

APPENDIX 1

To identify the potential control states for the analysis, we compared the Centers for Disease Control and Prevention's (CDC's) recommended funding levels for each state with the state's level of tobacco control program funding. This comparison was conducted so that states with tobacco control programs were not included as potential control states for the synthetic control group analysis. The funding thresholds selected are summarized in Table A1, and include 5%, 10%, 15%, and 20% values. These percentages indicate the actual level of funding in the state compared to the CDC-recommended funding level for the state. Operationalized, this means that for the 5% criteria, states whose funding levels exceeded 5% of the CDC-recommended funding level in any year of the post-treatment period (1999–2015) were excluded from the pool of potential control states. This exercise was repeated for 10%, 15%, and 20% funding levels. As an alternate specification, we relaxed the standards so that a state could have funding levels above the specified percentage level in some years but could not exhibit more consistent funding. For this specification, a state could have funding levels that exceeded the percentage threshold in no more than 3 of the 17 years. For this condition, states had on average 1 to 2 years of funding that exceeded the criteria level. We used the various threshold values and criteria in order to have a mix between conservative control state pools (as few as 4 states) and relaxing the criteria to include more states as potential control states (as many as 21 states).

In addition to varying the control states, we also varied the predictors that are used to select the synthetic control states in the pretreatment period. As noted in the paper, the predictors were the percentage of the population aged 18+, the percentage of the population that is male, the percentage of the population that reported making a quit attempt in the past year, the median income of the state, the poverty rate, the percentage of respondents who reported drinking in the

past week, and the percentage of adults who reported exercising any in the past week. These variables were averaged over the 1991–1999 period and augmented by adding 3 years of lagged smoking prevalence: 1991, 1995, and 1998. We varied these predictors in four models. Model 1 included just the three smoking lags as the predictors. Model 2 included the smoking lags as well as the percentage of the population aged 18+, the percentage of the population that is male, and the percentage of the population who reported making a quit attempt. Model 3 included the same predictors as Model 2 plus the median income of the state and the poverty rate of the state. Model 4 included with same predictors as Model 3 plus the percentage of respondents who reported drinking in the past week and the percentage of adults who reported exercising any in the past week. Using the synth package[1], we computed the mean square predicted error for each of the model specifications and potential control states to which combination most closely matched Florida in the pretreatment period. Table A1 presents the mean squared predicted errors for the various control state combinations as well as the various model specifications. The final model used a 15% funding threshold (with no more than 3 years exceeding a funding percentage of 15%) as well as the full set of predictors for Model 4.

Table A1. Mean Squared Predicted Errors (*100) for the various model specifications

Predictors	Control States Funding Criteria							
	5%	10%	15%	20%	5% Alternate	10% Alternate	15% Alternate	20% Alternate
Model 1	1.772	1.445	1.470	1.504	1.441	1.067	1.259	0.967
Model 2	2.092	1.641	1.577	1.583	1.674	1.297	1.127	1.124
Model 3	2.140	1.518	1.599	1.338	2.020	1.222	1.045	1.110
Model 4	2.140	1.747	1.636	1.367	2.030	1.101	0.885	1.035

Note: Model 1 includes 3 years of lagged smoking prevalence (1991, 1995, and 1998) as predictors. Model 2 includes 3 years of lagged smoking prevalence (1991, 1995, and 1998), as well as the percentage of the population aged 18+, the percentage of the population that is male, and the percentage of the population who reported making a quit attempt as predictors. Model 3 includes 3 years of lagged smoking prevalence (1991, 1995, and 1998), the percentage of the population aged 18+, the percentage of the population that is male, the percentage of the population who reported making a quit attempt as predictors, as well as the median income of the state and the poverty rate of the state. Model 4 includes 3 years of lagged smoking prevalence (1991, 1995, and 1998), the percentage of the population aged 18+, the percentage of the population that is male, the percentage of the population who reported making a quit attempt as predictors, the median income of the state, the poverty rate of the state, as well as percentage of respondents who reported drinking in the past week, and the percentage of adults who reported exercising any in the past week.

