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ABSTRACT

We use data from the Population Assessment of Tobacco Use and Health (PATH), a longitudinal data set including self-reported and biomarker measures of tobacco use, to examine the effects of state-level tobacco 21 (T21) laws on smoking and vaping. T21 laws reduce self-reported cigarette smoking among 18-to-20 year olds, concentrated in males. Initial non-users who "age-out" of treatment are less likely to subsequently initiate self-reported smoking or vaping. Treated smokers are less likely to buy their own cigarettes and more likely to buy cigarettes in a different state. Biomarker results are mixed, and we find some evidence of a reduction in nicotine exposure but less evidence for a reduction in exposure to tobacco. Finally, we test for non-classical measurement error. T21 laws reduce the probability that clinically identified likely cigarette smokers self-report as smokers, which may increase the apparent effect of T21 laws on cigarette smoking as measured by self-reports.

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1 Introduction

In 2019, over 30% of high school students reported using tobacco products in the last 30 days, and nearly 28% reported using electronic cigarettes (e-cigarettes) (Wang et al., 2019). Compared to 2015, overall tobacco use increased by 20% and e-cigarette use doubled (Singh et al., 2016). This rapid growth in tobacco use, driven by e-cigarette use, has alarmed public health officials (Centers for Disease Control and Prevention, 2018; U.S. Food and Drug Administration, 2019). The response of governments and public health officials to the large increase in e-cigarette usage has been to implement a series of restrictions on access to both e-cigarettes and traditional cigarettes (Centers for Disease Control and Prevention, 2019a).

In particular, in December 2019, the United States enacted a national Tobacco 21 (T21) law, which raised the minimum age of sale of all tobacco and nicotine products from 18 to 21 years across the United States (U.S. Food and Drug Administration, 2020). The national T21 law followed state and local-level T21 laws and other minimum legal age of sale laws for e-cigarettes. Hawaii became the first state to enact a T21 law in January 2016, followed by California in June 2016, Washington DC in February 2017, and 14 additional states before the national T21 law. Taken together, these T21 laws represent some of the most significant tobacco control policies since the Master Settlement Agreement in 1998. Thus, understanding the effects of these T21 laws is critical to having well-formulated tobacco product regulations by the FDA, CDC, and other public health authorities.

The general concept of T21 laws is that restricting the legal purchasing age for ***all tobacco products*** to 21 years old will reduce access to all tobacco products by minors during the critical youth initiation phase and, subsequently, reduce downstream adult smoking and vaping. This is particularly salient among adolescents and young adults, as most adult smokers initiate tobacco use as minors (Everett et al., 1999; Gilliland et al., 2006), and over 88% of regular smokers begin smoking by age 20 (Centers for Disease Control and Prevention, 2020). Further, given the complexities of youth smoker access to tobacco-related products, for example through social networks (Hansen, Rees, and Sabia, 2013), and the effects of time-inconsistent preferences (Crettez and Deloche, 2020), investigating how adolescents and young adults respond to new policies and with regard to new products is needed to improve population health.

In this paper, we investigate the effects of T21 laws enacted at the state level on a set of tobacco outcomes. We use data from the Population Assessment of Tobacco Use and Health (PATH) data set, a longitudinal data set of tobacco use and health outcomes covering both adolescents and adults that includes both self-reported measures of tobacco use, and, importantly, biomarkers of recent nicotine and tobacco exposure (PATH, 2023). We connect the enactment of state-level T21 laws to individuals in the PATH data set to examine how T21 laws change both self-reported measures of tobacco use and two biomarkers, urinary cotinine levels, a measure of overall nicotine exposure, and urinary NNAL levels, a measure of tobacco exposure, across a range of age groups.

We find that T21 laws lead to notable reductions in the self-reported probability that young adults (18-to-20 years old) initiate smoking cigarettes, which is driven by males. While we do not observe statistically significant effects of T21 laws on self-reported vaping in the whole sample, we find evidence for a reduction among those 18-to-20 years old in certain sub-samples. We also observe longer-run effects of T21 laws on smoking or vaping initiation among adults (21-to-25 years old) who were formerly treated by T21 laws, and find evidence that 18-to-20-year-olds evade T21 laws by having other people buy their cigarettes or cross-border shopping. Next we turn to clinical data to investigate how T21 laws impact clinically measured biomarker outcomes. This analysis yields evidence of a reduction in urinary cotinine levels, which could indicate a reduction in the use of any products that contain nicotine, including cigarettes and e-cigarettes. However, despite the large reductions in self-reported cigarette smoking, we only observe mixed evidence of statistically significant changes in urinary NNAL levels (e.g., tobacco consumption). Lastly, the PATH data allow for an explicit test of self-reporting bias, that is whether T21 laws meaningfully reduce the probability that likely smokers, as determined by their clinical NNAL levels, self-report as smokers. This raises concerns that estimates of the effects of T21 laws on smoking based on self-reported data may be overstated.

Our paper helps fill gaps in a growing literature examining the effects of T21 laws both in empirical approach and in the particular questions that can be addressed. Some of the best existing papers use individual-level health survey data (e.g., BRFSS, YRBS, MTF, etc.) to estimate the effects of T21 laws on the self-reported youth and adult consumption of cigarettes, e-cigarettes, and other potentially related goods. However, while papers such as Bryan et al. (2023) and Abouk, De, and Pesko (2024) are exceedingly well done, they nevertheless face constraints imposed by the nature of the data available. For example, the use of cross-sectional data structures prevents prior studies in this space from explicitly gauging how T21 laws impact within-person behaviors. The panel nature of the PATH data allows us to explicitly identify people as initial self-reported users or non-users of tobacco products to more directly study whether effects of T21 laws on tobacco use operate through initiation or cessation. Additionally, geographic controls may not completely account for unobservable factors that drive the adoption of T21 Laws and changes in smoking/vaping behaviors. As such, individual fixed effects models may provide a higher degree of control and more reliable estimates. Second, repeated cross-sectional data are unable to rule out that estimated behavioral changes are an artifact of sample composition brought on by changes in tobacco policies and may bias results or cloud interpretation. Third, cross-sectional data is unable to reliably investigate the effects of T21 Laws on formerly treated individuals after they "age-out" of treatment, relative to their never treated peers. This study leverages panel data to try to build upon the prior cross-sectional studies and address some of these issues.

Further, our data allow us to investigate how individuals' purchasing behaviors (e.g., own-purchase versus surrogate purchase, and cross-border shopping tendencies) are affected by T21 laws and, perhaps most importantly, to understand "net behavioral" effects across all tobacco/nicotine products and the accuracy/reliability of estimates when dealing with exclusively self-reported outcomes. Our analysis of cross border shopping adds to a long literature examining the effects of such behaviors in the markets for alcohol (e.g. Adams and Cotti, 2008; Lovenheim, Slemrod et al., 2010), cigarettes (e.g. Lovenheim, 2008; Merriman, 2010), and marijuana (e.g. Hansen, Miller, and Weber, 2020; Hao and Cowan, 2020). Self-reported outcomes may provide an incomplete measure of changes in tobacco use for a number of reasons. First, tobacco users may compensate for more stringent tobacco control policies by smoking each cigarette or vaping each e-cigarette more intensely to ingest more nicotine from each cigarette or e-cigarette. Second, tobacco control policies, especially ones that make use for certain age groups illegal, may affect the propensity of individuals to accurately report their tobacco use. This is related to concerns raised by DeCicca et al. (2008) that "anti-smoking sentiment" may drive the adoption of tobacco control policies and also reduce cigarette use. If T21 laws affect the propensity of individuals to accurately report tobacco use, any reduction in self-reported tobacco use in response to T21 laws may represent an increase in misreported tobacco use rather than an actual reduction in smoking or vaping.

