eAppendix: E-Cigarette Use and Combustible Cigarette Smoking Initiation among Youth: Accounting for Time-Varying Exposure and Time-Dependent Confounding

eAppendix 1: Inverse probability of treatment and censoring weight calculation and distributions

For each participant *i* and wave *j* for which exposure was measured, a stabilized weight was estimated equal to the inverse probability that a participant received the e-cigarette exposure history they received, given past exposure and covariates, represented by the following equation:

$$stw_i = \frac{\prod_{k=0}^{j} pr[ECIG_k = ecig_k \mid \overline{ECIG}_{k-1} = \overline{ecig}_{i(k-1)}, V_0 = v_{i0}, C_{k-1} = 0]}{\prod_{k=0}^{j} pr[ECIG_k = ecig_k \mid \overline{ECIG}_{k-1} = \overline{ecig}_{i(k-1)}, \bar{L}_{k-1} = \bar{l}_{i(k-1)}, C_{k-1} = 0]}$$

Stabilized weights reduce the probability of extreme weights and increase precision.[1,2] In the above equation, overbars represent covariate history (e.g., $\overline{ecig}_{i(k-1)}$ is exposure history through time *k*-1). The numerator represents the probability of e-cigarette use at time *k*, conditional on e-cigarette use history up until *k-1*, a vector of confounders measured at wave 1 only (V_0), and remaining uncensored at *k-1* (either due to loss to follow-up or having smoked a cigarette). The denominator represents the probability of e-cigarette use at time *k*, conditional on e-cigarette use history up until *k-1*, all confounders up until time *k-1*, and remaining uncensored at *k-1*. V are a subset of L (i.e., L contains both time-invariant and time-varying confounders).[3] Separate weights were estimated for each exposure specification using pooled logistic regression and the process outlined by Hernán et al. 2000.[3]

To estimate the weight denominator for the dichotomous exposure of ever vs. never e-cigarette initiation, a pooled logistic regression model was used to estimate the probability of never e-cigarette use at each time point (e.g., at wave 2, 3, and 4). Independent variables included all time-invariant covariates, time-varying covariates measured at the prior wave, and a variable for the visit to allow for a time-specific intercept.[3] The same model was used to estimate the weight numerator, excluding time-varying values of the covariates. The weight models were fitted on the subsample of observations for which no e-cigarette initiation had yet occurred. For

example, if a participant initiated e-cigarettes at wave 2, their probability of having initiated e-cigarettes at wave 3 was already 100%. Therefore, in the above equation, $\overline{ECIG}_{k-1}$ would be equal to 0.

The predicted probabilities from these models were then used to derive the probability of *observed* e-cigarette exposure at each time point. For participants that used e-cigarettes, their probability of observed exposure was equal to 1 minus the predicted probability from the above regression. For those who had not initiated e-cigarettes, their probability of observed exposure was equal to the predicted probability. Finally, to estimate the probability of e-cigarette history up to each time point, the probabilities were multiplied over time (e.g., at wave 4, the denominator was equal to the probability at wave 2 multiplied by the probability at wave 3 multiplied by the probability at wave 4).

A similar process was used to estimate the weights for the remaining three categorical exposures, however pooled multinomial logistic regression was used rather than binomial logistic regression. For the exposures of current/former/never e-cigarette use and vaping frequency, models were not restricted to the subsample of observations for which no e-cigarette initiation had yet occurred, as participants were able to switch from being a current user to a former user (and vice-versa), or switch between frequency categories. Therefore, in this case, $\overline{ECIG}_{k-1}$would be equal to the observed value of e-cigarette use at *k-1*.

