able to account for time invariant differences between counties.

$$(4)\ \Delta smoke_i = \beta_0 + \Delta\beta_1 TAX_i + \Delta\beta_2 X_i + \Delta u_i$$

In equation (4) $\Delta smoke$ takes three definitions in three separate specifications of the model: the difference in total smoking prevalence between the years 2004 and 2012, the difference in total female daily smoking prevalence between the years 2004 and 2012, and the difference in total male daily smoking prevalence between the years 2004 and 2012.

ΔTAX refers to the difference in the difference in the nominal cigarette tax between the years 2004 and 2012 in a county i. Nominal cigarette tax was used instead of the inflation-adjusted (or real) cigarette tax because counties that had no change in cigarette tax between the years 2004 and 2012 exhibited a negative change when inflation adjusted tax rates were used. Hence, nominal cigarette taxes captured the true behavior of cigarette tax rates in this model.

Results

Summary Statistics

Table 1 reports summary statistics for all dependent and explanatory variables. The mean number of COPD hospitalizations per 100,000 in Virginia counties in 2012 was 1744 ± 1133. The mean number of asthma hospitalizations per 100,000 in Virginia counties in 2012 was 843 ± 431. The mean total smoking prevalence was $26.25 \pm 4.02\%$ in 2004 and $23.27 \pm 4.28\%$ in 2012. The mean female daily smoking prevalence was $18.61 \pm 3.99\%$ in 2004 and $15.85 \pm 3.88\%$ in 2012. The mean male daily smoking prevalence was $22.95 \pm 4.28\%$ in 2004 and $18.3 \pm 3.98\%$ in 2012. The mean county-level total smoking prevalence declined by 2.98%% between 2004 and 2012. The mean county-level female daily smoking prevalence declined by 2.76% between 2004 and 2012. The mean county-level male daily smoking prevalence declined by 4.65% between 2004 and 2012. The mean nominal cigarette tax was $0.08 in 2004 and $0.11 in 2012.

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Total Smoking Prevalence, 2004	133	26.25	4.02	14.21	33.94
Total Smoking Prevalence, 2012	133	23.27	4.28	10.02	31.65
Female Daily Smoking Prevalence, 2004	133	18.61	3.99	8.21	27.21
Female Daily Smoking Prevalence, 2012	133	15.85	3.88	5.36	25.78
Male Daily Smoking Prevalence, 2004	133	22.95	4.28	9.92	29.3
Male Daily Smoking Prevalence, 2012	133	18.3	3.98	5.43	26.61
Nominal Cigarette Tax Rate, 2004	133	0.08	0.16	0	0.65
Nominal Cigarette Tax Rate, 2012	133	0.11	0.21	0	0.85
COPD Hospitalizations (per 100,000), 2012	132	1744	1133	13	6530
Asthma Hospitalizations (per 100,000), 2012	132	843	431	0	2626

Fifty counties experienced an increase in the cigarette tax between the years 2004 and 2012. Three counties experienced an increase in the total smoking prevalence between the years 2004 and 2012. Twelve counties experienced an increase in the female daily smoking prevalence. Zero counties experienced an increase in the male daily smoking prevalence. The median value of the median income in counties with a cigarette tax was $38,476.50 in 2004 and $35,316.51 in 2012. The median value of the median income in counties without a cigarette tax was $38,891 in 2004 and $35,294.23 in 2012. The median population in counties with a cigarette tax was 33,700 on 2004 and 35,038 in 2012. The median population of counties without a cigarette tax was 18,750 in 2004 and 18,816 in 2012.

Norton City had the most COPD hospitalizations per 100,000 (6,529) in 2012. Greensville County had the most asthma hospitalizations per 100,000 (2,626) in 2012. Hopewell County had the highest smoking prevalence (33.94%) in 2004, while Buena Vista City had the highest smoking prevalence (31.65%) in 2012. Newport News and Hampton Cities had the highest cigarette tax ($0.65/pack) in 2004, while Newport News City had the highest tax ($0.85/pack) in 2012.

Smoking Related Hospitalizations

Regression coefficients and population-adjusted standard errors estimated from equations (1) and (2) are displayed in *Table 2*. For a detailed table of regression coefficients from equations (1) and (2) see *Table 1* in the Appendix.

Equation (1) estimated a positive relationship between total smoking prevalence, and female and male daily smoking prevalence and the natural log of COPD hospitalizations per 100,000. Coefficients were statistically significant at the $\alpha = 0.05$-level. In the year 2012, a one percentage point increase in the total smoking prevalence was associated with a 0.0453% increase in COPD hospitalizations. Similar patterns exist with female and male daily smoking prevalence (*Table 2*).

