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Predicted Effect of California Tobacco Control Funding on Smoking Prevalence, Cigarette Consumption, and Healthcare Costs, 2012-2016

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Final Report*

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Executive Summary

This report contains the results of a new model of the effect of the California tobacco control program on smoking behavior and healthcare expenditure, and forecasts four alternative funding scenarios for the California tobacco control program.

We use time series regression analysis of aggregate data on tobacco control program funding, smoking behavior and health care expenditures in California compared to control states. The estimates measure the difference in smoking behavior and health care expenditures between California and the control states that can be attributed to differences in tobacco control funding. We use two different estimation methods to check the analysis and find that both produce almost identical results.

If the current funding levels are continued at 5 cents per pack (established by 1988's Proposition 99), the baseline scenario, then California smoking prevalence will stop declining increase from 12.9% to 13.3% between 2012 and 2016 and cigarette consumption per smoker will increase from 233 to 253 packs per year from 2012 to 2016. By 2016, prevalence and consumption per smoker would increase by 9% and 14% from the level in 2011, respectively. The contribution of smoking to healthcare costs in California will also begin to increase.

Cutting the funding level by half would to 2.5 cents per pack initially result in $39 million less in cumulative tobacco control spending per year. This reduction in spending will result in an increase in both prevalence and cigarettes consumed per smoker. Prevalence rises from about 13% to 13.5% from 2012 to 2016 and cigarette consumption per smoker increases from 235 to 261 packs per year. By 2016, prevalence and consumption per smoker would increase by 10% and 17% from the level in 2011, respectively. Compared to the baseline scenario, there would be 134 million more packs of cigarettes sold (worth $508 million the tobacco industry in pre-tax sales) and a cumulative increase in total California healthcare costs between 2012 and 2016 would be $2.2 billion.

An increase in funding by $0.20 per pack (to a total of $0.25 per pack) from the $1.00 tobacco tax increase (i.e., the proposed California Cancer Research Act initiative) would restore the decline in current smoking prevalence and cigarette consumption per smoker. Prevalence would decrease from about 11.2% to 10.9% between 2012 and 2016 and cigarette consumption per smoker would decrease from 199 to 189 cigarettes per year. By 2016, prevalence and consumption per smoker would decrease by 11% and 15% from the level in 2011, respectively. Compared to the baseline scenario, a total of 1.6 billion fewer packs of cigarettes would be smoked (worth $7.2 billion in pre-tax sales to the tobacco industry) and total healthcare costs would be reduced by $28.2 billion.

An increase in per capita funding to the level recommended by the US Centers for Disease Control and Prevention (CDC) *Best Practices* for California ($12.12 per capita, or 56 cents per pack), would initiate a rapid decline in smoking prevalence and a drop in consumption. Doing so would require increasing annual funding for the California Tobacco Control Program from $77.8 million in 2009 to a about $481 million per year. Smoking prevalence would decrease from about 12% to 11.1% between 2012 and 2016 and cigarette consumption per smoker would decrease from 210 to 139 packs per year. By 2016, prevalence and consumption per smoker would decrease by10 % and 38% from the level in 2011, respectively. Compared to the baseline scenario, total cigarette consumption would fall by 1.7 billion packs (worth $6.5 billion in pre-tax sales to the tobacco industry) and reduce cumulative total healthcare costs by $31.6 billion.

The forecast results indicate that if the current level of California tobacco control funding continues at the current 5 cents per pack, then smoking prevalence and consumption per smoker will slowly start to increase over time and estimated healthcare savings due to the reduction in smoking in California will be gradually eroded.

In order to continue progress in reducing harmful smoking behaviors in California, per capita funding for tobacco control programs should be substantially increased. Increasing per capita funding with a $1 excise tax increase as proposed in the California Cancer Research Act that devotes an additional $0.20 per pack sold or increasing per capita funding to the level recommended for California by the CDC would reduce smoking behavior at rates similar to those seen in earlier years of the California program, together with the attendant large reductions in healthcare costs that the California Tobacco Control Program created.

Table. Changes in current smoking prevalence and consumption per smoker, California healthcare costs and tobacco industry revenues between 2011 and 2016 under four scenarios

Scenario	Percent change between 2011 and 2016		Change in California Health Care Costs	Change in Tobacco Industry Sales
	Prevalence	Consumption per Smoker		
1. Status quo (baseline): $0.05 per pack	+9%	+14%	Baseline	Baseline
2. Cut program in half: $0.025 per pack	+10%	+17%	+ $2.2 billion	+$0.5 billion
3. Enact Calif Cancer Res Act: $0.25 per pack and $1 tax increase	-11%	-15%	-$28.2 billion	-$7.2 billion
4. CDC recommended funding: $12.12 per capita ($0.056 per pack)	-10%	-38%	-$31.6 billion	-$6.5 billion

NOTE: See Addendum at the end of this report for updated values for these estimates.

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Introduction

This report uses our previously published model to obtain an updated estimate of the impact of the California Tobacco Control Program on total health care expenditures and cigarette consumption through 2008 (the last year for which data are available) as well the effects of the Program in 2008, both in absolute dollars and as a fraction of health care expenditures (below the level predicted in the absence of the program).

The report also contains projections of future smoking behavior health care costs through 2016 under 6 funding scenarios for the California Tobacco Control Program:

1. Status quo funding as of 2010 (5 cents/pack nominal), or $1.34 per capita (baseline).
2. 50% cut to the TRDRP program funding, to 2.5 cents per pack (nominal) funding from 2012, or $0.85 per pack.
3. Pass a $1.00 increase in the cigarette tax effective July 1, 2011, with 20 cents allocated to tobacco control and a backfill of the reductions in Proposition 99 revenue decline due to the price increase associated with the tax (equivalent to about a 20 cent/pack increase in Tobacco Program funding above the current 5 cents/pack) plus a backfill to compensate for lost revenue to the program due to the tax increase. This scenario is based on the qualified initiative statute California Cancer Research Act This scenario results in $5.56 per capita funding.
4. Funding the California Tobacco Control Program at levels recommended by the US Centers for Disease Control and Prevention *Best Practices for Tobacco Control*. (Centers for Disease Control and Prevention (CDC) 2007) of $12.12 per capita or 56 cents per pack.

These estimates use an improved specification that used a more detailed and disaggregated model of smoking behavior than the previously published model (used for the estimates of total cumulative effects of the Program). The earlier model had one measure of smoking behavior: per capita cigarette consumption. The new model has two measures of smoking behavior: current smoking prevalence and cigarettes consumed per smoker. In the old model, per capita tobacco control funding influenced per capita cigarette consumption, and per capita cigarette consumption, in turn, influenced per capita health care expenditure. In the new model estimates cumulative per capita tobacco control funding affects the prevalence of current smoking and mean consumption per current smoker, which, in turn, jointly affect per capita health care expenditure.

Rationale for the new model

There are two rationales for use of the new more detailed measures of smoking behavior. First, we wanted to develop more detailed models to see if the estimated effects of both tobacco control funding on smoking behavior, and smoking behavior on per capita health care costs were robust to measures used for cigarette smoking behavior. Second, while the original model provided stable estimates of the effects of program funding for the past, the forecasts of the future using just per capita cigarette consumption as a measure of smoking behavior produced relatively unstable forecasts of the effects of Tobacco Control Program funding, which could not be improved by alternative specifications and estimation methods (such as different choices of control states, or weighting schemes for the control states).

Attempts were made to improve the original model's forecasts by adding various 'intercept adjustments', which are adjustments to out-of-sample forecasts based on recursive regression forecast performance. Recursive regression forecast performance is calculated by using estimates based on initial sub-samples to forecast the remaining observations in the sample that were not used for estimation. These 'intercept adjustments' are used when there is a slow drift in the estimated regression intercept or trend. Unfortunately, perhaps due to the small sample size, forecasts based on intercept adjustments were very sensitive to details of the specification of the intercept adjustment.

The new specification was suggested by preliminary estimates that indicated that prevalence and consumption per smoker were cointegrated with per capita tobacco control funding and price.

Simplified Description of the new model

In our earlier work from California (Lightwood, Dinno et al. 2008) and Arizona (Lightwood and Glantz 2011) we developed a model with two regression equations, one to estimate per capita cigarette consumption as a function of cumulative per capita tobacco control funding and another that predicted health care costs as a function of differences in per capita cigarette consumption in California or Arizona and control states that did not have substantial tobacco control programs or tobacco tax increases. The new adds a third equation to also estimate smoking prevalence and predicts consumption per smoker rather than per capita cigarette consumption for the entire population. These two measures of cigarette smoking are then used to estimate health care costs. This new model provides a better description of smoking behavior and provides better predictions of the future based on statistical tests of predictive value of the model than our earlier work.

Estimation of a model with prevalence of current smoking and cigarette consumption per smoker

Data

The data used for the estimation and forecasts are summarized in Table 1. All dollar amounts are in 2009 dollars.

The variables included in the analysis are

$prev_{j,t}$: Prevalence of current smoking in population *j*, for California and control states in year *t*, expressed as a proportion between 0 and 1.
$cps_{j,t}$: Cigarettes consumption per current smoker in population *j*, for California and control states in year *t*, in packs/year per smoker,
$EC_{j,t}$: Cumulative per capita funding in population *j*, for California and control states in year *t*,
$p_{j,t}$: Price per pack of cigarettes in population *j*, for California and control states in year *t*,

$y_{j,t}$: Per capita personal income in population *j*, for California and control states in year *t*,
$a_{j,t}$: Age (proportion of the population > 64 years old) , for *j* California and control states in year *t*, expressed as a proportion >0 and < 1.
$h_{j,t}$: Per capita health care expenditures in population *j*, for California and control states in year *t*,
j: Index for population $j = CA$ for California (intervention), = c for control state populations (aggregate population of 13 control states)
t: Time index. t = 1 to 25 (1984 to 2008 for current smoking prevalence and cigarette consumption per smoker equation; 1980 to 2004 for health care expenditure equation).

Prevalence of current smoking ($prev_{j,t}$) is from the Behavioral Risk Factor Surveillance System (BRFSS) as provided by the CDC State System(Centers for Disease Control and Prevention (CDC) 2011). Consumption per smoker ($cps_{j,t}$) is calculated by dividing per capita cigarette consumption for the respective populations by current smoking prevalence. Per capita cigarette consumption is from the *Tax Burden on Tobacco*, as provided by the CDC State System (Centers for Disease Control and Prevention (CDC) 2011). Cumulative tobacco control funding is calculated from databases provided by Tobacco Free Kids (personal communication) and the CDC State System (Centers for Disease Control and Prevention (CDC) 2011). Cumulative per capita funding is constructed by simply adding up real annual per capita funding. Price per pack of cigarettes ($p_{j,t}$) is from the *Tax Burden on Tobacco*, as provided by the CDC State System (Centers for Disease Control and Prevention (CDC) 2011). Per capita personal income ($y_{j,t}$) is from the Bureau of Economic Analysis U.S. National Income and Product Accounts data (Bureau of Economic Analysis (BEA) 2007). Healthcare expenditure ($h_{j,t}$) uses data from the Center for Medicaid & Medicaid Services (CMS) (Centers for Medicare and Medicaid Services (CMS) 2007).

The sample for the model connecting per capita tobacco control funding to smoking behavior consists of 25 annual observations from 1984 to 2008. The sample for the model connecting per capita tobacco control funding to health care expenditures consists of annual observations from 1980 to 2004.

The reason for the difference in sample periods is that CMS has not updated state estimates for years after 2004; preliminary estimates using National Income and Product Accounts definition of health care expenditure produce similar estimates, after adjustment for differences in the definition of expenditure. The sample period for the equations describing the effect of tobacco control funding on smoking behavior is 1984 to 2008 and the sample period for the equation describing the effect of smoking behavior and healthcare costs is 1980 to 2004.

We used a different forecasting technique for healthcare expenditure because of the lack of comparable data after 2004, the last year of state specific estimates of expenditure provided by CMS that we used to forecast smoking behavior. Therefore we constructed the predictions in two steps. First we calculated forecasts future levels of the prevalence of current smoking and consumption per smoker using a statistical forecast model. Second, we calculated the expected healthcare savings due to different levels of the two measures of smoking behavior (prevalence of current smoking and mean annual cigarette consumption per current smoker) assuming all other variables (most importantly control state per capita healthcare expenditure) remain the same under the different levels of smoking behavior; that is, we forecasted the differences from the baseline scenario. The details of the forecast methodology will be explained below.

Monetary values are expressed in 2009 dollars. Nominal dollars were converted to 2009 dollars using the Bureau of Labor Statistics' all-items and medical care components of the Consumer Price Index for All Urban Consumers (CPI-U) for each Census Region(Bureau of Labor Statistics 2007). Nominal monetary values for each state were deflated using the relevant Census Region price index. The CPI-U for All-Items is used to deflate nominal tobacco education, cigarette prices and, and personal income. CPI-U for Medical Care is used to deflate medical care expenditures. The Data and sources are summarized in Table 1.

Table 1.-Variables used in analysis and data sources.		
Variable	symbol	Source
Prevalence of current smoking	$prev_{j,t}$	Behavioral Risk Factor Surveillance System
Cigarette consumption per smoker per year	$cps_{j,t}$	Tax Burden on Tobacco, and estimates prevalence of current smoking
Cumulative per capita funding tobacco control	$EC_{j,t}$	Tobacco Free Kids and the CDC State System
Price per pack of cigarettes	$p_{j,t}$	Tax Burden on Tobacco
Per capita personal income	$y_{j,t}$	Bureau of Economic Analysis, Regional National Incompe and Product Accounts
Proportion of the population over age 64 years	$a_{j,t}$	Census Bureau, Population Estimates
Per capita health care expenditures	$h_{j,t}$	Centers for Medicare & Medicaid Services
Consumer Price Index, All Items and Medical Care	--	Bureau of Labor Statistics, Inlfation and Prices
Population projections, total, adult, and over 64 years	--	Census Bureau, Population Projections
Population (intervention versus control)	j	--
Time index	t	--

The aggregate variables for the control states are population weighted cross sectional averages of the values for each control state for per capita tobacco control program funding (annual and cumulative), current smoking prevalence, per capita health care expenditures, per capita personal income and age (proportion of population over age 64). The control state price of cigarettes is the cigarette consumption weighted cross sectional average of the control state values. The data for cigarette consumption per current smoker was the weighted by the population of current smokers in each state.

Similar results are obtained if the aggregate variables for the control states are defined as simple arithmetic cross sectional averages of the values for each control state. This weighting scheme is consistent with the Common Correlated Effects (CCE) estimator for nonstationary panels with unmeasured global stochastic trends(Pesaran 2006; Kapetanios, Pesaran et al. 2009). The idea of the CCE estimator is that cross sectional averages of the control state variables using fixed weights

Table 2.—Control States used in the analysis	
Number	Control State
1	Idaho
2	Illinois
3	Indiana
4	Minnesota
5	Montana
6	North Carolina
7	Ohio
8	Rhode Island
9	South Carolina
10	Tennessee
11	Utah
12	West Virginia
13	Wisconsin

represent common unobserved nonstationary trends that affect both California and the control states. Sensitivity analysis of the weighting scheme is not completed for a variety of reasonable weighting schemes and choice of control states.

The control states are chosen from the 38 control states that had no or minimal tobacco control programs and no or small tobacco tax increases before fiscal year 2000 or cigarette tax increases of $0.50 or more per pack over the study used in the previous model and consist of the 13 states (Table 2) that have data on smoking prevalence and consumption per smoker since 1984. (Under the assumption that the CCE approach, the absence of a substantial tobacco control program is no longer necessarily a good criterion for selection of control states. The effects of the explanatory variables as proxies for unobserved trends dominate the effects of the explanatory variables as indices of differences between populations, so the presence or absence of a significant tobacco control program no longer needs to be the principal criterion for choice of control state) This choice was made so that the resulting estimator would be comparable to various fixed weights for combining the annual cross section of control states into an annual aggregate average required for a CCE estimator that are being used in sensitivity analysis.