A similar process was used to estimate stabilized inverse probability of censoring weights, represented by the following equation:

$$scw_i = \frac{\prod_{k=0}^{j} pr[C_k = 0 \mid \overline{ECIG}_{k-1} = \overline{ecig}_{i(k-1)}, V_0 = v_{i0}, C_{k-1} = 0]}{\prod_{k=0}^{j} pr[C_k = 0 \mid \overline{ECIG}_{k-1} = \overline{ecig}_{i(k-1)}, \bar{L}_{k-1} = \bar{l}_{i(k-1)}, C_{k-1} = 0]}$$

The numerator represents the probability of remaining non-censored at time *k*, conditional on e-cigarette use history up until *k-1*, a vector of confounders measured at wave 1

only (V_0), and remaining non-censored at *k-1*. The denominator represents the probability of remaining non-censored at time *k,* conditional on e-cigarette use history up until *k-1,* all confounders up until time *k-1,* and remaining non-censored at *k-1*. To estimate the denominator, a pooled logistic regression model estimated the probability of being non-censored at each observation conditional on past covariates and exposure among the full sample at baseline. The independent variables included all time-invariant covariates, time-varying covariates measured at the prior wave, and a variable for the visit to allow for a time-specific intercept. The same model was used for the censoring weight numerator, excluding time-varying covariates. As with the exposure weights, the predicted probabilities from the censoring models were multiplied over time to derive stabilized inverse probability of censoring weights (e.g., at wave 4, the denominator was the probability of being non-censored at wave 2 multiplied by the probability of being non-censored at wave 3 multiplied by the probability of being non-censored at wave 4).

As recommended by Cole et al. 2008,[1] treatment and censoring weights were estimated using several different model specifications. The first iteration of models included a comprehensive list of 18 confounders with no changes to their operationalization. In subsequent iterations, categorical covariates were collapsed, a natural cubic spline was used for the continuous BSS score, and a smaller sufficient set of confounders was identified based on a directed acyclic graph to avoid positivity violations. In the final iteration, any covariates that did not change the final weighted estimate were excluded, for a total of 12 confounders in the final models. For each model specification, the mean, standard deviation, and minimum and maximum of the stabilized weights were calculated.

The final weight models included the time-invariant covariates: age (12–14 years, 15-17 years), sex (male, female), race/ethnicity (non-Hispanic Black, non-Hispanic white, Non-

Hispanic Asian, Non-Hispanic Other, Hispanic), parent's educational attainment (<high school or GED, ≥high school), past 12-month grade performance (Mostly A's or B's, all others grades), living with a user of any tobacco product (yes/no), Brief Sensation Seeking Scale (continuous score with a natural cubic spline). The final models also included time-varying covariates measured at the wave prior to exposure: externalizing mental health problems (high problems vs. medium/low problems), past 12-month alcohol, marijuana, and use of other tobacco products (yes/no), having a favorite tobacco advertisement (yes/no), believing e-cigarettes are less harmful than combustible cigarettes (yes/no), and cigarette susceptibility (yes/no susceptible).

The mean of the final stabilized weights used in analysis (the product of the inverse treatment and censoring weights) was 1.00 for ever vs. never e-cigarette use (min=0.09, max=9.2, median=0.99), 1.00 for current vs. former vs. never use (min=0.04, max=11.8, median=0.99), 1.00 for non-tobacco vs. tobacco flavored vs. never use (min=0.08, max=9.4, median=0.99), and 1.00 for vaping frequency (min=0.06, max=10.0, median=0.99). A mean of 1.0 provides reassurance of correct model specification.[1] We repeated the primary analysis after progressively truncating weights, however we found that the precision gained from truncation did not outweigh bias control; weights were therefore left untruncated.