Equation (2) estimated a positive relationship between asthma hospitalizations per 100,000 and total smoking prevalence, and female and male daily smoking prevalence. The coefficient for total smoking prevalence was statistically significant at the $\alpha = 0.1$-level, and the coefficient for female daily smoking prevalence was statistically significant at the $\alpha = 0.01$-level. There was a large difference in the magnitude of the coefficient between male and female daily smoking prevalence. While a one percentage point increase in female daily smoking prevalence was associated with about 39 more hospitalizations per 100,000, a one percentage point increase in male daily smoking prevalence was associated with about 5 more hospitalizations per 100,000.

Table 2: Smoking Related Hospitalizations Regressions, 2012

VARIABLES	**Total Smoking Prevalence (2012)**	**Female Daily Smoking Prevalence (2012)**	**Male Daily Smoking Prevalence (2012)**
ln(COPD Hospitalizations per 100,000 (2012)	0.0453**	0.0405**	0.0407**
	(0.0191)	(0.0188)	(0.0198)
Asthma Hospitalizations per 100,000 (2012)	26.90*	39.07***	4.746

	(14.13)	(13.65)	(14.81)

Population adjusted standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Measuring Cigarette Tax Efficacy

Regression coefficients and population-adjusted standard errors estimated from equation (3) are displayed in *Table 3*. For a detailed table of regression coefficients from equation (3) see *Table 2* in the Appendix.

An inverse relationship between nominal cigarette tax and smoking prevalence was observed for all measures of smoking prevalence. Coefficients for female and male daily smoking prevalence are statistically significant at the $\alpha = 0.1$-level. A one cent increase in the nominal cigarette tax was associated with about a 0.03 percentage point decrease in total smoking prevalence in 2004. Likewise, a one cent increase in the nominal cigarette tax was associated with decreases for female and male daily smoking prevalences by about 0.09 and 0.03 percentage points, respectively. Females appear to respond to increases in the cigarette tax with greater magnitude than males.

Table 3: Cross Sectional Regression, 2004

VARIABLES	Total Smoking Prevalence (2004)	Female Daily Smoking Prevalence (2004)	Male Daily Smoking Prevalence (2004)
Nominal Cigarette Tax (2004)	-0.0287	-0.0914*	-0.0301*
	(0.0165)	(0.0517)	(0.0170)

Population adjusted standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Regression coefficients and population-adjusted standard errors estimated from equation (4) are displayed in *Table 4*. For a detailed table of regression coefficients from equation (4) see *Table 3* in the Appendix.

Positive relationships between the nominal cigarette tax and total smoking prevalence, and male smoking prevalence were observed. An inverse relationship between the nominal cigarette tax and female daily smoking prevalence was observed. None of the coefficients estimated were statistically significant. A one cent increase in the nominal cigarette tax was associated with approximately a 0.002 percentage point increase in the smoking prevalence. A one cent increase in the nominal cigarette tax was associated with approximately a 0.023 percentage point decline in the female daily smoking prevalence, and approximately a 0.022 percentage point increase in the male daily smoking prevalence.

Table 4: First Difference Model (2004, 2012)

VARIABLES	**∆ Smoking Prevalence**	**∆ Female Daily Smoking Prevalence**	**∆ Male Daily Smoking Prevalence**
∆ Nominal Cigarette Tax	0.00163	-0.0230	0.0219
	(0.0127)	(0.0182)	(0.0168)

Population adjusted standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

DISCUSSION

Positive relationships revealed in regressions analyzing smoking related hospitalizations and smoking prevalence comes as no surprise. There are many scientific and economic studies that demonstrate a strong, positive relationship between smoking related hospitalizations and smoking prevalence. However, female daily smokers exhibit a distinctive relationship with asthma hospitalizations. A one percentage point increase in the female daily smoking rate is associated with about 39 more asthma hospitalizations per 100,000. Furthermore, the coefficient is strongly statistically significant (0.01 > p-value), indicating a high probability that this result is not occurring by chance. Results from the smoking related hospitalization models should provide compelling to federal, state, and local governments, and individuals to reduce smoking prevalence.

Results from equation (3) align with economic theory and prior literature. The coefficient for female daily smoking prevalence suggests that that females may be more sensitive to increases in cigarette taxes than males. Female smoking prevalence declines by about three times that of males with a one cent increase in the nominal cigarette tax.