Table A2 contains the list of potential control states for the selected model and the weights that were assigned to the selected control states using Stata's *synth* package[1]. Smoking trends in Florida prior to Florida's program funding are best reproduced by a combination of Alabama (21%), Michigan (15.6%), New Jersey (31.8%), Tennessee (11.2%), and Texas (20.5%). Georgia, Illinois, Iowa, Kentucky, Missouri, Nebraska, South Carolina, and Virginia were included as potential control states but were determined by the model to be excluded when constructing a synthetic control group.

Table A2. Control states and assigned weights

State	Weight
Alabama	21.0%
Georgia	0%
Illinois	0%
Iowa	0%
Kentucky	0%
Michigan	15.6%
Missouri	0%
Nebraska	0%

New Jersey	31.8%
South Carolina	0%
Tennessee	11.2%
Texas	20.5%
Virginia	0%
Sum	100.0%

Table A3 contains a comparison of Florida and the synthetic control group on select tobacco control policies since the start of the BTFF. This table shows that the synthetic control group had higher levels of taxes and more tax increases than Florida while Florida had higher levels of Clean Indoor Air Law (CIAL) coverage in workplaces and restaurants but lower in bars than the synthetic control.

Table A3. Comparison of Florida and the synthetic control group on select tobacco control policies.

State	CIAL Workplace	CIAL Restaurant	CIAL Bar	State Tax Levels	State Tax Increases
Florida	76.5%	76.5%	0.0%	\$0.75	1
Synthetic control weighted average	31.2%	31.1%	28.8%	\$1.28	2.22

Note: CIAL = Clean Indoor Air Law

Table A4 exhibits the results from the placebo tests. We conducted placebo tests for our selected synthetic control model following the procedure outlined in Abadie et al. (2010).[2] For the placebo tests, we replace Florida with each potential donor to the synthetic control group, placing Florida in the donor pool as a potential control state, and re-estimate the synthetic control model. We then calculate the ratio of the MSPE in the post program period to the MSPE in the pre-program period. This results in 13 tests in our case. We compare the ratio of pre to post

MSPE's in Florida to those for each potential donor to the synthetic control. The post MSPE/pre MSPE ratio for Florida, a measure of the magnitude of the intervention effect, shows that 2 of the 13 potential controls would have achieved a larger effect than what was observed in Florida.

Table A4. Placebo test results.

State	Weight	MSPE (pre)	MSPE (post)	MSPE Ratio (post/pre)
Texas	20.5%	0.86	2.07	2.40
Tennessee	11.2%	1.10	1.94	1.76
Florida	N/A	0.89	1.42	1.60
Iowa	0.0%	0.74	1.18	1.58
Illinois	0.0%	0.83	1.12	1.35
Kentucky	0.0%	3.32	4.47	1.35
Michigan	15.6%	1.21	1.54	1.27
New Jersey	31.8%	2.74	2.83	1.04
Missouri	0.0%	1.88	1.91	1.01
Virginia	0.0%	1.98	1.31	0.65
Nebraska	0.0%	1.71	0.91	0.54
Georgia	0.0%	2.51	1.15	0.46
South Carolina	0.0%	2.18	0.91	0.42
Alabama	21.0%	3.19	1.35	0.42

We also conducted a sensitivity analysis (Table A5). For this we conducted the synthetic control estimation and calculated the ROI for each of 6 model specifications which had the next 6 lowest MSPE's compared to our selected model. This creates a new synthetic control group and then compares Florida to the new synthetic control created. We report the mean and median ROIs across these 6 models. This gives us 6 new ROIs and to some extent measures the sensitivity of our results to the specific model and synthetic control group we create. The results show that the ROIs would be positive and relatively large across all these different model specifications and set of different synthetic controls.

Table A5. Results of Sensitivity Analysis

Model	Net Costs (Smoking Attributable Healthcare Savings - Program Costs)	ROI Healthcare Expenditures	SAM	YLL	Economic Costs Associated With YLL	ROI Mortality
Main Model	6,943,814,267	9.6	29,006	451,402	81,208,172,793	112.4
Sensitivity Analysis Mean	5,615,528,271	7.8	24,520	380,708	68,413,050,560	94.7
Sensitivity Analysis Median	4,109,925,658	5.7	24,520	213,908	38,178,305,228	52.9

Table A6 contains the actual adult smoking prevalence estimates for Florida from CDC's Behavioral Risk Factor Surveillance System as well as the smoking prevalence estimates for the synthetic control group.