Below, we include the SAS code for calculating the inverse probability weights and the MSM parameters for our primary analysis of ever vs. never e-cigarette initiation. See eTables 2-4 for the model coefficients from the weight estimation and the parameters on the log scale for our MSM.

```
/*Sort by imputation*/

    proc sort data=msm;
    by _imputation_;
    run;

/*Model 1: Numerator of Treatment Weight*/
```

```
proc logistic data=msm;
by _imputation_;
where ever_ecig_lag=0; /*restricted to participants who had not yet initiated e-cigarettes. For categorical exposure of current/former/never and vaping frequency, this statement is removed, and lagged exposure is included as an independent variable*/
class wave race_ethnicity  /param=ref;
model ever_ecig=
wave age sex race_ethnicity parents_ed lives_with_tobaccouser grades BSS_score
BSS_score1-BSS_score3  GAINSS_EXT_1 alcohol_1 marijuana_1 othertobacco_1 susceptible_1
perceived_harm_1 TobaccoAd_1; /*time-specific intercept and wave 1 confounders*/
output out=Model1 p=numer;
run;

/*Model 2: Denominator of Treatment Weights*/

proc logistic data=msm;
by _imputation_;
where ever_ecig_lag=0;
class wave race_ethnicity /param=ref;
model ever_ecig=
wave age sex race_ethnicity parents_ed lives_with_tobaccouser grades BSS_score
BSS_score1-BSS_score3 GAINSS_EXT_1 alcohol_1 marijuana_1 othertobacco_1 susceptible_1
perceived_harm_1 TobaccoAd_1
GAINSS_EXT_lag alcohol_lag marijuana_lag othertobacco_lag susceptible_lag perceived_harm_lag
TobaccoAd_lag; /*time-specific intercept, wave 1 confounders, and time-varying confounders at prior wave*/
output out=Model2 p=denom;
run;

/*Model 3: Numerator of Censoring Weights*/

proc logistic data=msm;
by _imputation_;
class wave race_ethnicity /param=ref;
model cens=
ever_ecig wave age sex race_ethnicity parents_ed lives_with_tobaccouser grades BSS_score
BSS_score1-BSS_score3 GAINSS_EXT_1 alcohol_1 marijuana_1 othertobacco_1 susceptible_1
perceived_harm_1 TobaccoAd_1; /*time-specific intercept, exposure, and wave 1 confounders*/
output out=Model3 p=numer_c;
run;

/*Model 4: Denominator of Censoring Weights*/

proc logistic data=msm;
by _imputation_;
class wave race_ethnicity /param=ref;
model cens=
ever_ecig wave age sex race_ethnicity parents_ed lives_with_tobaccouser grades BSS_score
BSS_score1-BSS_score3  GAINSS_EXT_1 alcohol_1 marijuana_1 othertobacco_1 susceptible_1
perceived_harm_1 TobaccoAd_1
GAINSS_EXT_lag alcohol_lag marijuana_lag othertobacco_lag susceptible_lag perceived_harm_lag
TobaccoAd_lag; /*time-specific intercept, exposure, wave 1 confounders, and time-varying confounders at prior wave*/
output out=Model4 p=denom_c;
run;
```

```
/*sort output datasets*/

        proc sort data=Model1; by _imputation_ personid wave;
        proc sort data=Model2; by _imputation_ personid wave;
        proc sort data=Model3; by _imputation_ personid wave;
        proc sort data=Model4; by _imputation_ personid wave;
        run;

/*Using predicted probabilities to derive stabilized weights*/

        data weights;
        merge model1 model2 model3 model4; by _imputation_ personid wave ;

        /* variables ending with _0 refer to the numerator of the weights
        variables ending with _w refer to the denominator of the weights */

        /* reset the variables for a new participant */

        if first.PERSONID then do;
                k1_0=1; k1_w=1; k2_0=1;k2_w=1;
        end;
        retain k1_0 k1_w k2_0 k2_w ;  /*retain statement carries forward the weights*/

        /* Inverse probability of censoring weights */

        k2_0=k2_0*numer_c;

        k2_w=k2_w*denom_c;

        /* Inverse probability of treatment weights */

        /* participants with no e-cigarette initiation */
        if wave_first_vaped>wave or wave_first_vaped=. then do;
        k1_0=k1_0*numer;
        k1_w=k1_w*denom;
        end;

        /* participants that start e-cigarette this wave */
        else if wave_first_vaped=wave then do;

        k1_0=k1_0*(1-numer);
        k1_w=k1_w*(1-denom);
        end;

        /* participants that have already started e-cigs */
        else do;
        k1_0=k1_0;
        k1_w=k1_w;
        end;

        /* Stabilized treatment weights */
        stabw_ever=k1_0/k1_w;

        /*Stabilized censoring weights */
        stabw_c_ever=k2_0/k2_w;
```

```
/*Stabilized treatment*censoring weights*/
stabIPCT_ever=(k1_0*k2_0)/(k1_w*k2_w);

run;

/*Final MSM model*/

proc genmod data=weights descending;
class PERSONID wave race_ethnicity /param=ref;
model ever_cig=
ever_ecig wave age sex race_ethnicity parents_ed lives_with_tobaccouser grades BSS_score
BSS_score1-BSS_score3 GAINSS_EXT_1 alcohol_1 marijuana_1 othertobacco_1 susceptible_1
perceived_harm_1 TobaccoAd_1; /*exposure, time-specific intercept, and wave 1 confounders*/
/dist=poisson link=log covb;
weight stabIPCT_ever;
by _imputation_;
repeated subject=PERSONID/type=ind corrw covb;
ods output GEEEmpPEst=gmparms ParmInfo=gmpinfo CovB=gmcovb;
run;
quit;

proc mianalyze parms=gmparms covb=gmcovb parminfo=gmpinfo;
modeleffects Intercept ever_ecig;
ods output ParameterEstimates=gmparms2;
run;

data MSM_results;
set gmparms2;
RR=exp(estimate);
LCL=exp(LCLMean);
UCL=exp(UCLMean);
run;

proc print data=MSM_results;
var PARM RR LCL UCL;
run;
```