This paper also contributes to a broader literature examining policies aimed at addressing e-cigarette use and estimating the economic relationship between e-cigarettes and traditional cigarettes. Many studies suggest that these two goods are economic substitutes (Pesko, Courtemanche, and Maclean, 2020; Cotti et al., 2022; Saffer et al., 2019, 2020; Dave et al., 2019; Pesko and Warman, 2022; Friedman, 2015; Pesko, 2023), while others suggest they are complements (Abouk and Adams, 2017; Cotti, Nesson, and Tefft, 2018). However, the nature of the economic relationship between cigarettes and e-cigarettes may vary across age groups, which has important implications for policy effectiveness.

2 Background

Hawaii enacted the first state-level T21 law in January 2016, followed by California in June 2016 and Washington D.C. in January 2017. Before December 2019, 14 additional states passed T21 laws. These state laws followed some earlier laws passed at the local level. Table A1 shows the states that passed T21 Laws and the effective dates of these policies. In December 2019, President Trump signed a large spending bill that included a national T21 law. Thus, it became illegal for retailers to sell tobacco products to people under 21 starting in December 2019. However, as Abouk, De, and Pesko (2024) note, questions remain about the enforceability of the national T21 law. In the time after the national T21 law, states have continued to pass their own T21 Laws. A growing literature in economics seeks to evaluate the effects of these T21 Laws on tobacco use. These papers join papers that evaluate the effects of age restrictions more broadly, for example, Friedman (2015), Abouk and Adams (2017), Pesko (2023), and DeSimone, Grossman, and Ziebarth (2023).

Bryan et al. (2023) use data from the Behavioral Risk Factor Surveillance System (BRFSS) and the Youth Risk Behavioral Surveillance System (YRBSS) which contain self-reported measures of smoking, vaping, and other substance use for those age 18 and over in BRFSS and students in grades nine through 12 in YRBSS. The authors find statistically significant declines in smoking participation and everyday smoking among 18-20 year olds in BRFSS and 18-year olds in YRBSS. However, they do not find large changes in self-reported quitting, suggesting that the changes in smoking participation are more likely changes in initiation. The authors find some evidence for declines in smoking among younger age groups, but these results are not as consistent. The authors additionally find evidence for decreased e-cigarette use, but e-cigarette questions in YRBSS start in 2017 so the authors miss the variation from the earliest state adopters of T21 laws. Examining how adolescents obtain e-cigarettes, the authors find that after T21 laws adolescent vapers are less likely to purchase their own e-cigarettes and more likely to borrow e-cigarettes from a friend. Finally, the authors find evidence for spillovers into decreased marijuana use and alcohol consumption among 18 year olds.

In a similar paper, Abouk, De, and Pesko (2024) use the Monitoring the Future (MTF) survey data and Nielsen Retail Scanner data from 2012 to 2019. They find that T21 laws reduce self-reported cigarette use among high school seniors by 35% and find smaller reductions for younger grades. The authors find that e-cigarette use falls across all grades. To examine possible biases in self-reports, the authors then examine sales in the Nielsen Retail Scanner data. Here they find that in counties with the highest quartile population percent under age 21, T21 laws reduce cigarette sales by about 12% and e-cigarette sales by nearly 50%. While this analysis may confirm the self-reported results from the MTF data, if individuals under age 21 purchase cigarettes and e-cigarettes online or in a different county, that may lead to a reduction in sales without necessarily a reduction in use.

Finally, Friedman and Pesko (2024) use the self-reported PATH data to examine the effects of T21 laws on smoking and vaping. The authors find that T21 laws reduce cigarette smoking prevalence among 18-20 year olds and some evidence of a reduction in cigar smoking prevalence and vaping prevalence, depending on the specification. The authors then examine other state policy attributes and their interaction with T21 laws, finding that provisions on the possession, use, or purchase of tobacco products lessen the effects of T21 laws.

Across these papers, a possible concern is the reliability of self-reported data. Economic theory predicts that smokers may compensate for increased cigarette prices by reducing the number of cigarettes they smoke but either switching to brands with higher nicotine contents or smoking each cigarette more intensely (Harris, 1980). Experiments find that when smokers were switched to light cigarettes, they smoked more intensely to ingest 60% more nicotine from each cigarette and smoked 25% more cigarettes, resulting in little to no change in their nicotine intake (Benowitz and Jacob III, 1984). Additionally, Benowitz et al. (1986) find that smokers forced to reduce the number of cigarettes they smoked by 85% responded by increasing nicotine intake per cigarette by three times, leading to a reduction in nicotine of only 60%. Economic research finds that smokers respond to cigarette excise tax increases by changing the brands that they smoke (Evans and Farrelly, 1998; Cotti, Nesson, and Tefft, 2016) or changing the way in which each cigarette is smoked (Farrelly et al., 2004; Nesson, 2017a,b), although the extent to which these compensating behaviors affect overall nicotine intake is less clear (Abrevaya and Puzzello, 2012; Nesson, 2017a,b; Cotti, Nesson, and Tefft, 2016).

Less research examines whether the reliability of self-reported smoking data is related to tobacco control policies. Tobacco control policies, especially ones that make use for certain age groups illegal, may affect the propensity of individuals to accurately report their tobacco use. This is related to concerns raised by DeCicca et al. (2008) that "anti-smoking sentiment" may drive the adoption of tobacco control policies and also reduce cigarette use. If T21 laws affect the propensity of individuals to accurately report tobacco use, any reduction in self-reported tobacco use in response to T21 laws may represent an increase in misreported tobacco use rather than an actual reduction in smoking or vaping.

3 Data

3.1 The Population Assessment of Tobacco Use and Health

Our main data source is the Population Assessment of Tobacco Use and Health (PATH) data set.[1] PATH is a longitudinal study of tobacco use and health including adults aged 18 - 90 and youths aged 12-17 that is matched over time. Wave 1 spans 2013-2014, Wave 2 spans 2014-2015, Wave 3 spans 2015-2016, Wave 4 spans late 2016-2017, Wave 4.5 for the youth sample (12-to-17 years old) was collected in 2018, and Wave 5 (again for all participants) spans 2018-2019. Collectively, PATH provides over 234,000 observations of roughly 65,000 unique individuals from across all 50 states and the District of Columbia, although coverage in some states is low. The average participant appears in the data set 4.3 times and approximately 60% of

[1]The PATH is a collaboration between the National Institutes of Health (NIH) and the Food and Drug Administration (FDA). Participants are picked by chance from a list of addresses. An interviewer visits these addresses and asks question to the people in the household to determine inclusion in the study. This study utilizes the restricted access PATH data.

participants appear five times or more.[2]

The PATH data contains a rich set of self-reported information about tobacco use, including measures of whether individuals currently use cigarettes and e-cigarettes. We create two self-reported measures of whether people report using cigarettes or e-cigarettes in the past 30 days, which is asked of respondents 12 years and older. Unfortunately, while PATH asks adult respondents about the number of cigarettes they smoke per day, they do not ask this question of adolescents. Thus, we focus mainly on the extensive margin of smoking and vaping for self-reports.