Table A6. Prevalence estimates for Florida and synthetic control group

Year	Florida	Synthetic Control
1991	25.0%	24.1%
1992	22.7%	22.6%
1993	22.1%	21.6%
1994	23.8%	23.0%
1995	23.2%	23.1%
1996	21.8%	23.8%
1997	23.6%	23.7%
1998	22.0%	22.9%
1999	20.6%	22.8%
2000	23.2%	23.1%
2001	22.4%	23.0%

2002	22.0%	22.7%
2003	23.9%	23.0%
2004	20.2%	22.0%
2005	21.7%	21.5%
2006	21.0%	20.3%
2007	19.3%	20.1%
2008	17.5%	18.9%
2009	17.1%	19.0%
2010	17.1%	17.6%
2011	19.3%	20.6%
2012	17.7%	20.6%
2013	16.8%	18.8%
2014	17.6%	18.2%
2015	15.8%	17.6%

Estimating Smoking-Attributable Healthcare Expenditures (SAE) in Florida

For our analysis, we examine both the direct and indirect costs associated with smoking. For direct costs, we focus on the healthcare expenditures in Florida associated with smoking-related illness. The Centers for Medicare and Medicaid Services (CMS) provides data on nominal annual total healthcare expenditure data by state of residence for the years 1991 through 2014 online. We downloaded data on total healthcare expenditures in Florida for 1999 through 2014 from the CMS website.[3] We estimated total healthcare expenditures in Florida in 2015 based on the average annual growth in total healthcare expenditures in Florida over the last 10 years of available CMS data (2004–2014). We adjusted nominal annual total healthcare expenditures in Florida for the years 1999 through 2015 for inflation using the national Consumer Price Index (CPI) for medical care produced by the Bureau of Labor Statistics.[4] All healthcare expenditures presented in this paper are expressed in real, inflation-adjusted, 2015 dollars

To estimate the healthcare expenditures associated with smoking, we also used a Smoking-Attributable Fraction (SAF) approach. The SAF for smoking-attributable healthcare expenditures represents the fraction of total healthcare expenditures in Florida that were due to smoking-related illness. We obtained estimates of the SAF of healthcare expenditures in Florida in 1993 from Miller et al.[5] They calculated SAFs based on a 2-part model of annual individual expenditures estimated using the 1987 National Medical Expenditure Survey.

Because new estimates of SAF specific to Florida are not readily available and are difficult to obtain given the data requirements for producing such estimates, we adjusted the 1993 SAF for Florida to account for changes in adult smoking prevalence in Florida over the years from 1994 through 2015. Based on year-over-year relative changes in adult smoking prevalence in Florida for the years 1994 through 2015, we adjusted the 1993 SAF for Florida using the formula below:

$$SAF_{Florida} = SAF_{Florida (Previous Year)} \\ \times (1 + \text{Relative \% Change in Annual Smoking Prevalence})$$

The SAF estimates reported by Miller et al.[5] exclude healthcare expenditures for dental care. We follow that approach and exclude healthcare expenditures for dental services from our analysis. Adult smoking prevalence estimates for Florida for the years 1993 through 2015 were obtained from the CDC's Behavioral Risk Factor Surveillance System (BRFSS).[6].