eAppendix 2: Causal Estimands

The product of the inverse probability and censoring weights were used in a weighted discrete-time Poisson regression model to estimate the parameters of the following MSM : $\log(pr[Y_a = 1|v]) = \beta_0(t) + \beta_1 a(t) + \beta_2 v$. For the ever vs. never e-cigarette initiation and flavor use at first initiation specification, β_1 is interpreted as the causal risk ratio (RR) for the effect of initiating e-cigarettes, comparing participants' risk of smoking initiation if they initiated e-cigarettes at or before wave *t* with their risk of smoking initiation if they never initiated e-cigarettes at or before wave *t*. For these two exposure specifications, we do not account for stopping vaping, and the causal estimand corresponds to an intention-to-treat effect of a hypothetical randomized trial in which participants were randomly assigned to initiate e-cigarettes at the second wave, third wave, fourth wave, or not at all.[4,5] For current/former/never e-cigarette use and vaping frequency exposures, the interpretation of β_1 changes slightly as the causal RR for the effect of most recent exposure at wave *t* on smoking initiation. For these two exposure specifications we accounted for switching between categories, and thus the estimand corresponds to an as-treated effect, or the effect of the most recent e-cigarette exposure on smoking initiation.[5,6]

eAppendix 3: Quantitative Bias Analysis for Exposure and Outcome Misclassification

A quantitative bias analysis was performed to assess the magnitude and direction of bias due to potential exposure and outcome misclassification for the primary association of ever e-cigarette initiation and ever smoking initiation.[7] Internal and external validation studies were identified to determine estimates for the sensitivity and specificity of self-reported e-cigarette use and cigarette smoking among youth.[8] There were no studies identified that provided misclassification probabilities for self-reported e-cigarette use, likely due to the relative novelty of e-cigarettes, and the lack of knowledge on the relationship between e-cigarettes and biomarkers such as cotinine. However, there were several studies that provided estimates of sensitivity and specificity of cigarette smoking. In addition, there was one validation study conducted among PATH adult and youth participants for validity of self-reported current any-tobacco use.[9] In this study, the authors found that among those who tested positive for nicotine in their saliva, 78% reported current tobacco use (sensitivity=78%); among those who tested negative for nicotine in their saliva, 93% reported non-current use (specificity=93%). External validation studies for self-reported cigarette smoking reported similar sensitivity and specificity. In a systematic review of validity of self-reported current cigarette smoking,[10] the average sensitivity and specificity for student populations were 78.5% and 91.8%, respectively. Importantly, the only validation studies available were for reports of current e-cigarette/cigarette use, rather than ever use. Sensitivity/specificity probabilities are likely greater for youth when reporting ever use than current use as they are not required to consider the time since last use.