The estimates using the simple arithmetic average values for controls states and different methods of choosing control states so far indicate that the results are not sensitive these choices. In particular, if it assumed that a random mechanism produced the pattern of states that first initiated BRFSS estimates of smoking prevalence after 1984 (so that these variables are missing at random), then the control state variables can be formed by averaging over more states as additional states include smoking prevalence in their BRFSS survey. The results so far indicate that different methods of choosing control states and calculating aggregate control state variables have produced no practical difference in the results. We chose to use the thirteen states listed in Table 2 with data on current smoking prevalence from 1984 because using a fixed set of states allowed use of fixed weights (for example, a simple average) consistent with CCE estimators and slowly varying weights (for example, population, or the mix of weights as described in the data section above that were actually used) consistent with the construction of aggregate indices describing cross sectional differences in population characteristics.

Regression Models

The unrestricted version of the new model consists of three equations:

- one for prevalence of current smoking
- one for cigarette consumption per smoker as a function of cumulative tobacco control funding and other variables in California and control states
- one for health care expenditures in California as a function of prevalence of current smoking and cigarette consumption per smoker and other variables in California and control states.

Prevalence Equation

$$prev_{CA,t} = f(prev_{c,t}, EC_{CA,t}, EC_{c,t}, p_{CA,t}, p_{c,t}, y_{CA,t}, y_{c,t}) \quad (1)$$

Cigarette Consumption Equation

$$cps_{CA,t} = f_{cps}(cps_{c,t}, EC_{CA,t}, EC_{c,t}, p_{CA,t}, p_{c,t}, y_{CA,t}, y_{c,t}) \quad (2)$$

Health Care Expenditure Equation

$$h_{CA,t} = f_h(h_{c,t}, prev_{CA,t}, prev_{c,t}, cps_{CA,t}, cps_{c,t}, y_{CA,t}, y_{c,t}, a_{CA,t}, a_{c,t}) \quad (3)$$

Linear regression was used throughout this study, so the model is linear in all the explanatory variables. Our previous research from California (Lightwood, Dinno et al. 2008) and Arizona (Lightwood and Glantz 2011) with the model using per capita cigarette consumption as the measure of smoking behavior strongly suggested that a linear specification performed better in terms of in sample fit and forecast performance than other models (such as, for example, a log log constant elasticity model).

Estimation methods

The problem of reliable specification and estimation was just as, or more, acute with the new model with additional variables than it was for the original model that measured smoking behavior with the single variable of per capita cigarette consumption. In order to increase the probability of correct specification we estimated the model using two different methods. The first method was to estimate a static cointegrating regression representing the long run equilibrium relationship between the variables using instrumental variables and check for stationary errors; that is, to check that the regression was cointegrating (Engle and Granger 1987; Maddala and Kim 1998), and then estimate the short run Equilibrium Correction Model (ECM). The second method was to estimate a reduced form specification of a reduced form vector auto-regression (VAR) using ordinary least squares (OLS), and use the resulting dynamic equation to solve for the long run static equilibrium relationship.

The reduced form VAR specification of a dynamic system is written as

$$y_t = \sum_{k=1}^{K} \alpha_k y_{t-k} + \sum_{j=1}^{J} \sum_{k=1}^{K_j} \beta_{j,k} x_{j,t-k} \tag{4}$$

and the long run equilibrium solution is written as

$$y_t = \frac{\sum_{j=1}^{J} \left(\sum_{k=1}^{K_j} \beta_{j,k} \right) x_t}{1 - \sum_{k=1}^{K} \alpha_k} \tag{5}$$

Use of the reduced form VAR specification is consistent with the ECM speciation for the first estimation method which includes only lagged first differences of the explanatory variables on the right hand side of the ECM equation.

Under the hypotheses that the variables are nonstationary due to unit roots and that a cointegrating relationship exists between the variables in each equation, these two different methods of estimation (direct estimation of the cointegrating regression followed by estimation of the ECM, versus estimation of the VAR and solving for the long run equilibrium solution) should asymptotically produce equivalent estimates. In other words, they both estimate the same short run and long run relationships.

Because the two methods produced the same specifications the reliability of model specification used for the final estimates is increased. The reliability is increased because, under the assumption of nonstationarity, we can estimate the same long run equilibrium relationships using two different methods: (1) irrelevant instrumental variables regression that estimates the cointegrating regression directly(Phillips and Hansen 1990; Phillips 2006), and (2) the reduced form VAR approach that estimates a short run dynamic model and then derives the long run equilibrium model (which assuming nonstationarity is the cointegrating regression) from the coefficients of the short run VAR model(Doornik and Hendry 2009).

Estimation of long run equilibrium relationship using instrumental variables

Estimation of the long run cointegrating regressions and the corresponding ECMs followed the method used in previous work for California and Arizona.

The long run equilibrium cointegrating static regression was estimated using generated irrelevant instrumental variables. The Phillips-Perron (Phillips and Perron 1988) and KPSS (Kwiatkowski, Phillips et al. 1992) tests were used to check for stationarity of the residuals. The original specification followed that of our original published models that used per capita cigarette consumption including for both California and control states as separate independent variables. After initial estimation of this equation with unrestricted coefficients for these two variables, we did an F-test to see if we could impose the restriction that the coefficients for these two variables were equal and of opposite sign, i.e., that we could simply use the difference between California (or Arizona) and the control states as the independent variable with a single regression coefficient.. We also tested a reduced model omitting coefficients that did not have a significance level of 0.05. A significance level of 0.05 was used because cointegrating regression coefficients converge to their true value at the rate of the number of observations (rather than the square root) so even in a small sample, all variables that belong in the cointegrating regression should be statistically significant at conventional levels of significance. The residuals for the reduced model were checked for stationarity, and other properties. The initial unrestricted regression was estimated without adjustment for finite sample unit-root bias. The adjustment for finite sample bias is an augmented regression that includes the first differences of the explanatory variables. The final specification was re-estimated with the adjustment in order to check results, and this version was used for the prevalence and cigarette consumption per smoker equations in the simulations.

The error correction model (ECM) for each equation was estimated using OLS. An initial ECM was estimated that included all the variables in the final specification of cointegrating regression with the coefficient restrictions imposed. Variables with insignificant regression coefficients were deleted one by one, starting with the variable with the least significance until all remaining coefficients were significant. Because of the convergence of the estimates is slower for the ECM than for the cointegrating regression and the small number of observations, the significance level was set at 0.10. Even if it failed this significance test, however, a variable was retained if its deletion resulted in serial correlation. The residuals were checked for serial correlation, normality, homoskedasticity, and influential observations.

For both the cointegrating regressions and the ECM estimates, robust estimates were calculated (Huber-Tucky biweight, and median regressions) if there were indications of influential observations.

Estimation of dynamic reduced form VAR specification

Estimation of the dynamic reduced form VAR equation used Autometrics(Doornik 2008; Doornik 2009; Doornik and Hendry 2009), an automated specification search algorithm. Autometrics uses a formal 'General to Specific' approach to model specification, using a structured search over hierarchical trees of different possible specifications, and encompassing tests and cut-point significance tests to delete variables that do not belong in the regression. Autometrics is designed to minimize pre-test bias, loss of power and loss of control of overall significance level that occurs because repeated tests and re-estimation. An automatic model selection algorithm was used to, as far as possible, take human judgment or bias out of the model selection process. Autometrics includes formal diagnostics of residuals (serial correlation, normality, homoskedasticity, and influential observations) as well as various stability tests for parameter constancy and for structural breaks. Autometrics presents a ‘best model’ which is chosen either because it is the unique minimal model that encompasses the original unrestricted model, or is chosen from several candidates based on the Szhwarz information criterion. We accepted the selection made by Autometrics, except where noted. Details of the Autometrics algorithm are presented in the Technical Appendix.

The long run equilibrium solutions (shown in equation 4) for each of the equations (Prevalence, Cigarette Consumption, and Health Care Expenditure) were derived from the dynamic reduced form VAR model (shown in equation 3) by setting all first differences (which are implicitly defined in the VAR) to zero. If all the variables are nonstationary and a cointegrating relationship exists between the variables, then the estimated long run equilibrium model derived from the reduced form VAR should be identical to the static regression estimated above using irrelevant instrumental variables, asymptotically.

OLS was used to estimate the VAR specification. Use of OLS is accepted practice in estimating reduced form VARs. All of the right hand side variables are lagged, and therefore predetermined, and there is OLS is a consistent estimator.

The decisions made for Autometrics by the user are 1) selection of variables to include in the regression, and 2) number of lags to include for each variable. The initial Autometrics estimates used unrestricted models, similar to those used for the instrumental variables regression for the cointegrating regressions. Due to small sample size, the maximum number of lags for initial Autometrics estimates was set to 2, but increased if degrees of freedom permitted, if the VAR regression did not produce well behave residuals.

Methods Used to Build the Forecast Model

Regression Specifications used for the Forecasts

The forecasts are for prevalence of smoking in California, cigarette consumption per smoker in California, and per capita health care expenditures. The forecasts use the irrelevant instrumental variables estimates of the long run equilibrium model for these dependent variables.

Two considerations went into this decision: (1) forecast using short run versus long run equilibrium equations, and (2) choice of estimate (irrelevant instrumental variables or VAR estimates). We used the long run equilibrium model for the forecasts instead of the short run model because there is less uncertainty about the specification of the long run model than for the short run model. The long run equilibrium models give more reliable estimates for the expected trend in the dependent variables over a forecast period of four years than the short run models and avoid confounding long turn trends with short run variation that would occur using either of the short run models (ECM with the cointegrating regression, short run dynamic reduced form VAR estimates). The cointegrating regression fit was good and as close to the mean of the observed values at the end of the sample as the long run solution to the VAR estimates, so there is some evidence from the estimates that the long run predictions are a good indicator of the mean of the observed values over the forecast horizon.

There are two estimates of the long run equilibrium model for the dependent variables: the irrelevant instrumental variables estimates, and the long run solution to the VARs. Asymptotically, the instrumental variables estimate will be equivalent to the long run equilibrium solution to the short run dynamic reduced from VAR estimates. Given that fact that the behavior of the cointegrating regression fits and long run solution to the VAR were very similar in the last third of the sample, we used the irrelevant instrumental variables estimates for two theoretical reasons. First, there can be no simultaneous equations bias because the instruments are constructed from formulas and cannot be correlated with the residuals in the regression equation. Second, the irrelevant instrumentals estimator can be adjusted to account for bias created by the unit root process in the variables that occurs in finite samples, and we used that adjustment for the final estimates for the forecast for the prevalence and cigarette consumption equation. There is theoretical and empirical finite sample evidence that the irrelevant instrumental variables estimates adjusted for unit root bias are less likely to be biased and the coefficient estimates have a normal distribution when the unit root process is highly correlated with the cointegrating regression residuals.

The specifications of the regression equations used for the forecasts are:

Prevalence Equation

$$(prev_{c,t} - prev_{CA,t}) = \alpha_0 + \alpha_1(EC_{CA,t} - EC_{c,t}) + \alpha_2(p_{c,t} - p_{CA,t}) + \alpha_3(y_{c,t} - y_{CA,t}) \quad (6)$$

Cigarette Consumption Equation

$$cps_{CA,t} = \beta_0 + \beta_1(EC_{CA,t} - EC_{c,t}) + \beta_2 p_{CA,t} \quad (7)$$

Health Care Expenditure Equation

$$h_{CA,t} = \gamma_0 + \gamma_1 h_{c,t} + \gamma_2(prev_{c,t} - prev_{CA,t}) + \gamma_3(cps_{c,t} - cps_{CA,t}) + \gamma_4(y_{c,t} - y_{CA,t}) + \gamma_5(a_{c,t} - a_{CA,t}) \quad (8)$$

Design of Forecasts and Calculation of Results

Two types of forecasts were calculated for this report. The first type of forecast is used for prevalence of current smoking and consumption per smoking. The second type of forecast is used for per capita health care expenditure.

The first type of forecast, forecasts of levels that will be expected to be realized *k* period in the in the future, must be calculated using the future values of all the explanatory for up to *k* periods following the last observation at time *T* in the sample period, *t* = 1,…*t*, … *T*, as can be seen in equation 9.

$$y_{T+k} = \gamma_0 + \gamma_1 x_{T+k} + \gamma_2 z_{T+k} \quad (9)$$

In order to forecast y_{T+k}, forecast observations for the explanatory variables x_{T+k} and z_{T+k} must be calculated too. This approach gives you the expected realized values of the dependent variable y_{T+k} conditional on the choice of policy variable x_{T+k} and conditional on the realized value of the other explanatory variables z_{T+k}.

The last available observations in the current smoking prevalence and cigarettes per smoker regressions are for 2008 or 2009, depending on the specific variable, and we have to forecast them over a time horizon of up to seven or eight years, which we thought was reasonable to attempt.

The second type of forecast is a counterfactual forecast of what would have happened under alternative values of the policy variable, all other factors being held constant. Another way of putting it is that you want to measure only the difference in the value of the dependent variable y_{T+k} due to different values of the vector of policy variables x_{T+k}. We do not try to forecast the absolute realized level of y_{T+k}, we just want to estimate the difference in y_{T+k} due to differences in the policy variable x_{T+k}. For this type of forecast you only need to know the values of the policy variable x_{T+k}, but not the other exogenous variables z_{T+k}.

To see this, assume that x^a_{T+k} and x^b_{T+k} are two alternative values of the policy variables and z_{T+k} is another explanatory variable that is not affected by the policy. We want to estimate

$$\begin{aligned}
&y^a_{T+k} - y^b_{T+k} \\
&= (\gamma_0 + \gamma_1 x^a_{T+k} + \gamma_2 z_{T+k}) - (\gamma_0 + \gamma_1 x^b_{T+k} + \gamma_2 z_{T+k}) \\
&= (\gamma_1 x^a_{T+k} - \gamma_1 x^b_{T+k}) \\
&= \gamma_1 (x^a_{T+k} - x^b_{T+k})
\end{aligned} \tag{10}$$

The advantage of this approach is that you do not have to forecast the explanatory variables z_{T+k}, since they drop out of the equation. The disadvantage is that you are not forecasting the future potentially observable levels of y_{T+k} conditional on the future value of the policy variables and the other explanatory variables. Instead, you are forecasting the difference in y_{T+k} attributable to different possible values of the policy variable x_{T+k}, implicitly holding the value of z_{T+k} constant and at the same value for both scenarios.

This second method of forecasting was chosen for per capita health care expenditures because one of the other explanatory variables in that equation is control state health care expenditure, and the last data we have for these expenditures are from 2004. The forecast horizon does not start until eight years after the last data observation so the forecast horizon ends more than ten years after the last year of observed data.

Applying the specification of equation (10) to the forecast of California healthcare expenditure the forecast equation is

$$
\begin{aligned}
& h^a_{T+k,CA} - h^b_{T+k,CA} \\
& = (\gamma_0 + \gamma_1(prev^a_{T+k,c} - prev^a_{T+k,CA}) + \gamma_2(cps^a_{T+k,c} - cps^a_{T+k,CA}) + \gamma_3 h_{T+k,cl}) \\
& - (\gamma_0 + \gamma_1(prev^b_{T+k,c} - prev^b_{T+k,CA}) + \gamma_2(cps^b_{T+k,c} - cps^b_{T+k,CA}) + \gamma_3 h_{T+k,c}) \\
& = (\gamma_1(prev^a_{T+k,c} - prev^a_{T+k,CA}) + \gamma_2(cps^a_{T+k,c} - cps^a_{T+k,CA}) \\
& - (\gamma_1(prev^b_{T+k,c} - prev^b_{T+k,CA}) + \gamma_2(cps^b_{T+k,c} - cps^b_{T+k,CA})) \\
& = \gamma_1((prev^a_{T+k,c} - prev^a_{T+k,CA}) - (prev^b_{T+k,c} - prev^b_{T+k,CA})) \\
& + \gamma_2((cps^a_{T+k,c} - cps^a_{T+k,CA}) - (cps^b_{T+k,c} - cps^b_{T+k,CA}))
\end{aligned}
$$

Using the counterfactual approach to forecasting we can avoid having to forecasting the future values of $h_{T+k,c}$, per capita health care expenditure for control states for eight to twelve years into the future (from 2012 through 2016, when we do not have data after 2004. Prevalence of current smoking and cigarettes per smoker are interpreted to be policy variables because they can be at least partially controlled by choice of per capita tobacco control funding.