We also use self-reported information from PATH regarding how adolescents and adults get their cigarettes. First, PATH asks about how individuals usually buy their cigarettes, in-person, from the internet, over the phone, or they did not buy their own cigarettes. From this, we create an indicator for whether a smoker purchased their own cigarettes. PATH also asks both adults and adolescents who purchase their own cigarettes, "Do you usually buy your cigarettes inside your own state or in another state." We combine these two variables together to form a second indicator variable for "legitimate" cigarette purchases: cigarette purchases made by the individual in their own state.

Importantly, PATH also collects biospecimens from a subset of the total PATH respondents. At the first wave, adult respondents were asked to consent to biomarker collection. Of the adults who provided usable samples, PATH randomly selected a subsample of adults whose samples were analyzed. In subsequent waves, these adults, along with previously underage individuals who turned 18, were asked to provide biomarker samples. Of the biospecimens, urine samples are the most widely connected and PATH analyzes a wide variety of biomarker compounds in each sample. One of the compounds measured is urinary cotinine levels, a major metabolite of nicotine. When nicotine is ingested, it is fairly quickly metabolized into cotinine, which has a much longer half-life in the body of 16-20 hours (Benowitz and Jacob III, 1994; Benowitz et al., 1994). Any product containing nicotine, including traditional cigarettes, e-cigarettes, smokeless tobacco, and anti-smoking products containing nicotine, will increase an individual's cotinine levels. Cotinine levels, whether sampled from the blood or urine, are a popular and accurate biomarker for levels of recent nicotine exposure (e.g., Adda and Cornaglia, 2006, 2010; Nesson, 2017a,b).

PATH also contains urinary levels of 4-(methylnitrosamino)-1-(3-pyridyl)-1-butanol (NNAL). NNAL is a metabolite of 4-(methylnitrosamino)-1-(3-pyridyl)-1-butanone (NNK), which belongs to a family of tobacco-specific nitrosamines (TSNA). As suggested by their name, TSNAs are found *only* in tobacco products and are not found in meaningful levels in e-cigarettes or nicotine-replacement therapies.[3] NNK is a potent carcinogen, and is strongly linked to lung cancers (Hecht, 1998). Importantly, about 95% of NNK is metabolized into

[2] In Wave 4 additional newly sampled people were added to replenish attrition that had occurred between Waves 1 and 4.

[3] For more information, see `www.cdc.gov/biomonitoring/NNAL_BiomonitoringSummary.html`

NNAL. NNAL has a longer half-life in the body than cotinine, with a half-life of 18-45 days (Goniewicz et al., 2009; Hecht et al., 1999). Because NNK is not found in large amounts in electronic cigarette vapor, urinary levels of NNAL are similar among exclusive vapers and non-smokers (Bustamante et al., 2018). Thus, measuring NNAL in people's urine is a reliable way to determine exposure to tobacco products, although it is not easy to differentiate between cigarettes or other tobacco products. Additionally, exposure to environmental tobacco smoke from cigarettes or hookah may increase NNAL levels, but this exposure is usually very light compared to own-tobacco use.

PATH also includes detailed demographic data. From this data, we create indicators for each individual's sex, racial categories (white, black, Asian, other and multi-racial, and missing), Hispanic ethnicity, ten household income categories, educational attainment categories (less than high school, high school or GED, some college or associates degree, bachelor's degree, and advanced degree), as well the individual's age. However, since our models include individual fixed effects, we only include age in our specifications due to collinearity.

3.2 Tobacco-related Policies and State Measures

We obtain the dates that states enacted T21 laws from the Preventing Tobacco Addiction Foundation (`https://tobacco21.org/`). A list of states that enact T21 laws, along with the effective date and whether that state contributes variation in PATH and has pre-existing sub-state T21 laws can be found in Appendix Table A1. A few states, Arkansas, Main, Massachusetts, Ohio, and Texas, allowed individuals ages 18-20 to purchase tobacco products after the T21 law enactment. For these states, we follow Friedman and Pesko (2024) and choose as the enactment date the date which the T21 law applies to all individuals under age 21. We include an additional indicator variable for this time period, which also measures states that have additional tobacco age restrictions for ages 19.

We also merge information on a series of tobacco-related policy measures to account for the potential effect these related policies may have on smoking and vaping utilization. In particular, we add data on per pack excise tax on cigarettes at the quarterly level, calculated as the real ($2020) federal plus state cigarette excise tax in each state (DeCicca, Kenkel, and Lovenheim, 2022; Cotti, Nesson, and Tefft, 2016), the state-level e-cigarette tax per fluid milliliter (Cotti et al., 2021), measures of smoke-free air laws, and an indicator for the legalization of recreational marijuana. This information was accessed via the CDC's State Tobacco Activities Tracking and Evaluation System (Centers for Disease Control and Prevention, 2019b), various state agencies, or investigation by the authors. Lastly, we add state-level unemployment rates to control for variation in economic activity, obtained from the Bureau of Labor Statistics.

3.3 Analytical Sample

In constructing our analytical sample, we begin by restricting the data to those 12-to-25 years of age. PATH has limitations, however, that further reduce the size of the overall analytical sample available in this study. First, while the mean number of observations across states in the 12-to-25-year-old sample is generally high, with California having the highest number of observation, some states have very low representation in the survey. Specifically, seven very rural and/or low-population states had collectively very few total observations, and, as a result, we drop observations from these seven states.[4] Second, PATH does not provide sub-state geographical identifiers. This presents an issue because some cities and counties enacted T21 laws before state-level T21 laws. We collect information on the prevalence of sub-state T21 laws from University of Michigan School of Public Health (2023), and we drop survey participants residing in states with significant populations covered by sub-state T21 laws prior to a state-level T21 law adoption (i.e., HI, IL, KS, MA, MO, NJ, NY, and OH).[5] This leaves us with a baseline analytical sample of approximately 107,000 observations across 38 states (plus D.C.), where nine implemented state-level T21 laws by the end of our sample time period in 2019. Appendix Figure A5 provides an geographical overview of T21 law heterogeneity across states as of 2019. The states in white are dropped from the PATH analysis due to low numbers of observations. The states in the lightest gray color are included in our analysis, but do not pass a T21 law before December 2019. The states in the middle shade of gray do pass a state T21 law, but are excluded from our main analysis because of substantial substate T21 law coverage predating the state ban. Finally, the states in the darkest shade of gray pass a T21 law and do not have substantial substate T21 law coverage predating the state law.

Table 1 shows summary statistics for key PATH variables by age group. Both self-reported smoking participation and vaping participation jump considerably for the age 18-20 group, and while smoking participation increases further for the age 21-25 age group, vaping participation falls slightly. Biomarkers of nicotine and tobacco exposure also suggest that use of cigarettes or e-cigarettes is higher in the 21-25 age group. Other characteristics are relatively constant across the sections, including exposure to T21 laws, demographic characteristics, and other state-level variables.

[4]The mean number of total observations across all states (before restricting states with under 25 observations) in the 12-to-25-year-old sample is about 2,575 people, with California having the highest number of observations at nearly 15,300 people. Certain low-population states, which were not formally sampled in the PATH and only represented from re-location (i.e., AK, DE, ND, RI, SD, VT, and WY), had collectively only 99 total observations, and, as a result, we drop the 99 observations from these seven states from the analytical sample.