Using a simple bias analysis approach, exposure misclassification and outcome misclassification were corrected separately. Exposure and outcome misclassification were then corrected together in a multiple bias analysis. In the multiple bias analysis, misclassification was

corrected in the reverse order with which it occurred in the study (e.g., outcome misclassification followed by exposure misclassification).[8] Because of the prospective design, exposure misclassification was assumed to be non-differential with respect to the outcome. Outcome misclassification was assumed to be differential with respect to e-cigarette exposure, and in both cases the misclassification was assumed to be independent.

Using a range of combinations of sensitivity and specificity probabilities, the expected true number of exposed/diseased was calculated and used to generate positive predictive values (**PPV**) and negative predictive values (**NPV**) of the observed data. For both exposure and outcome misclassification, it was necessary to truncate specificity values to avoid implausible (i.e., outside the logical bounds of 0 and 1) PPV/NPV values (90% for exposure misclassification, 95% for outcome misclassification). Implausible PPV/NPV values can occur when either 1-specificity is greater than sensitivity (unlikely in the current analysis), or when the prevalence of exposure/outcome is less than 1-specificity (likely in the current analysis given low prevalence of exposure and outcome).[11] The PPV and NPVs were then used to re-classify exposure and/or outcome using record-level Bernoulli trials.[11] For exposure re-classification, ever e-cigarette use at wave 2 was first corrected, and exposure at wave 3 was subsequently corrected among those who remained never e-cigarette users at wave 2, and exposure at wave 4 was subsequently corrected among those who remained never e-cigarette users at wave 3. Using the re-classified (i.e., corrected) exposure and outcome values, the primary analysis was repeated, including recalculating inverse probability weights and fitting the weighted model for the association between e-cigarette initiation and smoking initiation.

eTable 1: distribution wave 1 covariates and wave 2 exposure by loss to follow-up status

Covariates measured at wave 1	Lost to follow-up (n=2,152)	Retained (n=7,432)
12-14 years old	953 (44.3)	3,083 (41.5)
Female sex	1,032 (48.0)	3,689 (49.6)
Race/ethnicity		
non-Hispanic Black	262 (12.2)	1,116 (15.0)
non-Hispanic white	1,153 (53.6)	3,386 (45.6)
non-Hispanic Asian or other race	175 (8.1)	693 (9.3)
Hispanic	562 (26.1)	2,237 (30.1)
Parental Education		
< High School or equivalent	776 (36.1)	2,876 (38.7)
Some college or Associates degree	745 (34.6)	2,226 (30.0)
≥Bachelors degree	631 (29.3)	2,330 (31.4)
Lives with tobacco user	1,421 (66.0)	5,221 (70.3)
Brief Sensation Seeking Scale, median (IQR)	3.7 (3.0-4.3)	3.3 (3.0-4.0)
Externalizing mental health problems		
Low	887 (41.2)	2,863 (38.5)
Medium	694 (32.3)	2,399 (32.3)
High	571 (26.5)	2,170 (29.2)
Past 12-month alcohol use	190 (8.8)	651 (8.8)
Past 12-month marijuana use	57 (2.7)	199 (2.7)
Past 12-month other tobacco use	68 (3.2)	199 (2.7
Parent talked to youth about not using tobacco	1,101 (51.2)	3,777 (50.8)
Grades		
Mostly As	601 (27.9)	2,124 (28.6)
Mostly As and Bs	728 (33.8)	2,668 (35.9)
Mostly Bs	211 (9.8)	632 (8.5)
Mostly Bs and Cs or or lower	612 (28.4)	2,008 (27.0)
Susceptible to cigarette smoking	614 (28.5)	2,260 (30.4)
Believe e-cigarettes are less harmful than cigarettes	851 (38.5)	2,973 (40.0)
Has a favorite tobacco advertisement	135 (6.3)	488 (6.6)
E-cigarette use at wave 2		
Never use	2,017 (93.7)	6,972 (93.8)
Current use	41 (1.9)	117 (1.6)
Former use	94 (4.4)	343 (4.6)