The difference between the two methods of forecasting, assuming that there is nonstationary Common Correlated Effects (CCE) process in the data, can be illustrated graphically. Figure 1 shows two simulated series for per capita health care expenditures. The per capita health care expenditure for the intervention population (thick black line) and the control population (thick dashed line) both follow a common stochastic trend (thin dotted line) that cannot be directly observed. The common stochastic trend is determined by unobservable factors common to both the intervention and control populations, such as changes in federal health care policy, trends in industrial organization and delivery of healthcare, and technological progress.

If we try to estimate the per capita health care expenditure for California without adjusting the effect of this common stochastic trend, it will appear in the residual, the regression residuals will be nonstationary and convention statistical estimates and inference will be invalid.

The cross sectional averages of the control populations are added as explanatory variables to the regression to adjust for the presence of the common stochastic trend, and these work as proxies for the unobserved common stochastic trend. That use as a proxy is the rationale for including per capita health care expenditure for the control states as an explanatory variable in the per capita health care equation for California.

The first type of forecast, that predicts future levels of the intervention population (California), and this requires a forecast the unobserved stochastic trend. The natural choice for this forecast, under the CCE interpretation of the regressions, is a forecast of the explanatory variable that represents this common stochastic trend. The second type of forecast is for the difference between the respective levels of per capita health care expenditure in the intervention state (California) under alternative future values of a subset of the explanatory variables. In Figure 1, an alternative history of per capita health care costs for the per capita health care costs for California (thick dashed and dotted line) is shown, and the difference between the per capital health care expenditures in California is indicated by the vertical double headed arrow. The second type of forecast depends on the size of this arrow and forecasting it does not require a forecast of the common stochastic trend..

In addition to the forecast results describe above, the difference between Scenarios 2, 3 and 4 from Scenario 1($0.05 per pack funding, the baseline) were reported for annual health care expenditures per capita, annual total health care expenditures, annual total packs sold, cumulative total health care expenditures, cumulative packs sold, and cumulative value of pretax cigarette sales over the forecast

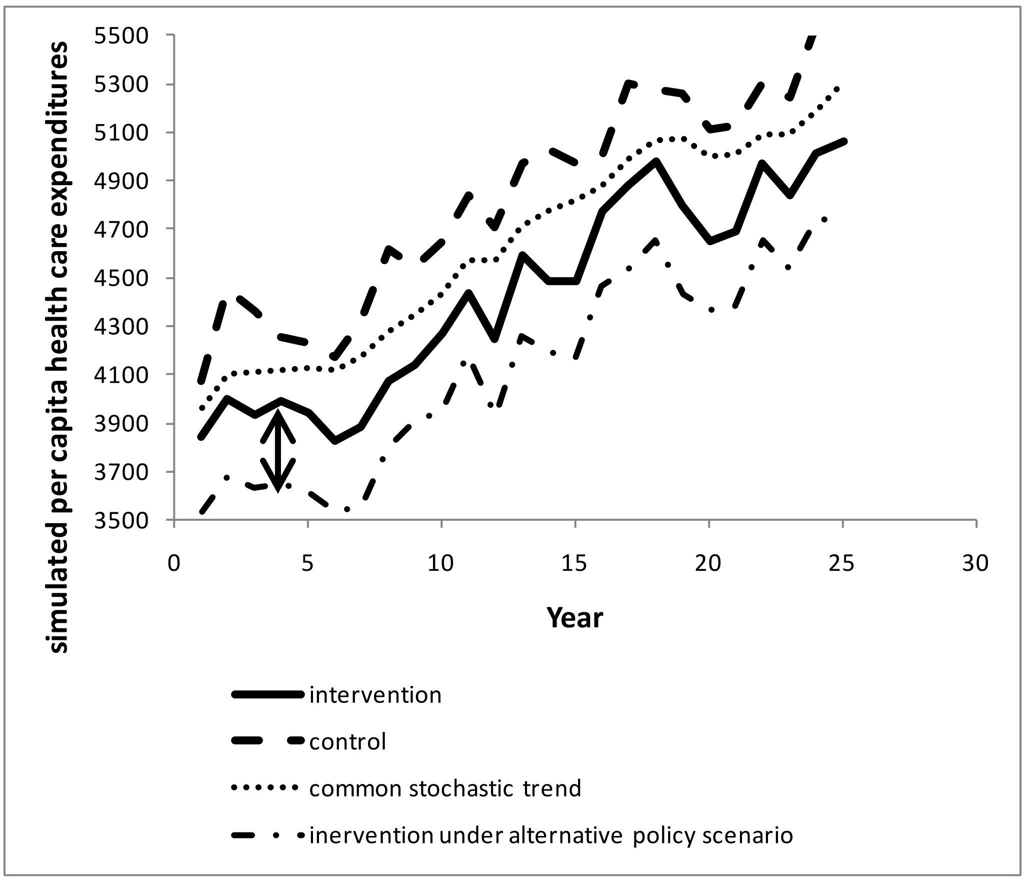

Figure 1. The role of stochastic trends in forecasts of levels versus forecasts that compare alternative counterfactuals. In this example, simulated per capita health care expenditure in the intervention population (solid line) and the control population (dashed line) follow a common nonstationary stochastic trend (dotted line) that is not directly observable. Forecasting levels of per capita healthcare expenditure requires forecasts of the common stochastic trend. Forecasting differences in the intervention state per capita health care costs between different scenarios of smoking behavior (arrow) does not require forecasts of the common stochastic trend.

horizon. The difference between 2011 and 2016 levels were reported for prevalence of current smoking and cigarette consumption per capita. The value of cigarette sales is calculated by multiplying each year's volume of sales reductions by that year's industry prices (exclusive of state and federal taxes).

Estimation of auxiliary predictive models for the explanatory variables

To build a statistical model for the level forecasts (the first type of forecast, for prevalence and cigarette consumption per smoker) more than one observation period into the future forecasts are needed for the explanatory variables. (i.e., per capita tobacco control funding, cigarette price, per capita personal income, prevalence of current smoking, cigarette consumption per smoker and proportion of the population over age 64 years for intervention and control populations). We wanted more options for forecasting the explanatory variables than subjective assessment of scenarios about their future evolution. A natural choice for another option is to build predictive models for the explanatory variables using a reduced form VAR specification with the Autometrics program.

Therefore, we used Autometrics to estimate reduced form VARs for the explanatory variables in the model. The criterion for selecting the best model for these variables was parameter stability, as assessed using Chow break point and CUSM tests and qualitative assessment of graphics of the evolution of regression coefficients from recursive regressions. No preference was given for structural models versus time series models, so if the most stable estimate was an autoregressive statistical model, that model was chosen as the best and used for the forecast model. The main a priori decision in the Autometrics estimation was modeling federal cigarette tax increases in years 1993, 2000 to 2002 in the VAR model for California and control state cigarette prices.

The same question arose about the choice of estimates to use for the forecasts of the explanatory variables as for the dependent variables: should long run or short run models be used? For these estimates we chose the type of estimate that seemed most likely to be close to the observed values over the forecast horizon. We preferred to use the long run equilibrium model, when the long run equilibrium represented some economic market process and there was reason to believe that the observed values would converge quickly to the long run equilibrium. However, there were exceptions. The best estimates selected by Autometrics for some variables were pure time series estimates and there was no obvious economic interpretation to the long run equilibrium. For example, the, the dynamic VAR model used to forecast real per capita personal income for the control states is a pure time series model. The estimated model is

$$y_{c,t} = 2035 + 0.952 y_{c,t-1}$$

The pure time series model for per capita control state per capita personal income has a statistical equilibrium value of

$$inc_{c,t} = 42{,}298,$$

This $42, 298 is far from recent observed values of about $37,000 for $inc_{c,t}$. There are no big jumps on an annual scale for this variable, so it is very unlikely the recent values of $37,000 would suddenly jump up to $42,298. The 95% confidence interval for $inc_{c,t}$ of the four year forecast from 2004 to 2008 estimated over 1980 to 2003 is from $35,000 to $40,700. Therefore, we used the short run dynamic forecasts for this variable.

The estimate chosen for the forecast of each explanatory variable is briefly noted below in the results section.

Time Horizon for the Forecasts

The time period for the forecasts was 2009 to 2016. Some observations required for estimation of of the full model were unavailable for 2009. Observations on the dependent variables current smoking prevalence and cigarette consumption per current smoker were available. The observation for the year 2009 was not included in the estimates and a forecast was made using data to 2008 to forecast the current smoking prevalence and cigarette consumption per capita for year 2009.and an initial forecast was calculated for 2009 to compare to the observed values. Policy changes were assumed to occur in fiscal year 2012

Results

Regression equation estimates for prevalence of current smoking cigarette consumption per smoker, and per capita health care costs

Static regressions of equations estimated using irrelevant instrumental variables were cointegrating and the corresponding ECMs had statistically significant error correction coefficients for prevalence of current smoking, consumption per current smoker, and per capita health care expenditure equations. All of the instrumental variables estimates of the cointegrating regressions and the ECMs for prevalence and consumption per smoker, showed evidence of one or more influential observations, while there was little evidence for influential observations for the ECMs. The robust estimates of for the cointegrating regressions and ECMEs of the equations produced results similar to instrumental variables estimates (for the cointegrating regression) and OLS (for the ECM).

The dynamic reduced form VAR regressions produced stable dynamic models for all three equations with well-behaved residuals. The long run solutions to the dynamic VARs were very similar to the instrumental variables estimates of the cointegrating regressions, which is taken as additional evidence that the static regressions are in fact cointegrating. Asymptotically under the assumption that the variables are nonstationary and equation (1) to equation (3) are cointegrating, these two estimates should be the same.

The forecast simulations were based on the irrelevant instrumental variables cointegrating regression estimates for the tobacco control regressions (which correspond to the long run equilibrium solutions of the dynamic VAR models) because they were very consistent with each other and therefore these estimates are considered more reliable for theoretical reasons. However, after reviewing the results, the irrelevant instrumental variable estimate of the cointegrating regression for California health care expenditure was not adjusted for unit root bias (discussed above) because in this case the adjustment did not seem necessary: none of the adjustment variables were close to conventional statistical significance, and the standard errors of the adjusted coefficient estimates were larger than those of the unadjusted estimates.

There was much more uncertainty in the correct specification of the short run models (the ECM equations corresponding to the cointegrating regressions, and the long run equilibrium solutions to the reduced form VARs). As discussed above, we decided to base the forecasts using the irrelevant instrumentals estimates of cointegrating and regressions for equations (1) to (3), which are asymptotically equivalent to the long run equilibrium solutions to the reduced form VAR dynamic estimates. Our decision to base the model forecasts on the cointegrating regressions instead of the short run dynamic reduced form VAR regressions reduced the likelihood of spurious annual variations in the forecasts that would be the result of incorrect specification of the short run model. However, basing the forecasts of equations (1) to (3) of cointegrating regressions also means that the forecasts are for long run trends, and forecast performance should be evaluated over the whole forecast time horizon, rather than only after the first one or two years of the forecasts. Specifically, they give reliable information about trends that will persist over time that are not confounded by short run variation. There is substantial uncertainty about the specification of the short run model, so over a relatively short time horizon this uncertainty would produce arbitrary annual jumps that might hide or be misleading about the long run trend. Therefore, using the long run estimates will more reliably indicate the long run direction and trends.

While the instrumental variables estimates of the cointegrating regressions were very similar to the long run solutions of the dynamic VAR models, the short run models were not. In other words, the ECM's estimated from the residuals of the cointegrating regressions were not consistent with the corresponding dynamic VAR specifications in lagged levels. The ECMs contained more lagged differenced variables than the VAR specification, which may indicate some over-fitting, i.e., some of the estimated lagged differences in the ECM equations appear to be statistically significant when they actually do not belong in the regression and were retained in the ECM equation when they should have been omitted. Overfitting and mistaken retention of variable in the ECM equation that do not belong will produce unreliable short run forecasts.

Prevalence of Current Cigarette Smoking Equation

Instrumental variables estimate of cointegrating and ECM regressions

The F-tests for the restrictions described in the methods described above, were not statistically significant, so the model was expressed in terms of differences between the variables for California and control states, the same type of specification used for the original model that was based only on with per capita cigarette consumption only. The results of the F-tests were the same in the irrelevant instrumental variables estimates that was unadjusted and adjusted for finite sample unit root bias. The residuals from the regression for prevalence of current smoking may contain a stationary ARMA process, but no statistically significant autocorrelation was found using the Portmanteau test, and the ARMA process was consistent with stationary residuals.

Dynamic VAR estimates

Autometrics selected a simple AR(1) time series model using a list of unrestricted explanatory variables in levels. Therefore, it was assumed that the tests for coefficient equality conducted for the instrumental variables estimates were correct and the Autometrics search algorithm was initialized with a list of lagged dependent and explanatory variables expressed as differences between California and control states, as in the cointegrating regression specification. Autometrics selected a dynamic model that with stable coefficients and well behaved residuals. A test for omitted variables accepted the null hypothesis that age did not enter the VAR.

Consumption per current smoker equation

Instrumental variables estimate of cointegrating and ECM regressions

Except for cumulative tobacco control funding, the control state variables did not enter the cointegrating regression at anything near conventional significance levels. The F-test (and subsequent t-tests) for equal coefficients of opposite sign for control state and California variables were rejected, and the variables with unrestricted coefficients of the control state variables were insignificant at the 5% level. These findings indicated that a model cannot be specified in terms of differences between corresponding California and control state variables. The only control variable that entered the equation, with equal and opposite sign to the corresponding California variable was cumulative per capita tobacco funding for the control states. The regression for consumption per smoker contains a strong AR(1) component consistent with a moving average process, but one that is stationary, which means that it can be described as a cointegrating regression.

Dynamic VAR estimates

Autometrics chose a model that is almost identical to the instrumental variables cointegrating estimates from a list of unrestricted variables. The absolute values of the coefficients for California and control state cumulative per capita tobacco control funding variables were almost identical and of opposite sign in the VAR estimates, which was consistent with the specification chosen for the irrelevant instrumental variables estimate. An F-test for a restriction of equal and opposite signs for California and control state per capita tobacco control funding was not rejected at the 0.05 significance level, so Autometrics was rerun with this restriction imposed. That was the only change made to the initial

Autometrics estimate. A test for omitted variables accepted the null hypothesis that age did not enter the VAR. Thus, the two different estimation procedures produced almost identical results.

Health care expenditures

Instrumental variables estimate of cointegrating and ECM regressions

The residuals of the cointegrating regression showed moderate AR(1) component, but not at conventional levels of significance; the data are stationary using cointegration tests and there is insufficient statistical evidence to conclude that the autoregressive process in the residuals will bias forecasts.