We calculated annual smoking-attributable healthcare expenditures in Florida by multiplying inflation-adjusted total healthcare expenditures in Florida by our annual estimates of the SAF for healthcare expenditures in Florida.

$$SAE_{Florida} = Total\ Healthcare\ Expenditures_{Florida (Real \$ 2015)} \times SAF_{Florida}$$

Estimating Smoking-Attributable Mortality (SAM) and Smoking-Attributable Years of Life Lost (YLL) in Florida

We obtained annual estimates of both total and smoking-attributable mortality as well as average remaining life expectancy in Florida for the years 1999 through 2015 from the 2017 Global Burden of Disease (GBD) study. The 2017 GBD study, produced by the Institute for Health Metrics and Evaluation (IHME), serves as a tool for estimating morbidity and mortality from a broad spectrum of diseases and risk factors across 195 countries and territories from 1990 through 2017. GBD data are collected and analyzed by a consortium of over 3,000 researchers in more than 130 countries. Data capture premature mortality and disability from more than 300 diseases and injuries by geography, year, age, and sex. These data are accessible on the IHME's Global Health Data Exchange (GHDx) website: <http://ghdx.healthdata.org/gbd-results-tool>. We downloaded GBD data on total mortality, smoking-attributable mortality (SAM), and average remaining life expectancy by sex, 5-year age group, and cause for Florida for the years 1999 through 2015 from the IHME website for the 2017 GBD study results.[7] Our analytic data set includes GBD data for 33 different communicable and non-communicable diseases associated with smoking-attributable mortality in Florida.

Using GBD on total and smoking-attributable mortality in Florida, we derive the Smoking-Attributable Fraction (SAF) of mortality associated with smoking in Florida. The SAF for smoking-attributable mortality represents the fraction of total deaths in Florida that were due to smoking. We derive annual SAFs for each sex, 5-year age group, and each of the 33 specific causes included in our analytic data. We estimate the SAFs for mortality using the following formula:

$$SAF_{Sex, Age, Cause} = \frac{\text{Smoking-Attributable Deaths}_{Sex, Age, Cause}}{\text{Total Deaths}_{Sex, Age, Cause}}$$

We calculated smoking-attributable years of life lost (YLL) using GBD data on smoking-attributable mortality (SAM) in Florida as well as GBD data on average remaining life expectancy by sex and 5-year age group. Average remaining life expectancy is the number of additional years a person is expected to live at a given age, assuming he or she will experience the age-specific mortality rate observed in a given year throughout the rest of his or her lifetime. The GBD data on average remaining life expectancy is reported by sex and 5-year age groups. The average remaining life expectancy associated with each 5-year age group (e.g. 50 to 54-year-olds) is equal to the average remaining life expectancy at the starting year of the age group. The GBD data on average remaining life expectancy is expressed with decimals to represent fractional years of average remaining life expectancy. We used a floor function and converted the average remaining life expectancy for each sex and 5-year age group to the nearest whole number. To calculate YLL, we multiply the annual number of smoking-attributable deaths for each sex and 5-year age group by the average remaining life expectancy for that sex and 5-year age group.

$$\begin{aligned} \text{Smoking-Attributable Years of Life Lost (YLL)}_{Sex, Age} \\ &= \text{Smoking-Attributable Deaths}_{Sex, Age} \\ &\times \text{Average Remaining Life Expectancy}_{Sex, Age} \end{aligned}$$

Estimating the Economic Value of Premature Mortality Due to Smoking in Florida

The measure of indirect costs associated with smoking in Florida that we examine in this study is the economic value of life lost due the premature mortality from smoking-attributable deaths. To calculate the economic value of life lost due to premature mortality, we calculated the present value for each year of life lost by age of death and then multiplied that currency amount by the number of smoking-attributable deaths in each age group. We calculated the economic value of premature mortality due to smoking in Florida using two different methods: a per capita GDP approach for the Value of a Life Year (VLY) and a Value of a Statistical Life Year (VSLY) approach. Both approaches consist of placing an economic (e.g. currency) value on the years of life lost (YLL) due to premature mortality associated with smoking. The number of smoking-attributable years of life lost (YLL) due to premature mortality is the same for both calculations. However, the currency value used to place an economic value of life year lost in the two calculations differs.