Estimates presented as unweighted frequencies (percentages) except where indicated

eTable 2. Coefficients from the denominator of treatment weights for the primary analysis: Pooled logistic regression predicting never e-cigarette use at each wave

Parameter	Coefficient
Intercept	2.9296
Wave (2)	-0.0291
Wave (3)	-0.4226
age	0.253
male	-0.1389
race_ethnicity (Non-Hispanic White)	0.0853
race_ethnicity (Non-Hispanic Black)	0.5125
race_ethnicity (Non-Hispanic All others)	0.2641
Parents_ed	0.0606
lives_with_tobaccouser	-0.298
grades	0.2205
BSS_score	0.0601
BSS_score1	0.8941
BSS_score2	-4.026
BSS_score3	6.2748
GAINSS_EXT_1	-0.0624
alcohol_1	-0.0384
marijuana_1	0.3396
othertobacco_1	0.1078
susceptible_1	-0.1881
Perceived_Harm_1	-0.0871
TobaccoAd_1	0.1737
GAINSS_EXT_LAG	-0.1591
alcohol_lag	-0.7811
marijuana_lag	-0.8757
othertobacco_la	-1.1748
susceptible_lag	-0.4400
Perceived_Harm _Lag	-0.4379
TobaccoAd_lag	-0.4349
From Imputation No. 10. Reference for Wave is wave 4 and reference for race_ethnicity is Hispanic	

eTable 3. Coefficients from the denominator of censoring weights for the primary analysis: Pooled logistic regression predicting remaining non-censored at each wave

Parameter	Coefficient
Intercept	1.4481
Wave (2)	-0.078
Wave (3)	0.3948
Ever_ecig	0.3514
age	0.1300
male	-0.0164
race_ethnicity (Non-Hispanic White)	-0.2864
race_ethnicity (Non-Hispanic Black)	0.202
race_ethnicity (Non-Hispanic All others)	-0.009
Parents_ed	0.0945
lives_with_tobaccouser	-0.2092
grades	0.1588
BSS_score	0.2591
BSS_score1	-1.3496
BSS_score2	7.672
BSS_score3	-20.863
GAINSS_EXT_1	0.0783
alcohol_1	-0.0098
marijuana_1	0.0503
othertobacco_1	-0.0857
susceptible_1	-0.0699
Perceived_Harm_1	-0.0025
TobaccoAd_1	0.0758
GAINSS_EXT_LAG	0.2158
alcohol_lag	0.143
marijuana_lag	-0.0614
othertobacco_la	-0.4589
susceptible_lag	0.1468
Perceived_Harm _Lag	0.0477
TobaccoAd_lag	-0.0038
From Imputation No. 10. Reference for Wave is wave 4 and reference for race_ethnicity is Hispanic	

eTable 4: MSM parameters on the log scale for the primary analysis

Parameter	**Coefficient**
Intercept	-2.1649
Wave (2)	-0.5924
Wave (3)	-0.4439
Ever_ecig	0.8596
age	-0.2099
male	0.2004
race_ethnicity (Non-Hispanic White)	0.2426
race_ethnicity (Non-Hispanic Black)	-0.4892
race_ethnicity (Non-Hispanic All others)	0.1029
Parents_ed	0.0453
lives_with_tobaccouser	0.2345
grades	-0.2155
BSS_score	-0.2445
BSS_score1	0.0074
BSS_score2	1.7218
BSS_score3	-7.5696
GAINSS_EXT_1	0.0099
alcohol_1	0.2078
marijuana_1	0.1029
othertobacco_1	-0.0379
susceptible_1	0.5783
Perceived_Harm_1	0.1627
TobaccoAd_1	0.1132
From Imputation No. 10. Reference for Wave is wave 4 and reference for race_ethnicity is Hispanic	

eTable 5. Quantitative bias analysis for non-differential misclassification of ever e-cigarette use exposure