[5]We also check whether our results are robust to expanding our sample to include states with substantial substate T21 coverage. For these analyses, we also include a substate T21 variable measuring the percent of the state's population living under a substate T21 law, and interactions between this variable and applicable age groups for analogous analyses to those in Panels B and C of Table 2. Our results are very similar to those presented in our main analyses.

4 Methods

Our primary statistical framework connects changes in an individual's exposure to a T21 law to within-person variation in tobacco product usage or related biomarker outcomes for those 12-to-25 years of age. Notably, 18-to-20-year-old young adults are the age group explicitly "treated" by T21 laws, as the younger population is bound by pre-existing minimum purchase age laws. Yet, there may be spillover effects onto the adolescent population, so we investigate both age groups in this analysis. We begin by examining self-reported measures of smoking or vaping within the last 30 days, and then cigarette purchase methods. After that, we examine levels of urinary cotinine and NNAL to estimate the relationship between T21 laws and ***overall*** nicotine and tobacco consumption.

We estimate each outcome of interest using both a standard difference-in-differences (DiD) two-way fixed effects approach and a triple-difference design (DDD). We utilize both approaches to help address concerns that smoking or vaping trends in the control group are notably different from those in the treatment group. In particular, standard DiD regression design assumes that confounders varying across groups are time-invariant, and time-varying confounders are group invariant; the classic common trend assumption (see Wing, Simon, and Bello-Gomez, 2018). To address this potential problem and leverage the panel nature of the data more completely, we also use a DDD, which is similar in approach to recent work on T21 laws by Bryan et al. (2023). Hence, for these estimates, we utilize a second comparison group that is not exposed to treatment but is exposed to the potentially problematic time-varying confounders. In this case, we use the individuals 21-to-25 years old, who are not bound by the T21 laws, but reside in locations with T21 laws as well as control locations without T21 laws during the sample period.[6]

Our main specifications estimate individual-level fixed effects linear probability models for individual i living in state s at year y and quarter q. In particular, we employ two slightly different DiD approaches. In Equation 1, we assess the treatment on 12-20 year-olds as a group, and in Equation 2, we separate the explicitly treated 18-to-20-year-old young adults from the under 18 adolescents group with interactions. Our preferred DDD approach is presented in Equation 3. All are detailed as follows:

Difference-in-Differences: 12-20 years old

$$Y_{i,s,yq} = \alpha + \delta \mathrm{T21}_{s,yq} + \sigma_{i,yq} + X_{s,yq}\beta + \mu_i + \tau_{yq} + \epsilon_{i,s,yq} \tag{1}$$

[6]We test the sensitivity of our results to a broader definition of the control group (e.g., 21-to-29 years old) and results prove robust.

Difference-in-Differences: 12-17 and 18-20 years old in separate groups

$$
\begin{aligned}
Y_{i,s,yq} =& \alpha + \delta_{t,u18}\mathrm{T21}_{s,yq} \times \mathrm{ageu18}_{i,yq} + \delta_{t,1820}\mathrm{T21}_{s,yq} \times \mathrm{age1820}_{i,yq} + \\
& \sigma_{i,yq} + X_{s,yq}\beta + \mu_i + \tau_{yq} + \epsilon_{i,s,yq}
\end{aligned} \tag{2}
$$

Triple Difference: 12-17 and 18-20 years old in separate groups

$$
\begin{aligned}
Y_{i,s,yq} =& \alpha + \delta\mathrm{T21}_{s,yq} + \delta_{t,u18}\mathrm{T21}_{s,yq} \times \mathrm{ageu18}_{i,yq} + \delta_{t,1820}\mathrm{T21}_{s,yq} \times \mathrm{age1820}_{i,yq} + \\
& \sigma_{i,yq} + \gamma\mathrm{FT}_{i,yq} + X_{s,yq}\beta + \mu_i + \tau_{yq} + \epsilon_{i,s,yq}
\end{aligned} \tag{3}
$$

All models include an indicator, $\mathrm{T21}_{s,yq}$, for whether an individual resides in a state after the implementation of a T21 law (or in the case of Equation 2 the interaction of a T21 law with age group indicators) and indicators ($\sigma_{i,yq}$) for an individual's age in years at the time of each survey.[7] For the DDD models in Equation 3, our independent variables of interest are the interactions between T21 and indicators for being under age 18 or between 18 and 20 years old ($\mathrm{ageu18}_{i,yq}$ and $\mathrm{age1820}_{i,yq}$). Thus, identification in these models comes from comparing persons who are affected by the T21 law (those under 21 in each group) with their peers in other states before and after T21 treatment (as in the standard difference-in-difference found in Equations 1 and 2), and then against the similar difference with those who are 21 or older in treated and non-treated locations before and after T21 implementation. Notably, some survey participants were treated by T21 laws and later "aged into" the older 21-to-25-year-old control population in treated states. As such, we add an indicator variable to the DDD models, $\mathrm{FT}_{i,yq}$, which identifies if an individual was formerly constrained by a T21 law when they were under 21. This allows us to control for these individuals contaminating our control group, but also investigate if the behaviors of those formerly treated by T21 laws are different in a measurable way relative to their never treated peers.

All models also include individual fixed effects and time period (year and quarter) fixed effects, given by μ and τ, respectively. The inclusion of individual fixed effects washes out time-invariant individual characteristics such as gender, race, or ethnicity.[8] We control for a vector of public policies and state controls discussed above that may affect smoking or vaping behavior in the vector $X_{s,yq}$ (cigarette excise taxes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes, a measure of the standardized state e-cigarette tax per fluid milliliter (Cotti et al., 2021), measures of smoke-free air laws in

[7] There are some states that have minimum legal purchasing ages of 19 throughout your sample (ex: Alabama and Alaska). All models include an indicator variable for states that have a purchasing age of 19.

[8] We examined whether our results were appreciably affected by using individual fixed effects instead of state fixed effects combined with a set of time-invariant individual level controls (e.g., gender, race, and ethnicity fixed effects). Appendix tables A6 through A9 show results from these regressions.

restaurants and bars, an indicator for the legalization of recreational marijuana, and the state unemployment rate). All standard errors are clustered at the state level.

One concern with our estimation strategy above is the growing realization the staggered treatment difference-in-difference designs may not generate coefficients that represent an average treatment effect on the treated. In Section 5.4 we show that our results are not affected by these concerns.

5 Results

5.1 Self-Reported Smoking and Vaping Participation

In Table 2, we begin by presenting estimates of the relationship between T21 laws and self-reported cigarette or vaping use in three panels. Panel A presents DiD estimates among all those 12-to-20 years old collectively (see Equation 1). Panel B presents DiD estimates for adolescents (12-to-17 years old) and young adults (18-to-20 years old) separately (see Equation 2). Lastly, Panel C presents estimates analogous to Panel B, but for the DDD model presented in Equation 3. We will follow this presentation construct throughout most of the results section.