Dynamic VAR estimates

Estimation suffered from the same problems as for the equation for current prevalence: Autometrics chose a pure time series model for California per capita health care expenditure that was a function of its own lagged values and control state health care expenditure. Therefore the Autometrics algorithm was initialized with lagged dependent and explanatory variables expressed as differences between California and control states. The VAR estimates differed from the instrumental variables estimates of the cointegrating regression in that per capita personal income and age (proportion of the population over age 64) were significant in both the dynamic model and the solution to the long run equilibrium model. This result is consistent with the respective strengths and weaknesses of the irrelevant instrumental variables estimate of the cointegrating regression and the OLS reduced form VAR estimates. Estimates of the static cointegrating regression in some cases have lower power than the corresponding long run equilibrium estimates of the cointegrating regression derived from a dynamic VAR regression model, but VAR estimates are sensitive to misspecification of the length of the lagged variables that need to be included. The omission or inclusion of income and age variables in the irrelevant instrumental variables estimate of the cointegrating regression do not make any substantial difference in the estimates of the coefficients of interest. Thus, the VAR estimates suggest that income or age variables may belong in the California health care equation, but their inclusion or omission to not make any practical difference in the estimated coefficients for the smoking behavior variables.

Regressions for Auxiliary Variables Needed for Forecasts

Autometrics usually chose satisfactory auxiliary VAR regressions for the explanatory variables needed for the forecsts that were stable and had well-behaved residuals. Some of the dynamic regression required 3 lags to estimate well-behaved residuals. Reduced form dynamic VAR estimates indicated that control state prevalence and consumption depended on control state tobacco control expenditures, and this dependence was included in the simulation model used for the forecast. Therefore, the results of the forecast depend on the tobacco control funding in the control states because of the information it information provides about unobserved secular trends in smoking behavior over all states (which is the rationale for its inclusion in the regression under the CCE modeling approach), and causal dependence of control state smoking behavior on control state tobacco control funding. Future analysis will attempt to disentangle these two possible roles of control state tobacco funding in the analysis of the California program.

The cointegrating (long run equilibrium) regression estimates used for forecasts

Table 3 presents the final estimates of the cointegrating regressions used for the simulations for the prevalence model, Table 4 presents the cigarette consumption model and Table 5 presents the health care cost model. These estimates used irrelevant instrumental variables regression of the cointegrating regression. These irrelevant instrumental variables estimates are very similar to the long run solutions to the dynamic reduced form VAR estimates. The instrumental variables estimates were chosen for use in the forecast because there are theoretical reasons and small sample simulation evidence that this estimator is least likely to result in bias due because of endogeneity of the explanatory variables or unit root bias in finite samples. The irrelevant instrumental variables estimates for the prevalence and cigarette consumption per smoker are adjusted for finite sample unit root bias from nonstationarity of the variables, but the coefficients of the adjustment variables are not reported.

Table 3.-Regression estimates for Prevalence of Current Cigarette Smoking model ($prev_{j,c}$ - $prev_{j,CA}$).

Source	SS	df	MS
Model	.006872513	6	.001145419
Residual	.001535721	18	.000085318
Total	.008408233	24	.000350343

Number of obs	25
F(6, 18)	13.68
Prob > F	0.0000
R-squared	0.8174
Adj R-squared	0.7565
Root MSE	.00924

$prev_c$ - $prev_{CA}$	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
EC_{CA} - EC_c	.0004842	.0001332	3.64	0.002	.0002044	0.0007641
p_c - p_{CA}	-.0170215	.0081617	-2.09	0.052	-.0341687	0.0001256
y_c - y_{CA}	8.44e-06	1.99e-06	4.25	0.000	4.27e-06	0.0000126
Constant	0.09659	0.015264	6.33	0.000	0.06452	0.1286603

Table 4.-Regression estimates for Consumption per current smoker model (cps_{CA}).

Source	SS	df	MS
Model	126888.918	4	31722.2296
Residual	5404.44224	20	270.222112
Total	132293.361	24	5512.22336

Number of obs	25
F(4, 20)	116.81
Prob > F	0.0000
R-squared	0.9591
Adj R-squared	0.9510
Root MSE	16.438

cps_{CA}	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
EC_{CA} - EC_c	-2.546605	.4215754	-6.04	0.000	-3.425996	-1.667214
p_{CA}	-24.79232	8.601561	-2.88	0.009	-42.73486	-6.849773
Constant	444.5244	20.83263	21.34	0.000	401.0683	487.9805

Table 5.-Regression estimates for Health Care Expenditure model (h_{CA}).

Source	SS	df	MS
Model	895588.267	10	89558.8267
Residual	39945.9327	9	4438.43697
Total	935534.2	19	49238.6421

Number of obs	20
F(10, 9)	20.18
Prob > F	0.0001
R-squared	0.9573
Adj R-squared	0.9099
Root MSE	66.622

h_{CA}	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
h_c	.6336023	.0865071	7.32	0.000	.4492167	.8179879
$prev_c$ - $prev_{CA}$	-10119.57	1868.231	-5.42	0.000	-14101.61	-6137.535
cps_c - cps_{CA}	-4.773737	.6515733	-7.33	0.000	-6.162533	-3.384942
y_c - y_{CA}	.0500923	.0231963	-2.16	0.047	-.0995341	-.0006506
a_c - a_{CA}	10468.7	11110.8	0.94	0.361	-13213.42	34150.81
Constant	2544.652	375.6276	6.77	0.000	1744.02	3345.283

The results of these regression estimates for the key variables linking tobacco control funding to smoking behavior and health care costs are as expected. Increased tobacco control funding reduces smoking prevalence and consumption per smoker, and these reductions in prevalence and consumption compared to control states reduce health care expenditures in California compared to control states.

One additional dollar in per capita (in 2009 dollars) tobacco funding in California reduces the prevalence of current smoking (expressed as a proportion between 0 and 1) by 0.0004842 (Standard error: 0.0001332), holding other factors constant. One additional dollar in per capita tobacco funding in California reduces the annual cigarette consumption of current smokers by 2.54 packs per year (Standard error: 0.422), holding other factors constant. Applied to California, a one dollar increase in cumulative per capita tobacco control funding (i.e., $37 million since the population of California is 37 million people) in 2011 would be associated with a reduction in 14,000 smokers in 2011 and a total drop in cigarette consumption of 12 million packs (3 million packs because of the reduction in prevalence plus 9 million packs because continuing smokers are smoking fewer cigarettes).

The coefficient estimates for the health care expenditure regression indicate that a marginal increase in health care expenditure (in 2009 dollars) due to a 1 percentage point increase California cigarette smoking prevalence, other factors held constant, is $10,120 (SE $1868), and that due to an increase in consumption of one pack peryear per smoker is $4.77 (SE $0.652).

The in-sample fit for the health care expenditure equation is shown below in Figure 1. The in-sample fit of the prevalence and cigarette consumption regressions can be seen in Figures 2 through 7 in the section below describing the forecasts.

Comparison with other estimates

In order to derive estimates that are comparable to the estimates from the published per capita cigarette consumption model, and existing cross sectional estimates, we used the same method as in the published article on California (Lightwood Dinno and Glantz 2008). We assume that the linear regression specification is an approximation of a more complex nonlinear process that is only valid within the range of the sample data, therefore simply plugging in the values for the variables in the cointegrating regression may produce unreliable estimates. Instead, we estimate the expenditure per capita by calculating the annual and cumulative difference in per capita health care expenditure between California and control states over the five years of the forecast horizon (2012 to 2016) by multiplying the regression coefficients for prevalence of current smoking and cigarettes per smoker by the average difference between the values of California and the control states in the sample used for estimation. The per current smoker expenditure is calculated by dividing by the average current smoking prevalence in California and control states over the sample period. This method is consistent with the interpretation of the regression as estimating the difference in per capita costs between California and control states attributable to differences in smoking behavior.

The coefficient from the health care regression result in an estimated per capita expenditure per smoker in California of $1094, and an expenditure per current smoker of $5026. Fifty-three percent this expenditure difference is attributable to the difference in prevalence of current smoking and 46% is due to the difference in cigarette consumption in current smokers. The estimates from the earlier published per capita cigarette model for California (Lightwood Dinno and Glantz 2008) in 2004 dollars are $926 per capita and between $3940 and $4800 per smoker. Using the Medical Care Price Index to convert to 2009 dollars, these estimates are $1116 per capita and between $4750 and $5790 per smoker. So, the estimated model healthcare expenditure as a function of prevalence and cigarette consumption per smoker is consistent with estimates using the per capita cigarette consumption model.

Details of the final irrelevant instrumental variables estimate for the per capita health care expenditure

The specification of the health care equation produced by Autometrics is the same as that produced by the instrumental variables estimate of the cointegrating regression, except that the per capita personal income and age (proportion of the population over 64 years of age) variable was added as an explanatory variable to the cointegrating regression on the basis of the evidence provided by the Autometrics VAR estimate. Addition of personal income was not significant at the 0.05 level, but was significant at the 0.10 level and its inclusion substantially reduced the estimated serial correlation in the residuals of the cointegrating regression. Thus, while personal income may belong in the cointegrating regression, it is not statistically significant due to lower power of the instrumental variables estimate.

The estimates for the healthcare expenditure equation were insensitive to the inclusion of the prevalence of former smoking and other measures of cumulative exposure to smoking such as average cumulative pack years per capita in California and the control states. These other measures do not appear to be part of a cointegrating regression. However, extreme multicollinearity occurs when the independent effect of several prevalence and per capita cumulative pack years of smoking exposure measures are estimated. Cumulative exposure as measured by pack years is highly correlated with current smoking prevalence and former smoking . Thus, based on the available data, current smoking prevalence and cigarette consumption per smoker produced superior models in terms of regression residuals, fit and parameter stability, so the current model is the best specification until more research is conducted into the relationship between the various measures of smoking behavior.

The in-sample fit for the health care expenditure equation is shown below in Figure 2.

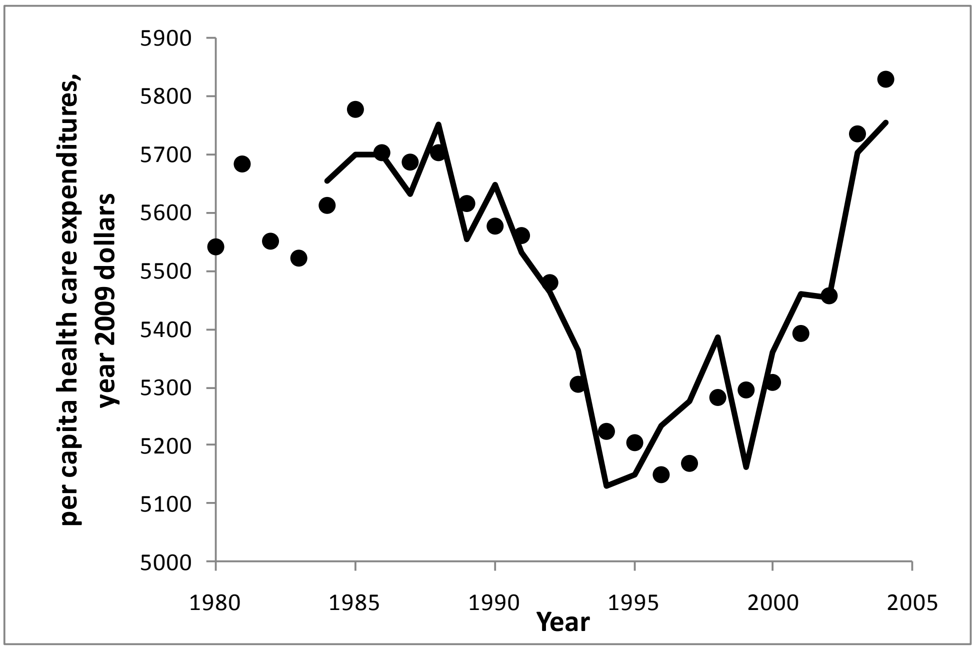

Figure 2.-Observed and estimated California per capita healthcare costs. Dots: observed. Solid line: predicted cointegrating relationship (long run equilibrium relationship).

Estimates of the Healthcare Cost Savings for the California Program from its Inception through 2008

The in-sample predictions of the irrelevant instrumental variables estimates that are used for the forecasts can be used to estimate the effect of the California tobacco control program compared to what would have occurred if there had been no program. Between 1990 (when the program actually started) through 2008 the annual reduction in California cigarette consumption attributable due to the program increased from 40 million packs in 1990 to 743 million packs in 2008. The cumulative reduction in consumption between 1990 and 2008 was 19 billion packs of cigarettes, worth $63 billion in pre-tax sales to the tobacco industry. The program prevented a total of 8 million person-years of smoking and 2 billion pack-years of cigarette consumption. The annual savings in total California health care costs compared to control state costs was $2 billion in 1990, increasingly steadily to $21 billion in 2008. The cumulative health care cost savings between 1990 and 2008 was $371 billion.

The health care savings attributable to the tobacco control funding are sensitive to the estimation procedure used to fit the model to the data. The short run dynamic reduced form VAR model is better at fitting short run variation in prevalence of current smoking in the middle of the sample than the cointegrating irrelevant instrumental variables regression estimates, or the long run equilibrium solution to the dynamic VAR. Selected estimates of reductions in total cigarette consumption savings between 1990 and 2008 corresponding to those reported above, using the short run reduced form VAR estimate are 21 billion packs (compared to 19 billion using the instrumental variables estimates of the cointegrating regression), and $230 billion in healthcare savings (compared to $371 billion from the instrumental variables estimates of the cointegrating regression).

Both these estimates are higher than those obtained based on our previously published model that only uses per capita cigarette consumption as the sole measure of smoking behavior (Lightwood, Dinno and Glantz, 2008). Applying that model (which was based on data through 2004) to the data through 2008 produces estimates of 6 billion packs of cigarettes not smoked and a cumulative health care cost saving of $139 billion in health care.

There are four possible explanations for the differences in the estimated effect of the program between the new model, using either the long run irrelevant instrumental variables estimates of the cointegrating regression or the dynamic VAR, and the estimates from previous published model for California that uses per capita cigarette consumption as the measure of cigarette smoking.

First, the irrelevant instrumental variables estimate of the static cointegrating vector chosen to forecast prevalence equation in the new model does not do a very good job of modeling year-to-year variations in of the prevalence of current smoking in California in the middle of the sample period. The irrelevant instrumental variables estimate also predicts a very large increase in current smoking prevalence in California in the years after 2004 under the "no program" counterfactual scenario used to estimate the effects of the program.

Second, the relationship between the health cost savings and reduction in number of packs consumed in the new model for per capita health care cost savings attributes a large expenditure to current smoking status with a smaller effect of the number of packs smoked.

Third, with regard to health care expenditure, development of the new model was focused on estimating a model that provided the most stable and reasonable out-of-sample forecasts to predict the effects of future changes to the current funding patterns (i.e., the effects of cutting or augmenting the current program). Little emphasis was placed on the best in terms of in-sample fit in the choice of the final estimate chosen to use for the forecast. If the model is to be used for both forecasting the future and estimating total past program effect, another estimate may be better, such as the dynamic VAR estimates, which produce estimates of the past effect of the program that are closer to those of the per capita consumption model. Using the dynamic reduced form VAR model for the forecasts would produce year-to-year changes in the forecast prevalence, cigarette consumption per smoker, and per capita healthcare expenditure that may be due to details of model specification or arbitrary time aggregation forced by the annual frequency of observations, so only averages over several years should be used if this estimation method is used.

Fourth, a more detailed model of smoking behavior that uses current smoking prevalence and cigarette consumption per smoker a may generate more uncertainty error in estimating program effect. The problem that arises is that some of the final estimates for total program effect (such as value of lost sales to the tobacco industry) are functions of coefficient estimates from more than one equation and the uncertainties compound as more of the equations are used to construct the estimate. The prevalence model predicts a larger difference between California and control states in the middle of the sample than observed in the data and the consumption per smoker equation also produces slightly higher predictions than observed during the same period in the middle of the sample. Therefore, propagation of uncertainty may be responsible for the differences between the estimates of program effect using the new model using prevalence and consumption per smoker compared to the published per capita consumption model.