	Specificity			
Sensitivity	**1.0**	**0.99**	**0.95**	**0.90**
1.0	2.4 (2.2-2.7)	2.4 (2.1-2.7)	2.6 (2.3-3.0)	3.4 (3.0-3.8)
0.99	2.4 (2.1-2.7)	2.5 (2.2-2.8)	2.7 (2.4-3.0)	3.6 (3.2-4.0)
0.95	2.5 (2.2-2.8)	2.6 (2.3-2.9)	2.8 (2.5-3.1)	3.8 (3.4-4.2)
0.90	2.7 (2.4-3.0)	2.7 (2.4-3.0)	3.0 (2.6-3.3)	3.9 (3.5-4.3)
0.85	2.8 (2.5-3.1)	2.9 (2.6-3.2)	3.1 (2.8-3.4)	4.5 (4.0-5.0)
0.80	3.0 (2.7-3.3)	3.0 (2.7-3.3)	3.5 (3.2-3.9)	4.6 (4.1-5.1)
0.75	3.1 (2.8-3.5)	3.1 (2.8-3.4)	3.6 (3.3-4.0)	5.2 (4.7-5.7)

Specificity truncated at 0.90 to avoid negative cells. Estimates represent MSM weighted risk ratios (95% CI) corrected for exposure misclassification. Assumes varying percentages of youth correctly classified as exposed (sensitivity) and percentages of youth correctly classified as unexposed (specificity).

eTable 6. Quantitative bias analysis for differential misclassification of smoking initiation with 100% outcome specificity

	Sensitivity | E-						
Sensitivity | E+	**1.0**	**0.99**	**0.95**	**0.90**	**0.85**	**0.80**	**0.75**
1.0	2.4 (2.1-2.7)	2.3 (2.1-2.6)	2.2 (2.0-2.5)	2.1 (1.8-2.3)	1.9 (1.7-2.2)	1.8 (1.6-2.0)	1.6 (1.4-1.8)
0.99	2.4 (2.1-2.7)	2.4 (2.2-2.8)	2.3 (2.0-2.6)	2.1 (1.9-2.4)	2.0 (1.8-2.3)	1.8 (1.6-2.0)	1.7 (1.5-1.9)
0.95	2.8 (2.5-3.2)	2.7 (2.4-3.1)	2.5 (2.3-2.8)	2.4 (2.1-2.6)	2.2 (2.0-2.4)	2.1 (1.9-2.4)	1.9 (1.7-2.1)
0.90	3.1 (2.8-3.5)	3.1 (2.8-3.5)	2.8 (2.5-3.1)	2.6 (2.4-2.9)	2.5 (2.3-2.8)	2.3 (2.1-2.6)	2.1 (1.9-2.3)
0.85	3.4 (3.1-3.8)	3.3 (3.0-3.7)	3.3 (3.0-3.7)	3.1 (2.8-3.4)	2.8 (2.6-3.1)	2.7 (2.4-2.9)	2.5 (2.3-2.8)
0.80	4.1 (3.7-4.5)	3.8 (3.5-4.2)	3.5 (3.2-3.8)	3.3 (3.0-3.6)	3.1 (2.8-3.4)	2.9 (2.7-3.2)	2.8 (2.5-3.0)
0.75	4.3 (3.9-4.7)	4.2 (3.8-4.6)	3.7 (3.4-4.1)	3.7 (3.4-4.0)	3.7 (3.4-4.0)	3.3 (3.0-3.6)	3.1 (2.9-3.4)

Estimates represent MSM weighted risk ratios (95% CI) corrected for outcome misclassification. Assumes perfect classification of youth without the outcome among youth exposed and unexposed (specificity), and varying percentages of youth correctly classified as having the outcome among exposed (sensitivity |E+) and unexposed (sensitivity | E-).

eTable 7. Quantitative bias analysis for differential misclassification of smoking initiation with 95% outcome specificity