In Columns (1) and (2) of Table 2 we present estimates of the relationship between T21 laws and smoking and vaping participation for the entire analytical sample. For this broad sample, we do not observe any effect of T21 laws on reported smoking or vaping participation among those aged 12-to-20 years old when grouped together (Columns (1) and (2) of Panel A), but effects emerge once we separate the sample into adolescents (12-to-17) and the explicitly treated young adults (18-to-20). In particular, in Column (1) of Panel B, we observe a 1.9 percentage-point (10%) reduction in the likelihood of smoking after a T21 law among the 18-to-20-year-olds, but find no corresponding change among adolescents. No statistically significant relationship is observed when looking at the likelihood of vaping among either age group in Column (2). When turning to the DDD models in Panel C, we observe very similar results. Specifically, we find a notable 2.6 percentage-point (14%) reduction in the likelihood of smoking after a T21 law among the 18-to-20 years old, but again see no corresponding change among adolescents. Further, we again do not observe a statistically significant relationship when looking at the likelihood of vaping among either age group, although the point estimates for the 18-to-20-year-old sample are similar to the point estimate for cigarette smoking in the DDD model.

Next, we investigate how estimates vary between individuals who were non-smokers and non-vapers at survey onset (Columns (3) and (4)) as compared to those who were identified as a smoker or vaper at survey onset (Columns (5) and (6)). Here we observe a very consistent and stable story for smoking participation, with some suggestive evidence of effects among vapers. First, in Column (3) we observe statistically significant reductions in cigarette use in all models, with a 1.3 to 2.2 percentage-point (14% - 25%) reduction in the likelihood of smoking among initial non-smokers/non-vapers in the 18-to-20 years old group. As with the full sample, in Column (4) the coefficient for vaping participation is negative, but not statistically significant in the DiD models, but in Panel C we do observe negative vaping effects for both adolescents and young adults. Results suggest a large 50% reduction in the likelihood to report vaping among participants 18-to-20-years-old and a 34% reduction among those 12-to-17-years-old. In Columns (5) we show statistically significant reductions in reported smoking among those who are self-reported users in the young adult group at survey onset, suggesting a possible cessation effect. Conversely, in Column (6), the DiD estimates show an increased in the likelihood of reporting vaping among the 18-to-20-year-old group, suggesting, at least for this population, there maybe substitution effects present between products. That said, there is no statistical effect among wave 1 users in the DDD models.

Lastly, in the final row of Table 2 (Panel C), the DDD model allows us to also investigate how being formerly treated by a T21 law (i.e., "aged out" of being treated) is related to smoking and vaping choices when an individual is over 21 years old and no longer bound by T21 laws, relative to otherwise similar non-treated peers. Being "formerly treated" by T21 laws reduces both vaping and smoking use among those survey participants who were non-smokers/non-vapers at survey onset (Columns (3) and (4)). This is again consistent with T21 laws working mostly by preventing initiation rather than increasing cessation. Further, the effects are of non-trivial size, with the estimated effects of a 3.2 - 3.4 percentage point reduction in the likelihood of smoking initiation and vaping initiation relative to their non-treated peers (aged 21-to-25).

Overall, the longitudinal estimates presented in Table 2 only provide consistent evidence of the effects of T21 laws on self-reported smoking behavior among those explicitly impacted by the laws (18-to-20-year-olds). The estimates seem to be driven by both those who were initially not cigarette users and also those who self identified as smokers at survey onset. Such findings suggest that the effect of T21 laws potentially manifests through reducing smoking initiation and also by increasing cessation. Further, the size of the effects are non-trivial, with a greater than 20% reduction in the likelihood of smoking participation observed for both the initially non-user and user samples. Collectively, the range of estimated effects of T21 laws on self-reported smoking participation among those 18-to-20-years-old (10% to 26%) is similar to work on this topic by (Bryan et al., 2023), who find a 9% to 15% negative effect on smoking participation, (Friedman and Pesko, 2024), who find a 37% decline in the odds of smoking, and (Abouk, De, and Pesko, 2024), who estimate a 12% reduction in cigarette sales. Importantly, we find some mixed evidence that T21 laws reduce initiation of vaping among initially non-users, but possibly substitution toward vaping among initial users. Further, and of note, estimates also indicate that among those "formerly treated", the effects of T21 laws persist beyond the explicit treatment age groups, suggesting the impact of T21 laws may be quite significant and provides further evidence about the importance of limiting access of risky products to the youngest adults.

In Figure 1 we show the event study estimates for the results in Panel A of Table 2. We track the coefficients for two and a half years before a T21 law and up to three years after a T21 law in six-month intervals. Following Panel A of Table 2, our sample includes individuals under 21. Figure 1 shows no meaningful evidence of trends in self-reported smoking or vaping before the enactment of a T21 law. Self-reported smoking prevalence declines after the imposition of the T21 laws, but the decline takes a few periods to appear. This drop appears to be driven by the non-users in Wave 1 and thus a decrease in smoking initiation. For vaping, trends after the enactment of T21 Laws show no general pre-trends and are very noisy post-treatment, but we do observe reductions in self-reported vaping a couple of years after T21 enactment.

5.1.1 Effects by Sex

Smoking behaviors vary considerably between males and females. For example, the smoking rate among females is notably lower than their male counterparts, and we observe similar patterns in the PATH data. Among 18-to-20-year-olds treated by a T21 law, 22% of males and 16% of females report smoking in the last 30 days. Recognizing that differences in the likelihood of smoking or vaping exist across sexes, in Table 3 we return to the main analytical sample and break the overall sample estimates down by these sub-populations to investigate for heterogeneous effects of T21 laws. Three general findings emerge.

First, the reductions in smoking participation related to the passage of T21 laws estimated in Table 2 are largely driven by behavioral changes among males (Column (1)) and are again isolated to the young adult (18-to-20-years-old) group when the age groups are separated. Second, we observe estimated increases in smoking among adolescent females (12-to-17 years old) after treatment in the DiD models (Column (2), Panel B). This effect loses statistical significance in the DDD model (Column (2), Panel C), indicating that differential trends in the DiD might be in issue for that estimation. That said, it is also possible that adolescent females may be substituting away to cigarettes after treatment. Third, we observe an estimated decline in vaping participation among the male-only young adult sample (Column (3)), but again see no effect for females. Overall, these estimates strongly indicate that the overall effects measured in Table 2 are driven by males.

5.1.2 Analysis of Purchase Behaviors

Next, we examine the effects of T21 laws on how affected individuals acquire cigarettes. Table 4 shows results from these models, which use the same general specifications as Equations (1) through (3). We make two quick notes regarding these specifications. First, PATH only asks self-reported smokers about whether they purchase their own cigarettes, and only asks people who purchase their own cigarettes about where they are purchased. Second, since PATH only reports individuals' state of residence, we are unable to investigate the effects of distance to the nearest state without a T21 law. We show results for two groups: a) individuals buying their own cigarettes; and b) individuals buying their own cigarettes in their own state. Across all methods, we find large effects of T21 laws on purchase behaviors, but these changes are more heavily driven by individuals between 18-to-20-years-old. Specifically, T21 laws reduce the probability that 18-to-20-year-old young adults purchase their own cigarettes by about 33 percentage points (see Column (1), Panel B and C), a large decrease off the pre-treatment mean of 89%. Simultaneously, T21 laws decrease the probability that 18-20-year-olds purchase their own cigarettes in their state of residence by approximately 44 percentage points, again representing very large increases off the pre-treatment mean of 86%. Hence, indicating a notable amount of cross-border shopping in response to the state-level T21 laws.