The conclusion is that, while the choice of estimation approach (short run dynamic reduced form VAR, long run equilibrium solution to the short run dynamic reduced form VAR, and irrelevant instrumental variables estimate of the cointegrating regression) all produce similar forecasts, they do not produce similar estimates of historical program effect. Further research, discussed in the limitations section is required to determine the best estimation approach to use for both forecasting the future and estimating historical program effect. Given the similarities of the two estimation approaches for prediction, we base our forecasts on the instrumental variables estimates of the cointegrating regression for the final forecasts presented in this report because of their theoretical properties and published evidence of good finite sample performance.

Forecast Scenarios through 2016

Baseline and three alternative scenarios

Four scenarios are forecast:

1. Continued funding level of five cents per pack (nominal) as established by Proposiiton 99, or $1.34 per pack. (Baseline Scenario)
2. The California Tobacco Control Program is cut in half. (2.5 cents per pack (nominal dollars) funding beginning in 2012, or $0.85 per pack
3. One dollar (nominal) tax imposed in 2012, with 20 cents per pack going to program funding in addition to the 5 cents per pack allocated by Proposition 99. (This amount includes 20 cents/pack as specified in the pending tax initiative plus the backfill funding provided to compensate for loss of revenue due to the reduction in cigarette sales because of the increase in price, which we estimate to be approximately 5 cents per pack) This scenario results in an effective funding level of $5.56 per capita.
4. CDC recommended funding level of $12.12 (nominal) dollars per capita starting in 2012, or 56 cents per pack.

Forecast assumptions (estimated using reduced form statistical models using automatic model selection)

Policy changes in the forecast scenarios are assumed to start in 2012. The forecast horizon from 2012 through 2016. Other explanatory variables that also needed to be forecast are price per pack of cigarettes, per capita personal income in California and the control states, and per capita tobacco control funding and prevalence in control states.

The models estimated to forecast the explanatory variables are as follows. The best model for real cigarette prices was a simple model in conditional means as a function of historical real tax rates. Real cigarette prices in California and control states and annual per capita tobacco control funding in the control states, will stay constant in real terms from 2010 through 2016 (except for the case of a $1 tax increase in California, in which case the full tax increase is added to the price).

The short run reduced form VAR model produced the most reasonable estimate of per capita personal income variables, as discussed above in the section 'Estimation of auxiliary predictive models for the explanatory variables'. The model for control state personal income was a second order autoregressive time series model, and a constant mean was the best estimate for the difference between California and control state per capita income. The short run dynamic reduced from VAR model estimate was used to forecast control state per capita income. Per capita personal income in control states will increase at about $2035 per year, and the difference between California and control states per capita income will remain constant, so Califonia per capita personal income will also grow at $2035 per year.

The best model as determined by Autometrics for control state smoking prevalence was a reduced from VAR equation in which control state prevalence is a function of lagged control state per capita income, proportion of the control state population that is elderly, and lagged per capita control state tobacco control expenditure. The long run equilibrium solution was used because it followed the trend of historical control state smoking prevalence with less variance than the dynamic predictions calculated directly from the VAR. The selected model forecast that smoking prevalence in control states is reduced by 0.23% per year.

The annual projected total and adult resident California population and proportion of the population elderly for control states were interpolated from U.S. Census Bureau projections.

Autometrics could not find an acceptable model fit for cumulative control state tobacco control funding. An acceptable model for annual control state funding was found, so forecasts of annual control state funding were used to construct a forecast of cumulative funding. The annual real cumulative expenditures were calculated by simple summing of the estimated annual funding. The best model for annual control state per capita tobacco control funding used past values of annual control state per capita funding and per capita personal income. The long run equilibrium solution was used for the forecasts, but these were nearly identical to the short run predictions that used the short run VAR model. Annual per capita funding for the control states continues at $2.50 per year, so that the cumulative control state per capita funding increases at $2.50 per year.

It is assumed that some current funding of CA tobacco control programs (interest income and the Proposition 10 backfill) in addition to the 5 (nominal) cents/pack provide by Proposition 99 for the California Tobacco Control Program will continue at average relative levels observed between 2004 and 2007. This estimate was chosen because inspection of available data suggested that there was a drop in the proportion funding from these sources after 2004 to a lower constant level than in previous years.

Forecast Results

The forecast results are shown below: first are the forecast results for current smoking prevalence and cigarette consumption per smoker in California; second are forecasts for health care savings due to changes in cigarette smoking behavior.

The forecast results are shown in Figures 3 to 6. Annual forecast results are shown in Table 6 and cumulative savings over the forecast horizon for totals are shown in Table 7. Changes in value of California cigarette sales are shown in Table 8.

Key for Figures 2 to 7

Black dots: observed value
Open dot: 2009 forecast (used to compare first model forecast with last year of available data)
Thick solid line: model prediction in-sample
Dashed line: model forecasts for 2012 to 2016
Thin solid line: short run dynamic model for CA prevalence

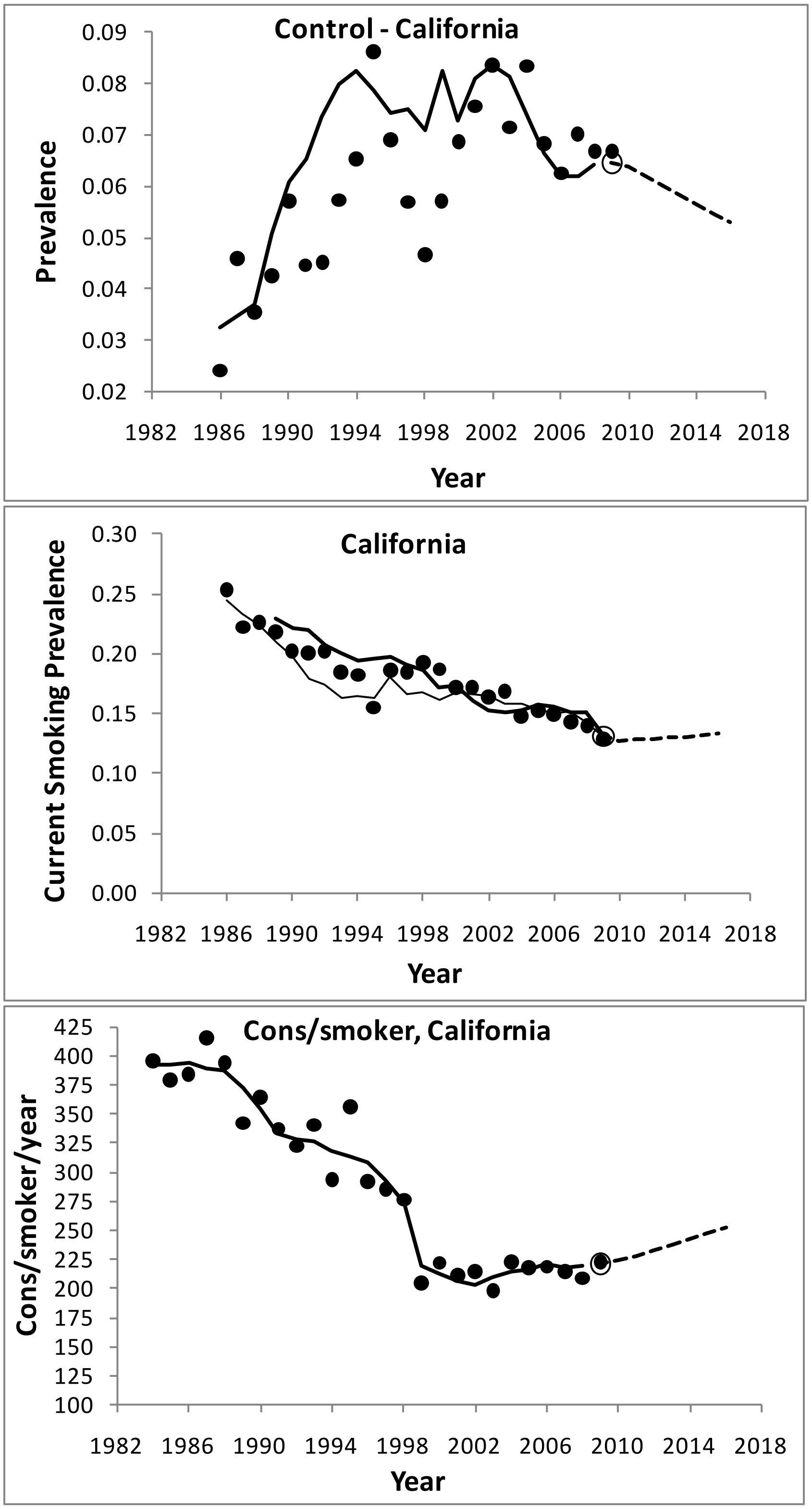

Figure 3. Scenario 1: Five cents per pack (nominal) funding from 2012 on, Prevalence in California approaches that of the control states, both the prevalence of current smoking and cigarette consumption per smoker increase in California, but at slower rates than when the program funding is cut in half. Top: difference in prevalence of current smoking, California – controls; Middle: prevalence of current smoking, California; Bottom: cigarette consumption, California

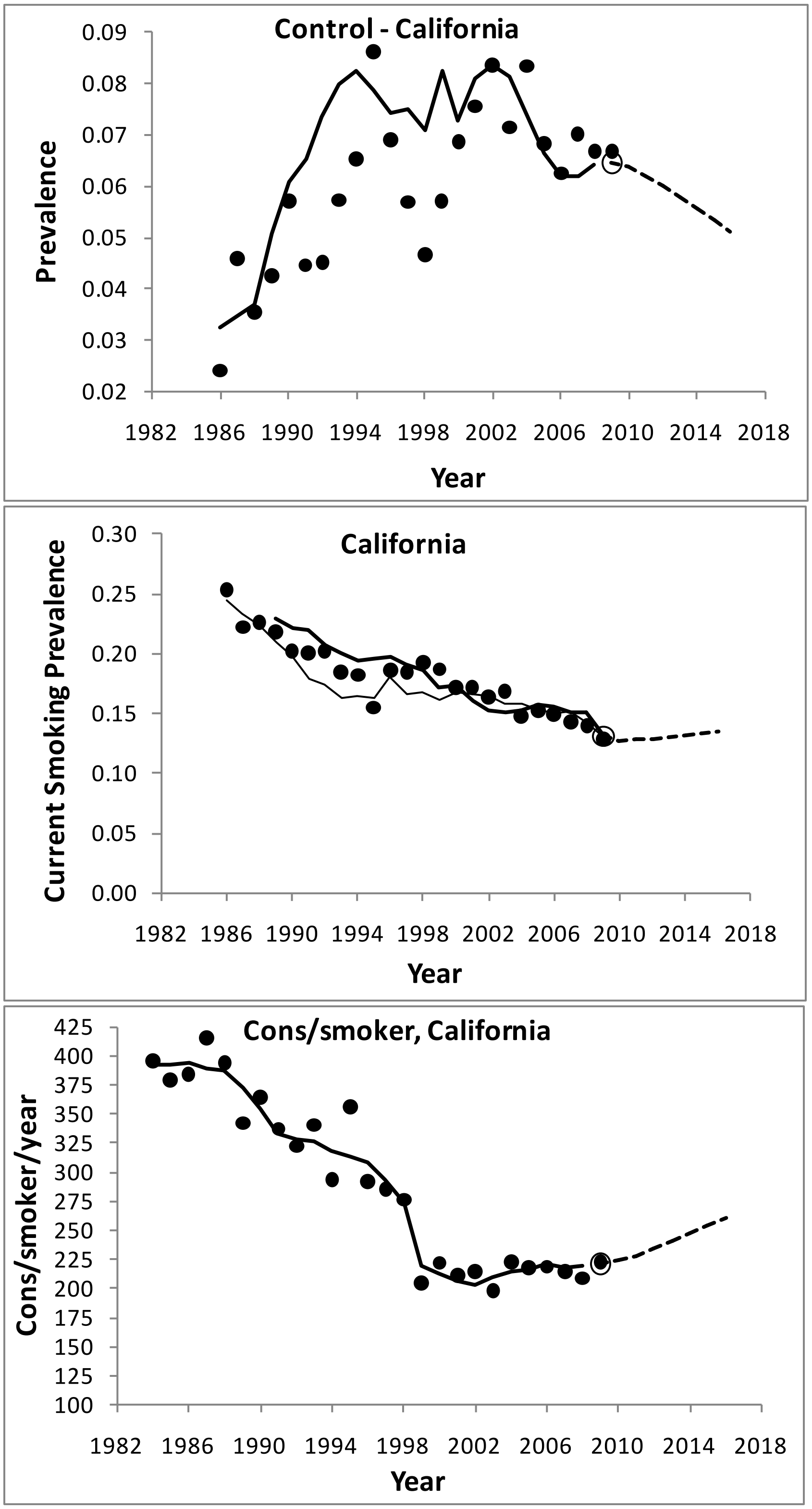

Figure 4. Scenario 2: 50% cut to the program, to 2.5 cents per pack (nominal) funding from 2012 Prevalence in California approaches that of the control states, both the prevalence of current smoking and cigarette consumption per smoker increase in California. Top: difference in prevalence of current smoking, California – controls; Middle: prevalence of current smoking, California; Bottom: cigarette consumption, California.

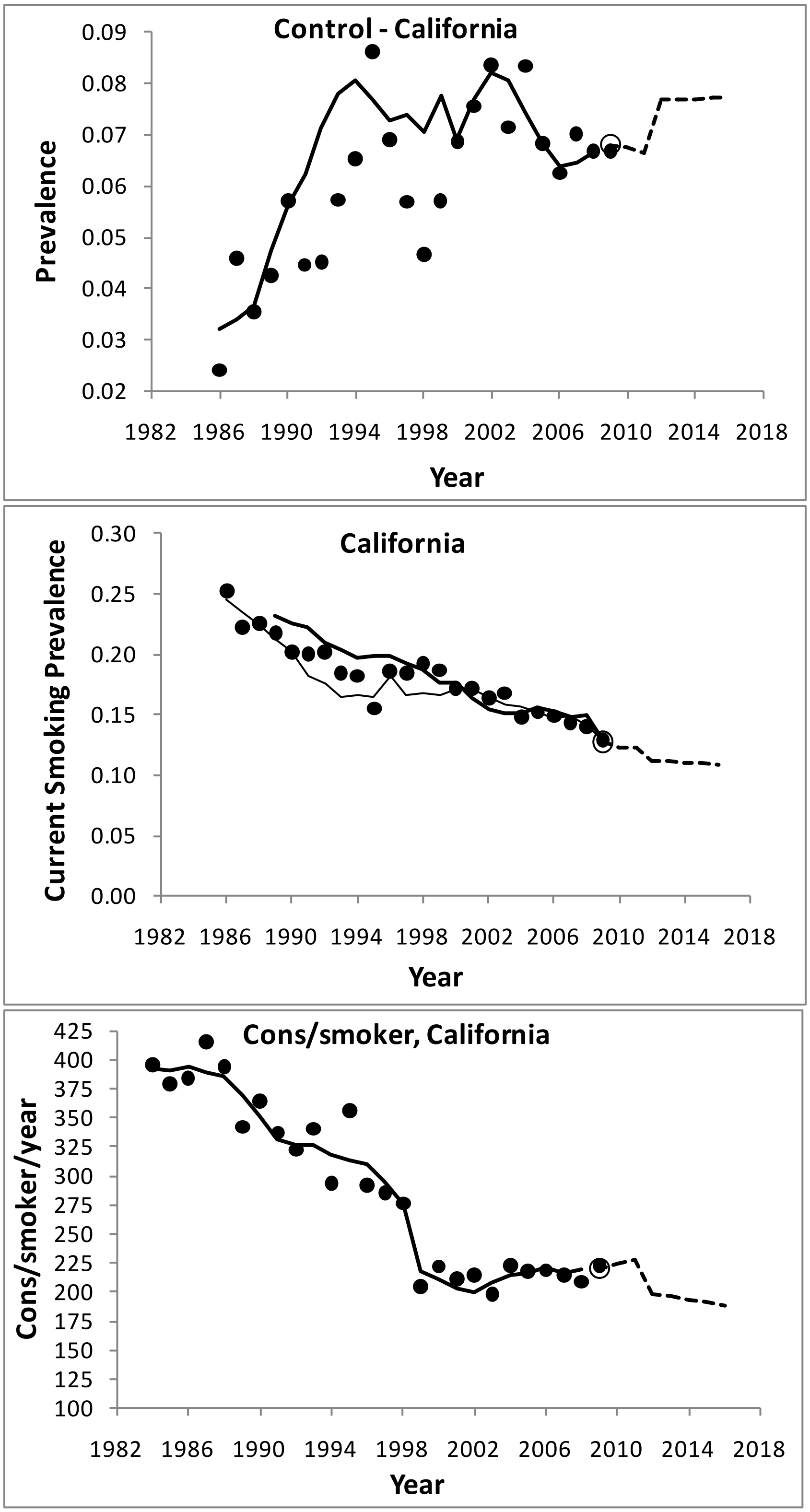

Figure 5. Scenario 3: One dollar (nominal) tax imposed in 2012, with 20 cents per pack going to program funding. Backfill funding is provided to compensate for loss of revenue due to increase in price, of 5 cents per pack in lost sales. Current smoking prevalence gradually declines, and consumption per smoker is reduced due to the tax increase, and then declines very gradually. Top: difference in prevalence of current smoking, California – controls; Middle: prevalence of current smoking, California; Bottom: cigarette consumption, California.