The first difference model revealed an interesting pattern between changes in cigarette taxes and smoking prevalences. While a one cent increase in the nominal cigarette tax was associated with increases in the total smoking prevalence and male daily smoking prevalence, female daily smoking prevalences were estimated to decline. However, none of the coefficients estimated were statistically significant. Hence, the results need to be interpreted with caution. Results from equation (4) are not supported by prior literature. [7, 20]

In models (3) and (4), female daily smokers respond uniquely to changes in the cigarette tax. In model (3), females respond to taxation with a greater magnitude than males, and in model (4) females respond to taxation in a completely different manner than males. Further, the extent to which asthma hospitalizations increase when female smoking prevalence increases is much higher than that of males, indicating that female daily smokers may pose a larger public health problem. The ways in which females respond to increases in cigarette taxes and increases in smoking prevalences merit further study. Policy makers may be interested in the difference between the patterns of female and male daily smokers and the ways in which females respond differently to cigarette taxation.

The main limitation to this study lies in the estimation of the first difference model. Since results do not align with prior literature, there may have been a methodological error in estimating the first difference model. Due to lacking data on factors such as cigarette smuggling, tax avoidance, and time varying health attitudes, there is a high probability that omitted variable bias is driving the results from the first difference model.

Furthermore, hospitalization data from 2004 was not available for this study. Therefore, it is important to use caution when comparing the results between models (1)/(2) and (3). Since data was limited for 2004, it was difficult to obtain proper data for ample control variables in this study. Future researchers should use more control variables in their models to limit error.

To my knowledge, this is the first study examining the efficacy of local cigarette taxes in Virginia. Since results from this study do not provide clear evidence on impact of local cigarette taxes on smoking prevalence, it is important for future researchers to study this relationship with more rigor. Future studies could improve upon this study by accounting for cigarette smuggling, tax avoidance, and time-varying health attitudes.

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APPENDIX

Table 1: Smoking Related Hospitalizations

VARIABLES	ln(COPD Hospitalizations per 100,000), 2012	Asthma Hospitalizations per 100,000 (2012)	ln(COPD Hospitalizations per 100,000), 20122	Asthma Hospitalizations per 100,000 (2012)2	ln(COPD Hospitalizations per 100,000), 20123	Asthma Hospitalizations per 100,000 (2012)5
Total Smoking Prevalence, 2012	0.0453**	26.90*	.	.	.	.
.	(0.0191)	(14.13)	.	.	.	.
Female Daily Smoking Prevalence, 2012	.	.	0.0405**	39.07***	.	.
.	.	.	(0.0188)	(13.65)	.	.
Male Daily Smoking Prevalence, 2012	.	.	.	.	0.0407**	4.746
.	.	.	.	.	(0.0198)	(14.81)
Median Income, 2012	2.86e-06	0.00749	-2.49e-07	0.00769*	9.73e-07	0.00315
.	(6.16e-06)	(0.00456)	(5.61e-06)	(0.00407)	(5.98e-06)	(0.00447)
Poverty Rate, 2012	0.0246**	13.88	0.0260**	13.06	0.0254**	16.80*
	(0.0113)	(8.380)	(0.0113)	(8.169)	(0.0114)	(8.495)
% Female, 2012	0.0286	47.99***	0.0149	40.09***	0.0336	41.81**
	(0.0216)	(16.02)	(0.0209)	(15.12)	(0.0229)	(17.11)
% Young Adult, 2012	-0.00980	9.286	-0.0135	10.49	-0.00840	3.361
	(0.0128)	(9.500)	(0.0124)	(9.010)	(0.0136)	(10.15)
% Middle Age, 2012	-0.00454	2.957	-0.00427	-1.031	0.00614	9.670
	(0.0236)	(17.45)	(0.0237)	(17.20)	(0.0232)	(17.34)
% Elderly, 2012	-0.00367	0.957	-0.00237	5.870	-0.00651	-4.091
	(0.0171)	(12.64)	(0.0174)	(12.61)	(0.0170)	(12.70)
% Black, 2012	-0.00221	10.47***	3.55e-07	12.62***	-0.00144	10.55***
	(0.00292)	(2.164)	(0.00311)	(2.255)	(0.00296)	(2.215)
% Asian, 2012	-0.0280***	-10.58	-0.0256**	-6.039	-0.0265**	-13.32