Figure 2 shows event studies from the analysis of cigarette cross-border purchases, following the same format as Figure 1. Here again, we do not see evidence of pre-trends in the propensity of smokers to purchase their own cigarettes. However, after the enactment of a T21 law, the probability of 18-to-20-year-old smokers buying their own cigarettes drops by close to 50 percentage points (top panel). Shifting to purchases made in other states, again we see no pre-trends in individuals making purchases out of state. However, after a T21 law, 18-to-20-year-olds who buy their own cigarettes are about 35 percentage points less likely to buy their own cigarettes in their home state.

5.2 Biomarkers

In addition to collecting individual-level longitudinal data on self-reported tobacco-related behaviors, PATH also collects urine samples from a sub-sample of survey participants and calculates the levels of a number of biomarkers from these samples. Included are measures of several tobacco and nicotine-derived metabolites. We focus on two biomarkers: cotinine, a biomarker of recent nicotine exposure, and NNAL, a biomarker of recent exposure to tobacco. Unfortunately, the PATH biomarker data sample has certain data constraints that are not present in the self-reported data. First, PATH does not collect sufficient biomarker data on youth (12-to-17) to allow analysis, so the youth sample is not included in the biomarker estimates. Second, PATH only collects biomarker data from a sub-sample of approximately 11,500 adults, of which about 3,200 are 18 to 25 years old and reside in one of the states for our analysis.[9] In investigating the relationship between T21 laws and cotinine or NNAL, we replicate the methods described in Equation (1), but only for

[9] These adults were selected from a diverse mix of six tobacco product use groups representing never, current, and recent former (within 12 months) users of tobacco products. This group constitutes the Wave 1 Biomarker Core, whose urine was collected during each subsequent survey wave.

young adults, and Equation (3), but only for those 18-25, except in both cases we replace smoking or vaping participation with measured levels of urine cotinine or NNAL, both measured in ng/ml, as the dependent variable, and use the PATH provided biomarker urine weights.

The results of this analysis are presented in Table 5 and provide an interesting contrast to the self-reported results. Specifically, while we do observe a statistically significant negative effect of T21 laws on measured cotinine for the entire sample (Column (2), Panel A and B) and Wave 1 non-users (Column (4) panel B), which is consistent with the self-reported reductions in smoking and vaping reported in Table 2, we do not observe much statistical evidence of an effect of T21 laws on tobacco-specific markers, as measured by NNAL levels. In particular, in Columns (1) and (3) of Table 5, we only observe a single negative marginally significant (p-value = 0.067) signal of a reduction in the clinical NNAL data (see Column (1), Panel A). [10]

Broadly the results in Table 5 present a puzzle compared to the results in Table 2. Specifically, the estimates presented in Table 2 show a clear reduction in self-reported cigarette smoking among young adults, suggesting we should see similar results for both NNAL and cotinine in Table 5. However, this isn't the case, as the NNAL results are much weaker and largely missing. Estimates in Table 5 are derived from a notably smaller sample, so should be viewed with some caution. Nevertheless, the lack of a clearer and more consistent NNAL (tobacco) effect is somewhat puzzling.

Next, we investigate the robustness of the biomarker results and attempt to reconcile the differences between the effects of T21 laws as estimated by self-reported outcomes and biomarker outcomes.

5.2.1 Investigation: Confounding from Other Related Products

One possibility for the differences in results between Tables 2 and 5 is that we have not accounted for use of other related products that can also impact NNAL and cotinine levels besides cigarettes and e-cigarettes. In particular, NNAL levels are a function of using cigarettes, smokeless tobacco, cigars, pipes, etc., while cotinine levels are also impacted by vaping as well as any nicotine-containing products (e.g., cigarettes, smokeless tobacco, nicotine gum, nicotine patch, etc.). So, if self-reported smokers and/or vapers switch to using these alternative options after T21 laws, this would impact NNAL and cotinine levels, which would confound interpretation. Hence, we consider this possibility.

First, we investigate if switching to alternative tobacco products (e.g., smokeless tobacco, pipes, cigars, hookah, or other tobacco-containing products) is affected by T21 laws, as then these users, who would still have high NNAL levels but are no longer cigarette smokers, might affect our identification of changes in the propensity to self-report smoking status. Given that a T21 law affects access to ***all*** tobacco products,

[10] Figure 3 shows the corresponding event study estimates for the results in panel A of Table 5. Notably, there are no observable trends in biomarker levels before a T21 law.

meaningful substitution to these alternative products seems unlikely. Nevertheless, to check whether using smokeless tobacco, pipes, cigars, hookah, or other tobacco-containing products affects our results, we rerun our models including a measure for whether individuals self-report use of any of these other products in the last 30 days. Our results are virtually unchanged, indicating that the estimates presented in Table 5 are not affected by product substitution.

Similarly, users of nicotine-replacement therapies (NRT) may also be defined as likely vapers using this method. As with users of other tobacco-based products, users of NRT would affect our cotinine estimates if T21 laws affect the propensity of impacted individuals to use NRT while stopping use of e-cigarettes. As we did observe T21-associated declines in cotinine in Table 5, this is less of a concern for interpretation. Nevertheless, we include an indicator for whether individuals use NRT and our results on vaping participation are unchanged. Overall, we do not find evidence that supports correlated variation in alternative tobacco or NRT product use are affecting the estimates presented in Table 5.

5.2.2 Investigation: Differential Sample Effects

The biomarker sample is notably smaller than the sample used in the self-reported analysis presented in Table 2. As such, the estimates presented in Table 5 may not provide very similar inferences as the self-reported findings in Table 2 because of differences in the sample composition. In order to investigate how stable the estimates of the effects of T21 laws on self-reported smoking and vaping participation are to the smaller sample available in the biomarker data, we re-estimate the Table 2 analysis of self-reported outcomes with the smaller biomarker sample used in the analysis of biomarkers presented in Table 5. These new estimates of self-reported use can be found in Table 6, which follows the same format as Table 2 with two exceptions. First, Table 6 only uses individuals for whom we have valid biomarker information. Thus, we are unable to examine adolescents as they are not asked to give biomarker samples. Second, we replace the overall PATH sample weights with the urinary sample weights as we examine the subset of individuals with urinary biomarker information.

While we no longer see a statistically significant effect of T21 laws on smoking participation overall (Column (1)), we still estimate large negative effects on smoking participation for those participants initially not smokers at survey onset (panel B, Column (3)), and also a large negative coefficient for Wave I smokers, although it is not statistically significant (panel B, Column (4)). [11]

[11] We do not show the coefficient for being "formerly treated," as this variable has too few observations for meaningful inference in this reduced sample.

5.3 Self-Reporting Bias and T21 Treatment: Concerns of Non-Classical Measurement Error

Self-reporting bias is a persistent concern with self-reported behavioral data. This concern is particularly salient when the policy under investigation affects whether respondents are legally allowed to purchase the product in question. For example, the desire to conform to heightened social expectations created by T21 laws may impact the willingness of treated respondents to be forthright and honest about their behavioral choices. The ability to match clinical biomarker results directly to an individual's self-reported behaviors in the PATH data allows us to investigate both the extent self-reporting bias and to reflect on how it might impact our estimates, in particular. If, for instance, 18-to-20-year-old smokers are less likely to self-report smoking participation ***because*** of a T21 law's imposition, this would result in an estimated reduction in self-reported smoking participation associated with T21 laws, even if there was no actual reduction in cigarette smoking. To the extent this is true, this would lead one to overestimate a reduction in smoking participation (as measured by self-reports).