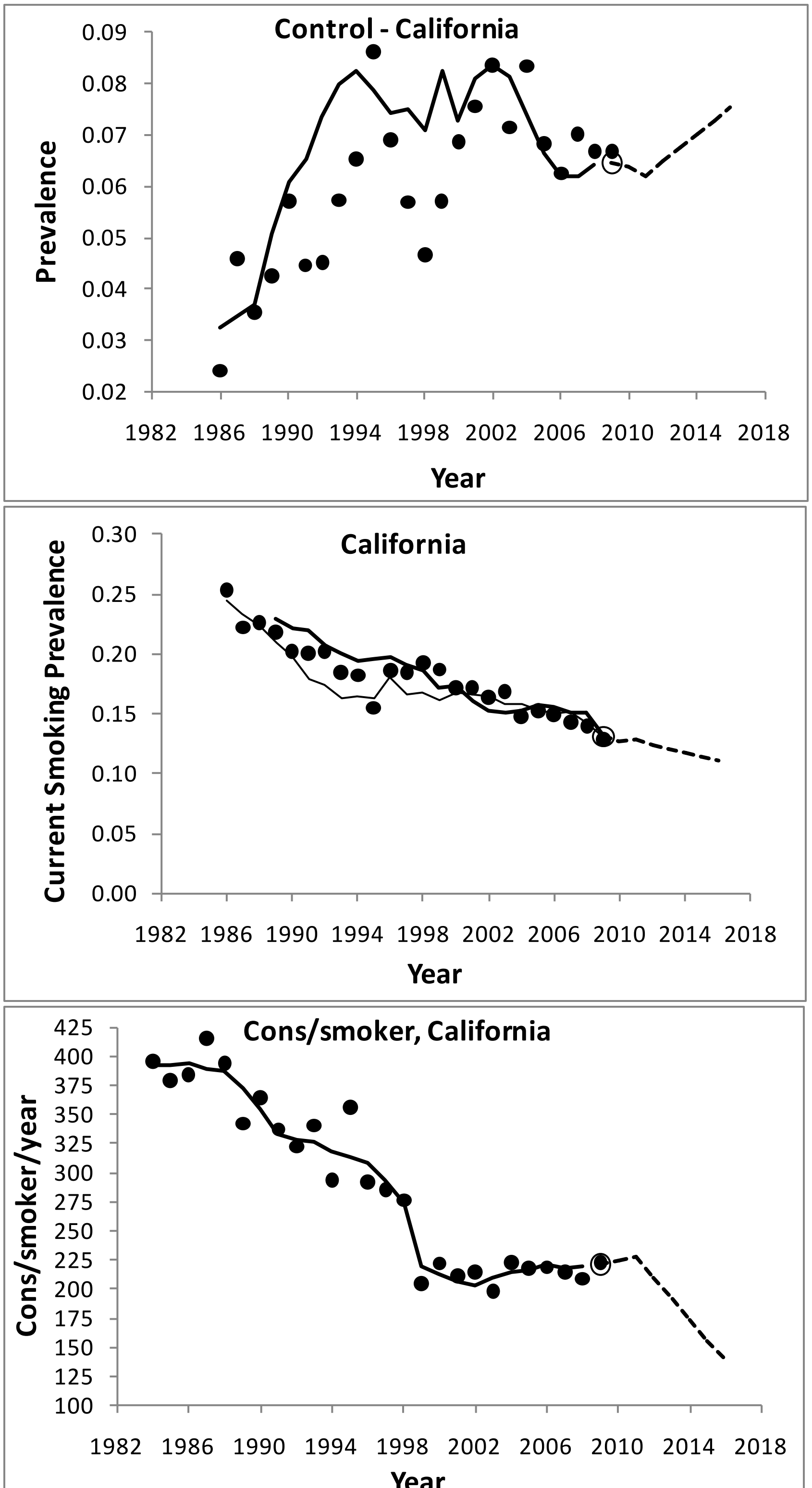

Figure 6. Scenario 4: CDC recommended funding level of $12.12 (nominal) dollars per capita starting in 2012. Reduction in Prevalence and consumption per smoker declines at about long run average since introduction of the program. . Top: difference in prevalence of current smoking, California – controls; Middle: prevalence of current smoking, California; Bottom: cigarette consumption, California.

Table 6.-Forecasts of alternative California tobacco control funding policies on smoking behavior and healthcare expenditures in California.

Year	Smoking Behavior			Difference, per capita health care expenditure, CA vs. control ($)	Savings to California compared to historical baseline (Scenario 1)		
	Preva-lence	Packs/ smoker	Packs sold/ consumed (millions)		Health care ($ per capita)	Health care, total ($millions)	packs sold/ consumed (millions)
Scenario 1: 0.05 per pack (nominal) , total per capita funding = $1.34 (baseline)							
2012	0.1289	233	879	759			
2013	0.1299	238	915	770			
2014	0.1309	243	952	781			
2015	0.1318	248	989	792			
2016	0.1336	253	1032	806			
Scenario 2: 0.025 pack, total per capita funding = $0.85							
2012	0.1292	235	888	763	-3.84	-149.5	-8.6
2013	0.1306	241	933	778	-7.61	-299.2	-17.5
2014	0.1318	248	978	793	-11.31	-449.1	-26.6
2015	0.1331	254	1025	807	-14.93	-599.1	-36.0
2016	0.1352	261	1078	825	-18.48	-749.2	-45.7
Scenario 3: One dollar tax, 20 cents per pack additional funding plus backfill, total per capita funding = $5.56							
2012	0.1124	199	653	667	104.97	4082.14	226.3
2013	0.1114	196	646	663	123.54	4855.14	269.1
2014	0.1104	193	639	659	141.75	5629.19	312.2
2015	0.1094	191	633	656	159.62	6404.47	355.8
2016	0.1093	189	632	654	177.15	7181.53	400.8
Scenario 4: CDC recommended funding, 12.12 dollars per capita in 2012 dollars (or $0.56 per pack)							
2012	0.1242	210	762	704	54.10	2103.9	117.7
2013	0.1206	191	683	662	107.14	4210.7	232.3
2014	0.1171	173	608	621	159.14	6319.7	343.7
2015	0.1136	156	537	581	210.12	8430.6	452.0
2016	0.1110	139	473	544	260.10	10544.4	559.6

Note: negative values indicate a negative savings, that is, an increase compared to the baseline scenario. Positive numbers indicate positive savings, that is, a decrease compared to the baseline scenario.

Table 7.- Cumulative savings over the forecast horizon due to alternative California tobacco control funding policies, compared to baseline.		
Scenario	Health care, total ($millions)	packs (millions)
Scenario 1: 0.05 per pack (nominal)	0	0
Scenario 2: 0.025 per pack	-2246	-134
Scenario 3: One dollar tax, 25 cents per pack funding plus backfill	28152	1564
Scenario 4: CDC recommended funding, 12.12 dollars per capita in 2012 dollars	31609	1705
Note: negative numbers reflect increased costs, corresponding to larger values than would occur compared with the historical baseline. Positive numbers are positive savings, corresponding to smaller values than would occur with the historical baseline.		

Table 8.- Cumulative change in pretax value of California cigarette sales over the forecast horizon due to alternative California tobacco control funding policies, compared to baseline.	
Scenario	Value of cigarette sales ($millions)
Scenario 1: 0.05 per pack (nominal)	0
Scenario 2: 0.025 per pack	-508
Scenario 3: One dollar tax, 25 cents per pack funding plus backfill	72369
Scenario 4: CDC recommended funding, 12.12 dollars per capita in 2012 dollars	6448
Note: positive numbers are increases in value of sales, negative numbers are decreases in value of sales, compared to historical baseline.	

Scenario 1: Baseline (Status Quo)

If the current funding levels are continued at 5 cents per pack, the baseline scenario, then California smoking prevalence slowly increases, from 12.9% in 2012 to 13.3% in 2016 and cigarette consumption per smoker will increase from 233 to 253 packs/year from 2012 to 2016. In 2016, prevalence and consumption per smoker would increase by 9% and 14% from the level in 2011, respectively. The contribution of smoking to healthcare costs in California will also begin to increase.

A funding rate of between $0.13 and $0.14 per pack would be required to stabilize the prevalence of current smoking and cigarette consumption per smoker, which would correspond to a per capita funding rate of about $3.5 per capita, or an average funding level for the California Tobacco Control Program of about $139 million annually over the forecast horizon of 2012 to 2016. The level of funding in 2009 was $77.8 million. (Details of these results not shown in Figures or Tables.)

Scenario 2: Cut Funding in Half

Cutting the funding level by half would result in a total of $39million less in cumulative tobacco control spending. This reduction in spending will result in an increase in both prevalence and cigarettes consumed per smoker. Prevalence rises from about 13% to 13.5% from 2012 to 2016 and cigarette consumption per smoker increases from 235 to 261 packs per year. In 2016, prevalence and consumption per smoker would increase by 10% and 17% from the level in 2011, respectively. Compared to the baseline scenario, there would be 134 million more packs of cigarettes sold (worth $508 million the tobacco industry in pre-tax sales) and a cumulative increase in total healthcare costs over the forecast horizon between 2012 and 2016 would be $2.2 billion.

Scenario 3: A $1.00 Increase in the Cigarette Tax with $0.20 Used to Increase Funding for the California Tobacco Control Program

An increase in funding by $0.20 per pack (to a total of $0.25 per pack) from a $1.00 tax increase (together with a backfill from Proposition 10, as specified in the pending tax increase initiative would restore a decline in current smoking prevalence and cigarette consumption per smoker. Prevalence would decrease from about 11.2% to 10.9% between 2012 and 2016 and cigarette consumption per smoker would decrease from 199 to 189 cigarettes per year. In 2016, prevalence and consumption per smoker would decrease by 11% and 15% from the level in 2011, respectively. Compared to the baseline scenario, a total of 1.6 billion fewer packs of cigarettes would be smoked (worth $7.2 billion in pre-tax sales to the tobacco industry) and total healthcare costs would be reduced by $28.2 billion. An average of 17% of the difference in *current smoking prevalence* between the 5 cents per pack funding scenario (baseline) and the 20 cents per pack increase in funding with the tax increase is due to changes the tobacco control funding level, the remainder due to change in price due to the tax. On average about 50% of the difference in *consumption per smoker* is due to changes in the funding, level

Scenario 4: Funding at *CDC Best Practices* Recommended Level

An increase in per capita funding to the level recommended by the CDC for California ($12.12 per capita) would initiate a rapid decline in smoking prevalence and a drop in consumption. Doing so would require increasing annual funding for the California Tobacco Control Program from $ 77.8million in 2009 to a total of $481million per year, a total increase in funding of $403 million between 2012 and 2016. Smoking prevalence would decrease from about 12% to 11.1% between 2012 and 2016 and cigarette consumption per smoker would decrease from 210 to 139 packs per year. In 2016, prevalence and consumption per smoker would decrease by10 % and 38% from the level in 2011, respectively. Compared to the baseline scenario, total cigarette consumption would fall by 1.7 billion packs (worth $6.5 billion in pre-tax sales to the tobacco industry) and reduce cumulative total healthcare costs by $31.6 billion.

Sensitivity analysis

Initial sensitivity analyses suggest that these results are sensitive to some forecast assumptions needed for explanatory variables. The forecasts of absolute levels are sensitive to different time paths of control state prevalence, control state cigarette consumption per smoker that may occur given recent variability, especially for per capita health care expenditures. However, the forecast levels are not sensitive to variations in control state per capita tobacco control funding, or changes in cigarette price (absent major changes in excise taxes), or per capita income, that are reasonable to expect given recent variation.

Limitations

There are several limitations in this research. The first is the standard limitation that these estimates are based on observational data and attendant problems with estimating the causal effect of interventions.

An issue related to the problems accompanying use of observational data is the role of the control states in these models. There has been considerable discussion among the investigators and the Scientific Advisory Committee and other reviewers of this research about the proper selection of control states and weighting of aggregate measures for the selected control states. One viewpoint is related to the use of controls in clinical trials that used the individuals as the unit of analysis, where observations on the controls are used to control for differences between intervention units and controls that may be correlated with the intervention due to lack of randomization. Another viewpoint is that in nonstationary time series, the control variables, when calculated as cross sectional averages over control populations, serve as proxies for unmeasured global trends that affect all cross sectional units (both intervention and control) that are needed to ensure stationary residuals for the regressions. This second viewpoint is the CCE interpretation of these regressions.

These are two uses of the controls have not been definitively resolved in this research. An implication of the first viewpoint is that there is a correct selection of the controls, and correct weighting scheme, and that an incorrect choice will change the results of the analysis. An implication of the second viewpoint, following the derivation of the CCE estimator, is that asymptotically any selection and weighting scheme which follows some very mild conditions will produce the same result.

A thorough sensitivity analysis of the published model using per capita consumption, and preliminary sensitivity analysis of the new model presented here, have shown that the regression results are very insensitive to the choice of controls and choice of weighting scheme, lending support to the second viewpoint. However, it seems intuitive that if two populations have very different age distributions and one wants to estimate a regression that properly identifies the independent effect of a policy intervention, arguments from the first point of view about the need to adjust for difference in the two populations' age structure seem valid. The estimates used in the report use population weighted averages for the control states, so are consistent with the concept of statistical adjustment in a stationary setting, but preliminary sensitivity analysis indicates the choice of weighting scheme or control state will make little difference in the results.

Further research should include selection of the best statistical estimate that can be used to both forecast future smoking behavior and per capita health care costs, and estimate attributable reductions in these variables due to the historical program. The short run dynamic reduced form VAR estimates, their long run equilibrium solutions, and the instrumental variables estimates of the cointegrating regression produce similar forecasts. The instrumental variables estimates of the cointegrating regression were chosen for the forecasts for theoretical reasons (that is there are good arguments that they are free of any possible endogeneity bias and finite sample unit root bias). However, these three estimates produce different estimates of program effect.

The first approach to this problem would be to do a detailed comparison of in sample fit and forecasts to determine if there is a best model to use for both estimating historical tobacco program effects and for forecasting. Improved estimation techniques should be explored (for example, joint estimation of the current smoking prevalence and cigarette consumption short run dynamic VAR regressions, rather than separate single equation OLS estimates) so determine whether a better model for both uses can be developed. The best method of estimating the effect of the California program versus no history of a program, and reasons for the difference in the estimates will be further investigated, and these estimates of program effect from the new model using prevalence and cigarette consumption per smoker should be considered very provisional.