	Sensitivity | E-						
Sensitivity | E+	**1.0**	**0.99**	**0.95**	**0.90**	**0.85**	**0.80**	**0.75**
1.0	3.5 (3.1-4.0)	3.5 (3.0-4.0)	3.0 (2.7-3.4)	3.0 (2.6-3.4)	2.7 (2.4-3.1)	2.5 (2.3-2.9)	2.4 (2.1-2.7)
0.99	3.4 (3.0-3.9)	3.3 (2.9-3.7)	3.1 (2.7-3.5)	2.9 (2.6-3.3)	2.9 (2.6-3.3)	2.6 (2.3-2.9)	2.4 (2.1-2.7)
0.95	3.7 (3.3-4.3)	3.7 (3.3-4.2)	3.7 (3.3-4.2)	3.3 (2.9-3.7)	3.0 (2.7-3.4)	2.7 (2.4-3.1)	2.6 (2.3-2.9)
0.90	4.1 (3.7-4.6)	3.8 (3.4-4.3)	4.0 (3.6-4.5)	3.9 (3.4-4.3)	3.5 (3.1-3.9)	3.2 (2.9-3.6)	3.1 (2.8-3.5)
0.85	4.8 (4.3-5.4)	4.3 (3.8-4.8)	4.1 (3.7-4.6)	4.0 (3.6-4.5)	3.6 (3.2-4.0)	3.5 (3.2-3.9)	3.3 (3.0-3.6)
0.80	4.9 (4.4-5.4)	4.5 (4.1-5.0)	4.8 (4.4-5.3)	4.0 (3.7-4.5)	4.3 (3.9-4.7)	4.1 (3.7-4.5)	3.8 (3.5-4.2)
0.75	5.4 (4.9-5.9)	5.3 (4.9-5.9)	5.3 (4.8-5.8)	4.6 (4.1-5.0)	4.5 (4.1-5.0)	4.4 (4.0-4.8)	4.0 (3.6-4.4)

Specificity truncated at 0.95 to avoid negative cells. Estimates represent MSM weighted risk ratios (95% CI) corrected for outcome misclassification. Assumes correct classification of 95% youth without the outcome among youth exposed and unexposed (specificity), and varying percentages of youth correctly classified as having the outcome among exposed (sensitivity |E+) and unexposed (sensitivity | E-).

eTable 8. Multiple bias analysis for non-differential misclassification of ever e-cigarette use and differential misclassification of smoking initiation: greater outcome sensitivity among unexposed

	Exposure Specificity		
Exposure Sensitivity	**0.99**	**0.95**	**0.90**
0.99	2.8 (2.5-3.1)	3.2 (2.8-3.6)	4.6 (4.2-5.2)
0.95	2.9 (2.6-3.3)	3.2 (2.9-3.6)	4.9 (4.4-5.4)
0.80	3.6 (3.3-4.0)	4.4 (4.0-4.8)	6.4 (5.8-7.0)

Values represent MSM weighted RR (95% CI) after correction for exposure and outcome misclassification. Outcome specificity=1.0. Outcome sensitivity among exposed=0.95. Outcome sensitivity among unexposed=0.99

eTable 9. Multiple bias analysis for non-differential misclassification of ever e-cigarette use and differential misclassification of smoking initiation: greater outcome sensitivity among exposed

	Exposure Specificity		
Exposure Sensitivity	**0.99**	**0.95**	**0.90**
0.99	2.3 (2.0-5.9)	2.5 (2.2-2.8)	3.3 (2.9-3.7)
0.95	2.4 (2.1-2.7)	2.6 (2.4-3.0)	3.4 (3.0-3.8)
0.80	2.8 (2.5-3.1)	3.2 (2.9-3.6)	4.1 (3.7-4.6)

Values represent MSM weighted RR (95% CI) after correction for exposure and outcome misclassification. Outcome specificity=1.0. Outcome sensitivity among exposed=0.99. Outcome sensitivity among unexposed=0.95.

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