To investigate this possibility, we re-estimate the effect of T21 laws on self-reported smoking and vaping participation, but only for individuals whose clinically measured biomarker levels clearly indicate that the survey participant is almost certainly a smoker or vaper. Thus, we can measure the effect of T21 laws on ***self-reported*** cigarette or e-cigarette use among a sample of clinically defined users of these products. A statistical relationship between self-reported user status and the T21 laws among this sample would suggest the willingness of participants to be honest in self-reported behaviors is affected by the presence of the T21 laws.

First, we define cigarette smokers as individuals with an NNAL level over 0.03 ng/ml (30 pg/ml), a level that clinically should only include cigarette smokers.[12] Second, we define likely vapers who are not also cigarette smokers by a combination of urinary cotinine levels and NNAL levels. We choose a urinary cotinine level that is high enough to suggest own use of nicotine products but an NNAL level that is low enough to exclude likely users of cigarettes or other tobacco products. Goniewicz et al. (2011) examines optimal urinary cotinine cutoffs across six samples and finds an optimal cutoff of 31.5 ng/ml across adults, and in a population more similar to our setting, Benowitz et al. (2017) finds optimal cutoffs of 25 ng/ml to 30 ng/ml identified light/intermittent smokers and 30 ng/ml for active users.[13] Hence, we choose a cutoff value of 25

[12]The optimal NNAL cutoff level to distinguish smokers from non-smokers is not completely resolved in the literature. For example, Goniewicz et al. (2011) finds that a cutoff level of 47.3 pg/ml of NNAL is an optimal cutoff level to classify adults as smokers compared to passive smokers, while Benowitz et al. (2018) finds that 10 pg/ml of NNAL is an optimal cutoff level to classify adolescents as smokers. Benowitz et al. (2018) also write that, "the optimal urine NNAL cutoff point to discriminate smokers from nonsmokers appears to vary from approximately 10 to 50 pg/mL." Thus, we choose the median of these two numbers, 30 pg/ml, or 0.03 ng/ml.

[13]Goniewicz et al. (2017) conducts an experiment where smokers switched to electronic cigarettes. Total nicotine levels remained fairly constant after the switch, indicating that cotinine levels that distinguish cigarette smoking should also work for

ng/ml and combine this cotinine level with a restrictive NNAL level of below 0.025 ng/ml to isolate vapers who are not also smokers.

We modify our empirical strategy from Equations (1) and (3) to conduct this analysis:

Difference-in-Differences: 18-20 years old

$$Y_{i,s,yq}|U_{i,s,yq} = \alpha + \delta \mathrm{T21}_{s,yq} + \sigma_{i,yq} + X_{s,yq}\beta + \mu_i + \tau_{yq} + \epsilon_{i,s,yq} \tag{4}$$

Triple Difference: 18-25 years old

$$\begin{aligned} Y_{i,s,yq}|U_{i,s,yq} =& \alpha + \delta \mathrm{T21}_{s,yq} + \sigma_{i,yq} + \delta_{t,1820}\mathrm{T21}_{s,yq} \times \mathrm{age1820}_{i,yq} + \\ & \gamma \mathrm{FT}_{i,yq} + X_{s,yq}\beta + \mu_i + \tau_{yq} + \epsilon_{i,s,yq}. \end{aligned} \tag{5}$$

Here, all terms are as in Equations (1) and (3), except that we now examine self-reported smoking or vaping ($Y_{i,s,yq}$) conditional on biomarker-determined likely use of the product ($U_{i,s,yq}$). As the biomarkers are only consistently measured for adults, we only examine those aged 18-to-25. Our independent variable of interest is still the interaction of T21 laws and an indicator for an individual aged 18-to-20, measuring the differential impact of T21 laws on self-reporting among individuals impacted by the T21 law.

Table 7 shows the results from these regressions. In the first Column, for self-reported smoking, we find evidence that the probability that these individuals self-report as smokers drops by approximately 70 to 74 percentage points for individuals under age 21 in the DiD and DDD models, respectively. This is troubling and would suggest that the negative estimates of T21 laws on the likelihood of smoking participation estimated in Table 2 may be the result of self-reporting bias corresponding to the passage of a T21 law. Given that the negative T21 effects on self-reported smoking status are largely driven by those who were initially not users (as measured in Wave 1 of the PATH survey), this would perhaps suggest that participants who were not smokers when first interviewed are less likely to honestly admit their smoking behaviors once tobacco purchases are made illegal, hence biasing estimates toward overestimating any negative effect on self-reported smoking after treatment.

Next, we replicate this approach for the sample of clinically identified likely vapers to measure if a similar bias is present in self-reported vaping participation. As noted above, it is more complicated to clearly identify vapers who are not also smokers, and our restriction of individuals with a cotinine level greater than 25 ng/ml ***and*** a NNAL level below 0.025 ng/ml leaves us with a smaller sample than with the likely smokers. The results, presented in Column (2), show positive but not statistically significant effects of T21 laws on the

vaping.

likelihood of self-reporting vaping participation among likely vapers. Hence, we do not find that the decline in vaping participation after the passage of T21 laws shown in Table 6 (Column 4) are similarly caused by reporting bias correlated with T21 laws. However, we note that the sample sizes in Table 7, especially in the vaping analysis, are very small.

Figure 4 shows an event study to examine the parallel trends assumptions presented in Table 7, Column (1). Because of the small sample size in the vaping analysis, we do not event study analysis for the results in Table 7, column (2). Figure 4 shows no evidence of pre-trends for self-reported smoking among likely users. However, after a T21 law, likely smokers become less-likely to correctly self-report as smokers.

Owing to the age restrictions and the need to identify clinically defined smokers/vapers with the biomarker measures, the sample sizes of the estimates provided in Table 7 are quite small. Hence, a degree of caution should be taken. However, these outcomes suggest that the results of self-reported outcomes may, in and of themselves, not be reliable unless it can be shown that they are not influenced by the presence of the policy reform itself. Particularly in situations where the reform creates illegality or affects social desirability around the behavior illegal for survey respondents.

5.4 Robustness to Heterogeneous and/or Dynamic Treatment Effects

An important concern with the results presented in Tables 2 through 7 is the extent to which our two-way fixed effects results may be biased by heterogeneity and dynamic treatment effects as described in the growing literature on difference-in-differences models with staggered treatment roll-out (e.g. Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2022). A central concern raised within this literature is that, in the presence of treatment effect heterogeneity and dynamic treatment effects, two-way fixed effects models compare later treated units to earlier treated units (e.g., forbidden comparisons), which can lead to negative weighting and biased estimates of the overall average treatment effect on the treated. To assess the potential importance of such bias in the estimates presented above, we apply a procedure proposed by Callaway and Sant'Anna (2021) that is robust to heterogeneity and dynamics in treatment effects with a staggered treatment roll-out. The approach allows considerable heterogeneity in treatment effects across treatment intensity, calendar time, and covariates.