Another issue is the stationarity of the data. All of the variables used in this analysis can be assumed to be nonstationary from previous research on the old per capita cigarette consumption model and contain an autoregressive unit root, except California and control state prevalence of current smoking. It has proven almost impossible to determine whether smoking prevalence is nonstationary with a unit root, or a highly autoregressive process fluctuating around a deterministic trend. Much of the difficulty is due to the short time span and small number of observations for prevalence of smoking, and very strong deterministic trend (if the series is stationary) or drift (if nonstationary). Fortunately, instrumental variables estimators have been developed recently that are designed for highly persistent series that either contain a unit root, or a near unit root, and these techniques will be adopted as soon as practicable.

Comparison with the Older Model Based only on Per Capita Cigarette Consumption

The new model is an improvement over the old one in several ways.

First, for modeling the effect of tobacco control funding on smoking behavior, it does away with the use of the deterministic trend to model per capita cigarette consumption that was needed to estimate differences between California and the control states due to unobserved factors in the published model (Lightwood Dinno and Glantz 2008) and used in the interim report for this project. The interpretation of the deterministic time trend in the old per capita cigarette consumption model was acceptable as a matter of mathematical modeling because prevalence, cigarette consumption and per capita consumption were linearly related, and using per capita consumption as an index was formally acceptable. However, it may be that the linear trend really functioned in the old model to compensate for misspecification induced by a one dimensional model of smoking behavior.

Second, there is evidence that the convergence of the estimated values in this relatively small sample to the asymptotic value seems quicker in the new model. The more rapid convergence can be seen in the out-of-sample forecast exercises based on recursive regression estimates that use initial subsamples. The coefficients for the prevalence equation converge rapidly enough to produce a good out-of-sample forecast over five (from 2004 to 2008) and seven years (from 2002 to 2008) (Figure 7) from estimates using the first 20 and 18 years of data in the sample period, respectively. The coefficients for the consumption per smoker equation converge rapidly enough to produce a good out-of-sample forecast over the last ten to twelve years (Figure 8) from estimates using the first 15 and 17 years of data in the sample period, respectively. These recursive estimates use the irrelevant instrumental variables estimator that is not adjusted for finite sample unit root bias. The adjusted irrelevant instrumental variables estimator cannot be used for recursive regressions because of the reduction in the degrees of freedom needed to calculate the adjustment. These results on the stability of the regression coefficients and evidence for out-of-sample forecast accuracy are much better than corresponding results for the older model that just used per capita cigarette consumption.

Third, using a two dimensional measure of smoking behavior allows a more detailed understanding of relationship between health care expenditures and the prevalence of current smoking and cigarette consumption per smoker. The results show that population based tobacco control funding works through two channels: reducing prevalence of current smoking and reducing consumption per smoker and that both prevalence and consumption have a significant impact on per capita health care costs. Effective population based tobacco control programs work through both dimensions to reduce health care expenditures attributable to smoking. About half the savings in per capita health care costs are attributable to the reduction in consumption per smoker and half due to the reduction in prevalence.

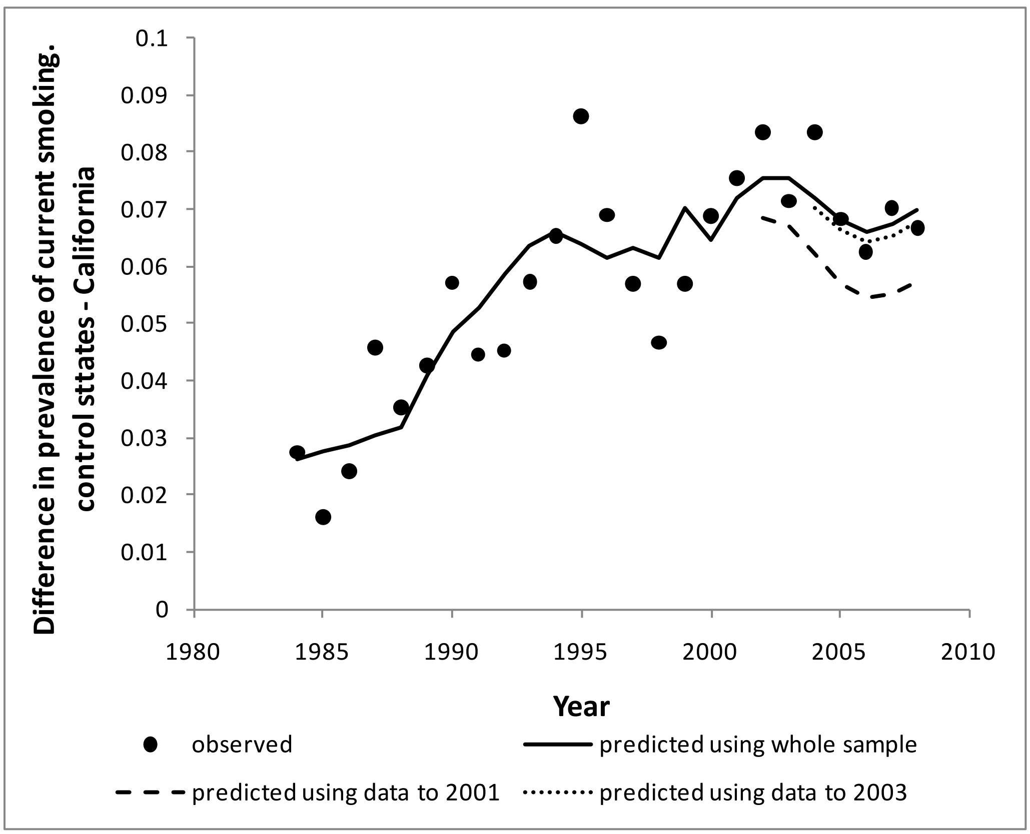

Figure 7.-Out of sample forecasts for cointegrating regression for difference in current smoking prevalence between control and CA, from 2002 and 2004 to 2008, estimated using initial subsamples. The observed values for difference in prevalence of current smoking are shown as solid dots. The in-sample fit using the whole sample from 1984 to 2008 is shown as a solid line. The forecast of values for years 2004 to 2008 using the model estimated using data from 1984 to 2003 (in other words, the multistep recursive regression forecast for 2004 to 2008) is shown with a dotted line. The forecast of values for years 2002 to 2008 using the model estimated using data from 1984 to 2001

(in other words, the multistep recursive regression forecastfor 2002 to 2008) is shown with a dashed line. Note: this estimate uses the instrumental variables estimate that is not adjusted for finite sample unit root bias, rather than the adjusted estimates used for the forecasts. Adjustment for unit root bias used too many degrees of freedom to calculate recursive forecasts.

Fourth and finally, the new estimates of the new health care expenditure equation for expenditure per capita and per smoker in California as a function of current smoking prevalence and cigarette consumption per smoker are consistent with those in the old per capita consumption model after conversion into 2009 dollars. However, when the cointegrating regression estimates for the prevalence, cigarette consumption smoker and health care cost equations are combined to estimate the total saving attributable to the program since its inception, the estimated attributable savings are substantially larger than the older (Lightwood, Dinno and Glantz, 2008) model. As discussed above, this difference may be due to the relatively poor fit of the cointegrating regression model in the middle of the sample period and failure of the model in estimating the counterfactual of no history of the program after 2004. Use of the short run dynamic models produced estimates that were more consistent with the published per capita cigarette consumption model due to a better fit of the model for prevalence in the middle of the sample period.

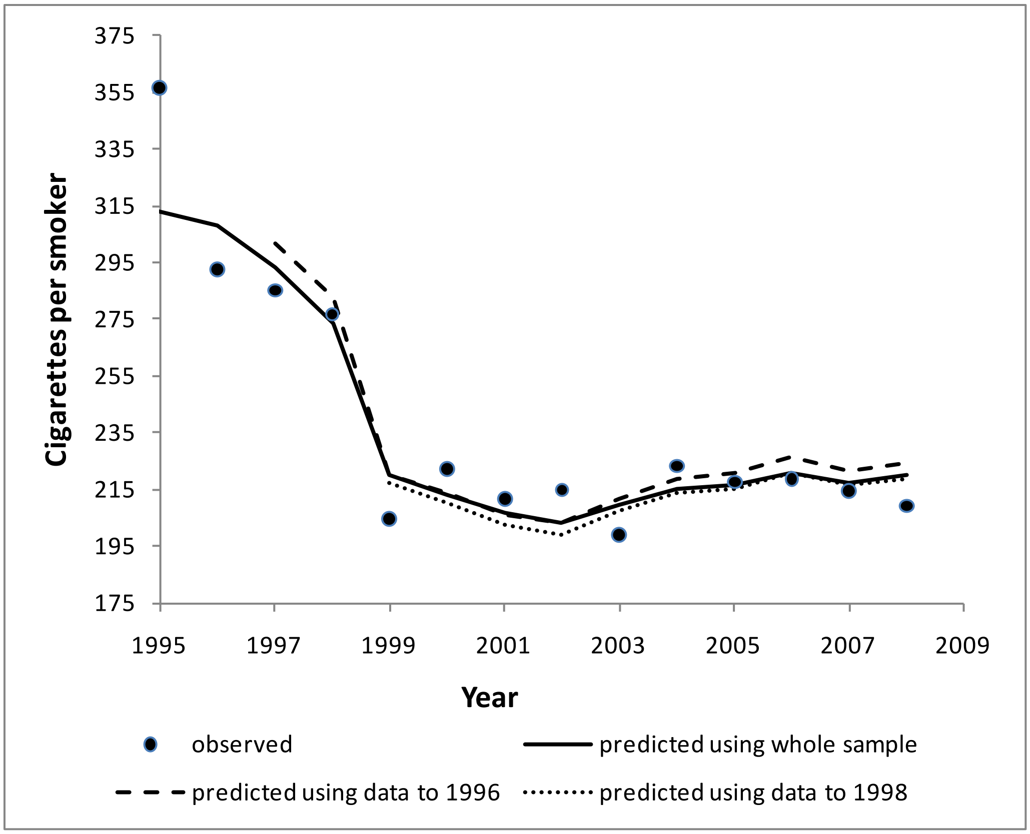

Figure 8.-Out of sample forecasts for cointegrating regression for cigarettes per current smoker in CA, from 1997 and 1999 to 2008, , estimated using initial subsamples. The observed values for difference in prevalence of current smoking are shown as solid dots. The in-sample fit using the whole sample from 1984 to 2008 is shown as a solid line. The forecast of values for years 1999 to 2008 using the model estimated using data from 1984 to 1998 (in other words, the multistep recursive regression forecast for 1999 to 2008) is shown with a dotted line. The forecast of values for years 1997 to 2008 using the model estimated using data from 1984 to 1996 (in other words, the multistep recursive regression forecast for 1997 to 2008) is shown with a dashed line.

Conclusions

While historically the California Tobacco Control Program has had a dramatic effect on smoking and the associated healthcare costs, the real value of program funding per pack sold has been reduced because inflation has seriously eroded the purchasing power of the 5 cents per per pack allocated to the Tobacco Control Program by Proposition 1988 in 1988. As a result, the Program is losing effect and California smoking prevalence will slowly rise to around 13.3% by 2016 and cigarette consumption per smoker will increase from 233 to 253 packs/year. The contribution of smoking to healthcare costs in California will also begin to increase.

A funding rate of between $0.13 and $0.14 per pack would be required to stabilize smoking behavior (about $139 million annually compared to the $77.8 million funding in 2009.

Cutting the Program funding level would further increase the healthcare costs due to smoking. A cut in half would reduce tobacco control spending by a total of $39 million between 2012 and 2016, resulting in an increase in smoking prevalence 13% to 13.5% and cigarette consumption per smoker increases from 235 to 261 packs per year. Compared to the baseline scenario, there would be 134 million more packs of cigarettes sold (worth $508 million the tobacco industry in pre-tax sales) and the cumulative increase in total healthcare costs over the forecast horizon between 2012 and 2016 would be $2.2 billion..

An increase in Tobacco Control funding by $0.20 per pack (to $025 per pack total) from a $1.00 tax increase as specified in the pending initiative would restore a decline in current smoking prevalence and cigarette consumption per smoker. Prevalence would decrease from about 11.2% to 10.9% between 2012 and 2016 and cigarette consumption per smoker would decrease from 199 to 189 cigarettes per year. Compared to the baseline scenario, a total of 1.6 billion fewer packs of cigarettes would be smoked (worth $7.2 billion in pre-tax sales to the tobacco industry) and total healthcare costs would be reduced by $28.2 billion.

An increase in per capita funding to the level recommended by CDC *Best Practices* for California ($12.12 per capita) would initiate a rapid decline in smoking prevalence and a drop in consumption. This increase in annual funding for the California Tobacco Control Program by about $403 million per year (for a total increase in funding of $1.6 billion between 2012 and 2016) would decrease from about 12% to 11.1% between 2012 and 2016 and cigarette consumption per smoker would decrease from 210 to 139 packs per year. Compared to the baseline scenario, total cigarette consumption would fall by 1.7 billion packs (worth $6.5 billion in pre-tax sales to the tobacco industry) and cumulative total healthcare costs would be reduced by $31.6 billion.

These estimates are based on a statistical model that uses more realistic two dimensional measures of smoking behavior (prevalence of current smoking and cigarette consumption per smoker) instead of the one dimensional model based just on overall state per capita cigarette consumption.

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ADDENDUM

UPDATED MODEL

(February 2012)

Summary

Subsequent research after publication of the original report[1] indicated that two revisions to the model that produce better estimates of the California Tobacco Control Program effect and better forecasts of the effects of alternative future tobacco control funding policies than those originally presented. The first revision is a change to the regression specification of the equation for cigarette consumption per smoker. The second revision is use of a more robust estimation method, that provides more accurate estimates of observed values for all dependent variables, as opposed to long run equilibrium values that were estimated in the original report[1] omitting short run dynamics. This addendum reports the results of estimation using a reduced from vector autoregression (reduced form VAR) that includes combined effect of both the long run equilibrium and short run adjustment process.[2]

Using this improved model and estimation procedure, we now predict under the status quo that smoking prevalence decreases more slowly than in the past, from 11.1% in 2012 to 10.0% in 2017. Packs consumed per year per continuing smoker increases from 198 per smoker in 2012 to 220 per smoker in 2017. If the proposed California Cancer Research Act (CCRA) passes and the tobacco tax is increased by $1 with 20 cents being added to funding for the California Tobacco Control Program, the new model predicts that smoking prevalence decreases from 11.1% in 2012 to 8.7% in 2017 and packs consumed per year per continuing smoker decreases from 198 per smoker 2012 to 163 in 2017.

Compared to the status quo, if the CCRA passes the cumulative reduction cigarette sales over the forecast time horizon is 867 million packs in California, the pretax cigarette sales revenue to the tobacco companies is reduced by $5.02 billion, and annual healthcare expenditures reduced by $3.0 billion in 2013 to $ 9.1 billion in 2017, yielding a cumulative difference of in healthcare expenditures of $32 billion over five years.

This Addendum contains the following sections:

1) The new model specification

a) a new specification of the regression for cigarette consumption per smoker

b) a description of the new reduced form VAR estimation method and required specification

2) Estimation results of the revised model for cigarette consumption per smoker

3) Scenario forecasts for the revised model: for two scenarios

a) status quo

b) $1 increase in the cigarette tax with 20 cents devoted to tobacco control funding

1) The new model specification

The specification of the equation system presented in Equations 6 to 8 of the original report is

Prevalence Equation

$$(prev_{c,t} - prev_{CA,t}) = \alpha_0 + \alpha_1(EC_{CA,t} - EC_{c,t}) + \alpha_2(p_{c,t} - p_{CA,t}) + \alpha_3(y_{c,t} - y_{CA,t}) \quad \text{(A1)}$$

Cigarette Consumption Equation

$$cps_{CA,t} = \beta_0 + \beta_1(EC_{CA,t} - EC_{c,t}) + \beta_2 p_{CA,t} \quad \text{(A2)}$$

Health Care Expenditure Equation

$$h_{CA,t} = \gamma_0 + \gamma_1 h_{c,t} + \gamma_2(prev_{c,t} - prev_{CA,t}) + \gamma_3(cps_{c,t} - cps_{CA,t}) + \gamma_4(y_{c,t} - y_{CA,t}) + \gamma_5(a_{c,t} - a_{CA,t}) \quad \text{(A3)}$$

The variable definitions are shown in Table A1, which is reproduced from the main text of the original report.