Value of a Statistical Life Year (VSLY) Approach: We used a life-year value of \$200,000 (the midpoint of 3 VSLY estimates used in the literature).[8-10] We updated this for inflation using the Consumer Price Index (CPI) to \$235,135 in real, inflation-adjusted, 2015 dollars. Consistent with the US Food and Drug Administration practice, we used a social discount rate of 3% in calculating life-year values.[11]

Estimating the Impact of the Florida Tobacco Control Program on Smoking-Attributable Mortality and Costs

For this analysis, we are assessing the impact of the Florida Tobacco Control Program by estimating what adult smoking prevalence in Florida would have been from 1999 through 2015 if the Florida Tobacco Program had not existed. All of the smoking-attributable mortality (SAM), years of life lost (YLL), healthcare expenditures, and economic value of premature mortality outcomes for Florida are all modeled and estimated as a function of adult smoking prevalence in Florida. To estimate what impact the Florida tobacco control program has had on these smoking-attributable outcomes, we estimate what those outcomes would have been in adult smoking prevalence in Florida over the years from 1999 through 2015 would have remained at the levels estimated by our “Synthetic Control Group” instead of the historical smoking prevalence observed in Florida over those years. The difference between the smoking-attributable outcomes in Florida under the Synthetic Control Group and the historical adult smoking prevalence observed in Florida is the estimated impact that the Florida Tobacco Control Program has had on smoking-attributable mortality (SAM), smoking-attributable years of life lost (YLL), smoking-attributable healthcare expenditures (SAE), and the economic value of premature mortality due to smoking.

To estimate what smoking-attributable outcomes would have been in Florida if annual adult smoking prevalence in Florida over the years from 1999 through 2015 had been at the levels estimated by the “Synthetic Control Group”, we calculate separate annual SAFs for smoking-attributable mortality (SAM) and smoking-attributable healthcare expenditures (SAE) in Florida. We do this by adjusting the original SAFs for our analysis by the relative annual difference in smoking prevalence in Florida between the Synthetic Control Group and the historical adult smoking prevalence observed in Florida. The annual SAFs for the Synthetic Control Group are calculated as follows:

$$SAF_{Synthetic\ Control} = SAF_{Florida} \times [1 + \Delta Prevalence]$$

$$SAF_{Synthetic\ Control} = SAF_{Florida} \times \left[1 + \frac{(Prevalence_{Synthetic\ Control} - Prevalence_{Florida})}{Prevalence_{Florida}} \right]$$

We calculate annual SAFs separately for smoking-attributable mortality (SAM) and smoking-attributable healthcare expenditures (SAE). The annual SAFs for smoking-attributable mortality for the Synthetic Control Group scenario are calculated separately for each sex, 5-year age group, and specific disease included in our analytic data. The annual SAFs for smoking-attributable healthcare expenditures are calculated at the state level and result in a single SAF per year.

We use the SAFs for the Synthetic Control Group to calculate smoking-attributable mortality (SAM) and smoking-attributable healthcare expenditures (SAE) in Florida over the years from 1999 through 2015 that would have been expected had adult smoking prevalence in Florida been equal to the level for the Synthetic Control Group over those years. We calculated smoking-attributable mortality for the Synthetic Control Group by multiplying annual estimates of total mortality in Florida by sex, age group and cause from the GBD study by the adjusted SAFs that we calculated for the Synthetic Control Group. We calculated smoking-attributable healthcare expenditures for the Synthetic Control Group by multiplying annual estimates of total health expenditures in Florida by the adjusted SAFs that we calculated for the Synthetic Control Group. We calculated smoking-attributable years of life lost (YLL) and the economic value associated with premature mortality due to smoking in Florida for the Synthetic Control Group using the same methods as described earlier in this section.

To estimate the impact of the Florida Tobacco Control Program on smoking-attributable mortality, years of life lost (YLL), healthcare expenditures, and the economic value of premature mortality due to smoking in Florida over the years from 1999 through 2015, we take the difference in each of those smoking-attributable outcomes in Florida between the Synthetic Control Group scenario and the estimates for Florida based on historical estimates of adult smoking prevalence in Florida.

$$Program\ Impact_{Outcome} = Outcome_{Synthetic\ Control} - Outcome_{Florida}$$

Where Outcome =

- Smoking-Attributable Mortality (SAM)

- Smoking-Attributable Years of Life Lost (YLL)
- Smoking-Attributable Healthcare Expenditures (SAE)
- Economic Value of Years of Life Lost Due to Premature Mortality from Smoking

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