	(0.0105)	(7.760)	(0.0109)	(7.919)	(0.0109)	(8.115)
% Other, 2012	-0.0134	-38.60	0.0149	-17.86	-0.0274	-31.77
	(0.0552)	(40.94)	(0.0552)	(39.99)	(0.0572)	(42.74)
% Hispanic, 2012	- 0.0308***	-5.047	-0.0302***	-6.200	-0.0280***	-2.561
	(0.00963)	(7.138)	(0.00966)	(7.001)	(0.00953)	(7.128)
Constant	5.031**	-3,204**	6.204***	-2,891**	4.853**	-2,171
	(1.978)	(1,466)	(1.818)	(1,318)	(2.105)	(1,574)
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Observations	132	132	132	132	132	132
R-squared	0.789	0.570	0.787	0.586	0.787	0.558

Population adjusted standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2: Cigarette Taxes and Smoking Prevalence: Cross Sectional Regression

VARIABLES	Total Smoking Prevalence, 2004	Female Daily Smoking Prevalence, 2004	Male Daily Smoking Prevalence, 2004
Nominal Cigarette Tax, 2004	-0.0287*	-0.0914*	-0.0301*
	(0.0165)	(0.0517)	(0.0170)
Median Income, 2004	-0.000187***	-0.000154***	-0.000244***
	(4.61e-05)	(4.44e-05)	(4.75e-05)
Poverty Rate, 2004	0.150	0.263**	-0.0530
	(0.117)	(0.113)	(0.121)
% Female, 2004	0.0388	0.0635	-0.0465
	(0.0980)	(0.0965)	(0.101)
% Young Adult, 2004	-0.227**	-0.252**	-0.298**
	(0.113)	(0.111)	(0.117)
% Middle Age, 2004	0.238**	0.230**	0.167
	(0.116)	(0.111)	(0.119)
% Elderly, 2004	-0.405***	-0.460***	-0.465***
	(0.116)	(0.113)	(0.120)

% Black, 2004	-0.0120	-0.0927***	0.0157
	(0.0148)	(0.0142)	(0.0152)
% Asian, 2004	-0.508***	-0.461***	-0.550***
	(0.161)	(0.155)	(0.166)
% Other, 2004	0.00155	-0.0214	-0.101
	(0.261)	(0.249)	(0.269)
% Hispanic, 2004	0.191***	0.109	0.197***
	(0.0699)	(0.0668)	(0.0721)
Constant	38.33***	30.41***	49.01***
	(11.04)	(10.94)	(11.38)
Observations	133	133	133
R-squared	0.703	0.728	0.723

Population adjusted standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Cigarette Taxes and Smoking Prevalence: First Difference Model

VARIABLES	**∆ Total Smoking Prevalence**	**∆ Female Daily Smoking Prevalence**	**∆ Male Daily Smoking Prevalence**
∆ Nominal Cigarette Tax	0.00163	-0.0249*	0.0237*
	(0.0127)	(0.0149)	(0.0122)
∆ Median Income	-8.17e-05*	-0.000153***	8.82e-05**
	(4.20e-05)	(4.95e-05)	(4.06e-05)

Δ Poverty Rate	0.0312	-0.0907	0.104*
	(0.0571)	(0.0673)	(0.0551)
Δ Total Population	8.71e-06	6.01e-06	-3.81e-06
	(5.55e-06)	(6.54e-06)	(5.36e-06)
Δ % Female	-0.317	0.122	-0.489*
	(0.300)	(0.354)	(0.290)
Δ % Young Adult	0.244*	-0.488***	0.712***
	(0.144)	(0.169)	(0.139)
Δ % Middle Age	0.264**	-0.469***	0.497***
	(0.131)	(0.154)	(0.126)
Δ % Elderly	0.154	-0.738***	0.935***
	(0.178)	(0.210)	(0.172)
Δ % Black	0.190**	-0.0645	0.304***
	(0.0750)	(0.0885)	(0.0725)
Δ % Asian	-0.240	-0.331*	0.447***
	(0.153)	(0.180)	(0.148)

Δ % Other	0.706	0.702	1.607***
	(0.602)	(0.709)	(0.581)
Δ % Hispanic	-0.286**	-0.205	-0.282**
	(0.129)	(0.152)	(0.125)
Constant	-3.788***	-1.613**	-7.221***
	(0.636)	(0.750)	(0.614)
Observations	133	133	133
R-squared	0.222	0.158	0.364
Number of FIPS	133	133	133

Population adjusted standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$