The specification for the updated model is

Prevalence Equation

$$(prev_{c,t} - prev_{CA,t}) = \alpha_0 + \alpha_1(EC_{CA,t-1} - EC_{c,t-1}) + \alpha_2(p_{c,t-1} - p_{CA,t-1}) + \alpha_3(y_{c,t-1} - y_{CA,t-1}) \quad \text{(A4)}$$

Cigarette Consumption Equation

$$(cps_{c,t} - cps_{CA,t}) = \beta_0 + \beta_1(EC_{CA,t-1} - EC_{c,t-1}) + \beta_2(p_{c,t-1} - p_{CA,t-1}) + \beta_3(y_{c,t-1} - y_{CA,t-1}) \quad \text{(A5)}$$

Health Care Expenditure Equation

$$h_{CA,t} = \gamma_0 + \gamma_1 h_{c,t-1} + \gamma_2(prev_{c,t-1} - prev_{CA,t-1}) + \gamma_3(cps_{c,t-1} - cps_{CA,t-1}) + \gamma_4(y_{c,t-1} - y_{CA,t-1}) \quad \text{(A6)}$$

There are two differences in the system of equations estimated in the original report and those in this Addendum.

Table A1.-Variables used in analysis and data sources.		
Variable	symbol	Source
Prevalence of current smoking	$prev_{j,t}$	Behavioral Risk Factor Surveillance System
Cigarette consumption per smoker per year	$cps_{j,t}$	Tax Burden on Tobacco, and estimates prevalence of current smoking
Cumulative per capita funding tobacco control	$EC_{j,t}$	Tobacco Free Kids and the CDC State System
Price per pack of cigarettes	$p_{j,t}$	Tax Burden on Tobacco
Per capita personal income	$y_{j,t}$	Bureau of Economic Analysis, Regional National Incompe and Product Accounts
Proportion of the population over age 64 years	$a_{j,t}$	Census Bureau, Population Estimates
Per capita health care expenditures	$h_{j,t}$	Centers for Medicare & Medicaid Services
Consumer Price Index, All Items and Medical Care	--	Bureau of Labor Statistics, Inlfation and Prices
Population projections, total, adult, and over 64 years	--	Census Bureau, Population Projections
Population (intervention versus control)	j	--
Time index	t	--

a) New specification for cigarette consumption per smoker equation

There is a new specification for cigarette consumption per smoker (Equation A2 from the original report and Equation A5 in the new model). Below we compare the specification in the original report and discuss why it was chosen. Then we discuss the new specification.

In the original report cigarette consumption per smoker in California was modeled as a function of the difference between California and control cumulative per capita tobacco control funding, and the price of cigarettes in California. This specification (Equation A2) is based on the best specification chosen by the automatic specification search algorithm, Autometrics.[3, 4] The specification chosen by Autometrics included only the three variables mentioned above in

Equation A2, but with separate coefficients for California and control cumulative per capita cigarette consumption per smoker as shown below in Equation A7).

$$cps_{CA,t} = \beta_0 + \beta_{1,CA} EC_{CA,t} - \beta_{1,c} EC_{c,t} + \beta_2 p_{CA,t} \qquad \text{(A7)}$$

A subsequent t-test for the restriction that $(\beta_{1,CA} + \beta_{1,c} = 0)$, the null hypothesis, was not rejected at the 5 percent level, so the specification of Equation A2 was adopted for the original report.

The variables included in the new revised specification (Equation A5) are the same as for the original equation for smoking prevalence (Equation A1), and these are

- difference between California and control cumulative per capita tobacco control expenditure
- difference between control and California cigarette price
- difference between control and California per capita personal income.

This specification was suggested by published research on the effectiveness of tobacco control programs in Arizona.[5]

The difference between the original and new models (Equations A2 and A5, respectively) is that the new model (Equation A5) includes more information about common trends across California and controls. Equation A2 includes only information about a common trend for cumulative per capita tobacco control funding, while Equation A5 includes common trends for all variables in the equation. The variable for the common trend in cigarette consumption per smoker (for control states) has a coefficient restricted to unity and so it can be moved to the left hand side of the equation; as a result the dependent variable is expressed as the difference between control and California cigarette consumption per smoker.

The main difference in the original and new specifications concerns how many common trends are needed in order to estimate unbiased and stable estimates for California cumulative per capita tobacco control funding. The specification in the original report (Equation A2) assumed that only the common trend for cumulative per capita tobacco control funding was needed, white the new specification presented in this Addendum (Equation A5) assumes that measures of common trends for all the variables for California that enter the equation.

b) Estimation using reduced form vector autoregression (reduced form VAR) specification

The other difference is the best specification of the model for estimation. For the new results the reduced form VAR specification was used to estimate the model rather than a static cointegrating regression that was used for the TRDRP Report.

The equations in the original report (A1 to A3) are static cointegrating regressions that estimate the long run relationship between the variables and omit the short run adjustment process (the 'error correction model') that keeps the long run relationships close to equilibrium.[2] A static regression is appropriate for estimating long run relationship between nonstationary variables with an autoregressive unit roots in the data. The equations presented in this Addendum (A4 to A6) are called reduced form vector autoregressions (reduced form VARs). The term 'reduced form' means that all variables on the right hand side of the equations are lagged by at least one period. The reduced from VAR is appropriate for both stationary and nonstationary data and estimates a combination of the long run equilibrium relationship and short run adjustment process. The reduced form VAR specification can be used to predict the actual observed values. The static cointegrating regression predicts the long run equilibrium values, and the actually observed values will be distributed around these long run equilibrium values as determined by the short run adjustment process.

The static cointegrating regression specification is appropriate for estimating long run relationships between nonstationary variables. For nonstationary variables, in large samples, the static cointegrating regression specification will produce unbiased coefficient estimates for any regression error process that is stationary. In small samples, stationary variables with high degrees of persistence will behave as if they were nonstationary, and use of a static cointegrating regression specification may be appropriate.[6, 7] The reduced from VAR can be used for both stationary and nonstationary data, and for that reason are more robust, however, the VAR specification will be more sensitive to violations of standard assumptions needed for well behaved error terms (for example, the assumption that there is no heteroskedasticity or autocorrelation in the regression error terms).

Re-examination of the results, and results of different predictions and forecasting simulations suggested that the reduced from VAR estimates provide an in-sample fit that was beter in some respect, and better out-of-sample forecasts for both smoking prevalence (Equation A1) and cigarette consumption per smoker (Equation A2) than the results presented in the original report. Also, even though in small samples with stationary data with high persistence may be more robust than, for example, estimating a distributed lag model assuming stationarity, there is more experience using the reduced form VAR approach in small samples than estimation of a cointegrating regression. Both considerations lead to the adoption of estimating the reduced form VAR specification, rather than a static cointegrating regression specification for further research.

2) Estimation results of the new model

Reduced form VARs for Equations A4 to A6 were estimated using artificially generated irrelevant instrumental variables, using the same method as for the cointegrating regressions in Equations A1 to A3, except that the standard errors for Equations A4 to A6 were estimated using a robust technique (Heteroskedastic and Autocorrelation Consistent, or HAC), for the standard errors.[8] The use of HAC estimates for standard errors was preferred for the reduced form VAR estimates because that approach will be more sensitive to violations of usual assumptions for the error terms (for example, the presence of heteroskedasticity, or possible outliers).[8] There were no substantial differences in the results for the cointegrating regressions for smoking prevalence and per capita healthcare expenditure, so only results for cigarette consumption per smoker from the original report (Equation A2) and the new model (Equation A5) will be shown.

Table A2 shows the results for the new specification and estimation procedure. For the new specification and estimates, an additional \$1 in cumulative per capita California tobacco control funding reduces California cigarette consumption per smoker by 1.39 (SE 0.197) packs/year. An increase in price of \$1 decreases consumption per smoker by -26.9 (SE 4.87) packs/year, and an increase in \$1000 in per capita personal income increases consumption by 2.99 (SE 1.01) packs/year. (Note that per capita income was measured in units of \$1000.) The residuals for all three regressions were homoskedastic and showed no statistically significant autocorrelation, though there may be one or two outliers in the residuals.

Results for both the original Equation A2 using static cointegrating regression estimates, and for the new Equation A5 using reduced from VAR estimates, showed statistically significant effects of cumulative per capita tobacco control expenditure on cigarette consumption per smoker. The estimated coefficients Table 4 in the original report and Table A2 are not directly comparable. The coefficients for the cointegrating regression shown in the original report’s Table 4 represent the long run equilibrium relationship between the explanatory variables and the dependent variables that omits the short run adjustment process to equilibrium. The coefficients shown in Table A2 show the combined long run relationship and short run adjustment process. Direct comparison of the coefficients is also difficult because of the different specifications of the regressions.

Table A2.-Regression estimates for Consumption per current smoker model (cps_{CA}) for the new model (Equation A5 in this Addendum)

Instrumental variables (2SLS) regression

Number of obs =	24
Wald chi2(3) =	101.11
Prob > chi2 =	0.0000
R-squared =	0.8081
Root MSE =	16.461
first order autocorrelaton =	0.148

$(cps_{c,t} - cps_{CA,t})$	Coef.	HAC Std. Err.	z	P>|z|	[95% Conf.	Interval]
$(EC_{CA,t-1} - EC_{c,t-1})$	1.38639	.1098987	12.62	0.000	1.170993	1.601788
$(p_{c,t-1} - p_{CA,t-1})$	-26.92773	4.870294	-5.53	0.000	-36.47333	-17.38213
$(y_{c,t-1} - y_{CA,t-1})$	2.994345	1.008019	2.97	0.003	1.018664	4.970026
constant	68.06827	8.420013	8.08	0.000	51.56535	84.5712

Results for both the original Equation A2 using static cointegrating regression estimates, and for the new Equation A5 using reduced from VAR estimates, showed statistically significant effects of cumulative per capita tobacco control expenditure on cigarette consumption per smoker. The estimated coefficients Table 4 in the original report and Table A2 are not directly comparable. The coefficients for the cointegrating regression shown in the original report's Table 4 represent the long run equilibrium relationship between the explanatory variables and the dependent variables that omits the short run adjustment process to equilibrium. The coefficients shown in Table A2 show the combined long run relationship and short run adjustment process. Direct comparison of the coefficients is also difficult because of the different specifications of the regressions.

3) Scenario forecasts for the revised model: status quo and increase in tax and per capita tobacco control funding

This section presents forecasts of two of the four scenarios from the original report that are adapted to be relevant to current policy decisions at the beginning of 2012. The two scenarios are

Scenario 1: Continue current funding for California Tobacco Control Program

Continued funding level of five cents per pack

Scenario 2: California Cancer Research Act (CCRA) passes in June, 2012

$1 tax per pack of cigarettes sold, starting in 2013

20 cents of tax goes to tobacco control funding

Added to the 5 cents per pack already allocated by Proposition 99

Backfill to replace any funding lost to lower tobacco sales due to higher after tax price.

The forecast time horizon for both scenarios is 2011 to 2017. Scenarios 1 and 2 are identical to those presented in the original report, except that the end of the forecast horizon is shifted forward one year to match the current policy decision regarding the California Cancer Research Act in 2012.

The main difference in the forecasts concerns prevalence and cigarette consumption per smoker, so only the results for those forecasts will be presented in detail here, in Table A3. Under Scenario 1 (status quo) using the new model, smoking prevalence decreases more slowly than in the past, from 11.1% in 2012 to 10.0% in 2017. Packs consumed per year per continuing smoker increases from 198 per smoker in 2012 to 220 per smoker in 2017. Under Scenario 2 (CCRA passes) using the new model, smoking prevalence decreases from 11.1% in 2012 to

8.7% in 2017 and packs consumed per year per continuing smoker decreases from 198 per smoker 2012 to 163 in 2017.

Table A3.—Forecasts using new model				
Year	Scenario 1: status quo		Scenario 2: pass the CCRA	
	Prevalence (%)	Cigarette consumption per smoker (packs)	Prevalence (%)	Cigarette consumption per smoker (packs)
2011	11.3	206	11.3	206
2012	11.1	199	11.1	199
2013	10.9	202	10.4	183
2014	10.6	205	9.68	175
2015	10.4	208	9.30	169
2016	10.1	216	8.92	164
2017	10.0	220	8.72	163

Under Scenario 2, compared to Scenario 1, the cumulative reduction cigarette sales over the forecast time horizon is 867 million packs in California, the pretax cigarette sales revenue to the tobacco companies is reduced by $5.02 billion, and annual healthcare expenditures reduced by $3.0 billion in 2013 to $ 9.1 billion in 2017, yielding a cumulative difference of $32 billion over five years.

Conclusion

There are two sources for substantial differences between the new results and the model presented in the TRDRP Report.

The first source is differences in the forecast for California smoking prevalence. The forecast for Scenario 1 in the original report was for a slight increase in smoking prevalence, the forecast for the new model is for a decrease in prevalence, but one that is only about half of rate average rate of decrease over history of the Proposition 99 program. The reason for this slowing is that inflation is continuing to decreases in the real value of per capita tobacco control funding (5¢ per pack) is reducing the effectiveness of the California Tobacco Control Program. As a result, smoking prevalence may soon be stable (that is, there will be no change over time) in California or even start increasing . Note that the model specification for prevalence has not changed for smoking prevalence, but the estimation method (and required regression specification in terms of lagged explanatory variables) has changed from a static cointegrating regression (that estimated long run equilibrium values of the observed variables) to a reduced form VAR (that estimates future observed values), and the timing of the scenarios has changed. The forecast that smoking prevalence will decline at a slower rate than previously because of the recent and continuing decline in California tobacco control funding is a robust result, consistent with a small increase or decrease in smoking prevalence over the next five years.

The second cause of substantial differences between the old and new model is that the reduction in cigarettes consumed per smoker under Scenario 2 is greater using the new model than the old one presented in the original report. The change in the forecast for cigarette consumption per smoker is due to changes in the specification of the cigarettes consumed per smoker equation (from Equation A2 from the original model to A5 for the new model) in addition to changes in estimation method and scenario timing. The difference in the forecast values under Scenario 2 are partly due to the change from Equation A2 to Equation A5, which embody different assumptions about the importance of different common trends in California and the rest of the US in determining cigarette consumption by current smokers, and how those trends interact with future forecast values of the explanatory variables for California.

It may be difficult to determine the best specification in small samples using conventional statistical criteria (such as informal diagnostics of residuals, commonly used information criteria, etc.) that depend on the properties of the in-sample fits, particularly in time series analysis with a relatively small number of time series observations. That situation appears to be the case with the specification for the equation for cigarette consumption per current smoker. Since a major objective of this research is to develop models that can be used to forecast the future effects of policy decisions, standard statistical criteria that depend on the characteristics in-the sample fit (versus the ability to produce accurate out-of-sample forecasts) may not be able to determine between several candidate specification each of which perform well on in-sample fit criteria. One goal of future research will focus on the out-of-sample predictive performance of specifications that perform well using conventional criteria based on in-sample fit. The new specification for cigarette consumption per smoker, and the new estimation method (reduced form VAR regressions instead of static cointegrating regressions) produce forecasts of future smoking behavior that are ‘conservative’ in the sense that that they produce smaller estimated savings over five years after increased funding for California tobacco control. The best model for cigarette consumption per smoker will be a focus of future research.

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