The results of this robustness analysis are shown in Appendix Tables A2 through A5 and in Figures A1 through A4. As is evident, the estimated effects of T21 laws on self-reported smoking and vaping in Appendix Table A2 are similar or a bit stronger (particularly for vaping) than those shown in Table 2. While these results provide some added statistical significance for some outcomes, they, importantly, indicate that there is no obvious concern that the results in Table 2 are an artifact of bias created by the staggered treatment roll-out. In Appendix Table A3 we demonstrate that the results of T21 avoidance behavior presented in Table 4 are robust to heterogeneity and dynamics in treatment effects with a staggered treatment roll-out. Appendix Table A4 shows similar point estimates to Table 5 for changes in cotinine and NNAL levels among 18-20 year olds after the imposition of T21 laws (DiD model). That said, large standard errors prevent the coefficients from being statistically significant, but also flip signs at times, indicating that under these models there is less evidence of a effect in the biomarkers data. Finally, Appendix Table A5 shows results for examining whether likely smokers and vapers change their self-reporting after T21 laws. Here again, we find a steep drop in the propensity of likely smokers to self-report. Taken as a whole, the Callaway and Sant'Anna Models, while only DiD, present evidence of a T21 effect in the self-reported data that is not replicated in the clinical bio-markers data, with strong evidence that the effect is likely driven by non-classical measurement error (as shown in Appendix Table A5) . We again caution that, especially in the results for Column (2), the sample size is very small.

6 Conclusion

In this study, we utilize individual-level panel data from the PATH to examine the relationship between T21 laws and smoking/vaping participation among young adults and adolescents; measured by self-reports and laboratory-collected biomarkers. The panel structure of the PATH allows us to control for individual-level fixed effects, providing clearer evidence of detailed within-person changes in consumption behavior in response to the implementation of T21 laws. Moreover, access to biomarkers measures allows us to investigate the net effects of these policies on tobacco and nicotine consumption, as well as investigate the accuracy of self-reported measures.

We find that T21 laws lead to notable reductions in the self-reported probability that young adults (18-to-20 years old) initiate smoking cigarettes, which are largely driven by males in the sample. While we do not observe effects of T21 laws on self-reported vaping for the entire sample, we do observe reductions within certain sub-samples. We also observe longer-run effects of T21 laws on smoking or vaping initiation among adults (21-to-25 year olds) who were formerly treated by T21 laws, and evidence of cross-border shopping, as 18-20 year olds who buy their own cigarettes are more likely to buy cigarettes in a different state after the enactment of T21 laws. These results follow much of the previous literature on T21 laws. For example, the magnitude of the reductions in self-reported smoking in Table 2 appear similar to the magnitude of reductions among 18-20 year old smokers in Bryan et al. (2023) using the YRBS data and Abouk, De, and Pesko (2024) using the MTF data. Our mixed results on vaping also mirror the previous literature, where Bryan et al. (2023), Abouk, De, and Pesko (2024), and Friedman and Pesko (2024) all report some evidence connecting T21 laws to a reduction in underage vaping.

Our investigation of biomakers both supports and contradicts our self-reported findings. We find some evidence that T21 laws reduce overall nicotine exposure among 18-20 year olds, mirroring the mixed results from the self-reported vaping analysis. However, the large reductions in self-reported smoking do not translate to a reduction in urinary NNAL outcomes. We provide evidence that this contradiction is unlikely to be explained by substitution to other tobacco products or differences in sample composition. Rather, investigation reveals that self-reporting bias may explain this apparent contradiction. We find evidence supporting the hypothesis that T21 laws lead to changes in the probability that likely smokers, as determined by biomarkers, correctly report their smoking status.

This finding raises concerns that estimates of the effects of T21 laws on smoking based on self-reported data may be overstated. This last analysis is constrained by small sample sizes, and thus, we believe this result calls for future research into the measured effects of T21 and other tobacco control policies using self-reports and biomarkers. This research could either use the PATH data as more waves and biomarker data become available, or other datasets containing sufficient sample sizes of both self-reported measures of tobacco use and biomarkers of recent nicotine or tobacco exposure.

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Table 1: Descriptive Statistics, PATH, 2013 - 2019

	Means by Age Group		
	Ages 12-to-17	Ages 18-to-20	Ages 21-to-25
Dependent Variables			
Smoking Participation (Smoked in past 30 days)	0.033	0.207	0.284
Vaping Participation (Vaped in past 30 days)	0.050	0.182	0.149
Urinary Cotinine (ng/ml)*		670.324	1,044.955
Urinary NNAL (ng/ml)**		0.063	0.096
Tobacco Control Policies			
Tobacco 21 State Law	0.082	0.070	0.073
Cigarette Excise Tax (Real)	2.835	2.812	2.799
Any E-Cigarette Tax	0.164	0.134	0.127
E-Cigarette Minimum Purchase Age Law	0.813	0.795	0.793
State Cigarette Bar Ban	0.574	0.570	0.569
State Cigarette Rest Ban	0.805	0.796	0.788
State Unemployment Rate	4.759	4.956	4.958
State Recreational Marijuana Law	0.147	0.127	0.129
Demographics			
Female	0.489	0.493	0.497
Hispanic	0.252	0.244	0.223
White	0.663	0.677	0.679
Observations	63,477	19,664	22,416

Notes: All means are weighted with appropriate survey weights. Data on smoking/vaping and biomarker outcomes and individual demographic measures were obtained from the PATH. State unemployment rate data obtained from BLS. Data on state excise taxes on cigarettes were obtained from the CDC's State Tobacco Activities Tracking and Evaluation System (CDC STATE). Data on recreational marijuana laws, as well as e-cigarette minimum legal purchasing age laws, were obtained from various state agencies and individual investigations on these policies. *Cotinine measures are derived from a biomarker sub-sample of 9,006 observations from participants 18-to-25 years of age. **NNAL measures are derived from a biomarker sub-sample of 8,943 observations from participants 18-to-25 years of age.

Table 2: The Effect of Tobacco 21 Laws on Cigarette and E-Cigarette Use

	All Participants Sample		Wave 1 Non-Users Sample		Wave 1 Users Sample	
	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation
Panel A. DiD Models						
Tobacco 21 State Law	-0.003	-0.005	-0.013*	-0.007	-0.146***	0.086*
	(0.005)	(0.006)	(0.007)	(0.008)	(0.047)	(0.044)
Observations	83,141	82,903	47,466	47,370	3,557	2,125
Pre-Treat DV Mean (12-20)	0.072	0.073	0.046	0.059	0.768	0.575
Panel B. DiD Models by Age						
T21 × 18-20 yr old	-0.019**	-0.013	-0.022**	-0.017	-0.163***	0.116***
	(0.007)	(0.013)	(0.009)	(0.011)	(0.050)	(0.041)
T21 × 12-17 yr old	0.006	0.000	-0.004	0.002	0.028	-0.163
	(0.004)	(0.008)	(0.006)	(0.010)	(0.136)	(0.186)
Observations	83,141	82,903	47,466	47,370	3,557	2,125
Panel C. DDD Models						
T21 × 18-20 yr old	-0.026**	-0.038	-0.018*	-0.049**	-0.096*	0.028
	(0.010)	(0.024)	(0.009)	(0.023)	(0.048)	(0.055)
T21 × 12-17 yr old	0.001	-0.025*	-0.004	-0.034***	0.074	-0.370
	(0.008)	(0.013)	(0.008)	(0.011)	(0.136)	(0.224)
Tobacco 21 State Law	-0.003	0.019	-0.005	0.024*	-0.055**	0.135***
	(0.006)	(0.015)	(0.007)	(0.013)	(0.025)	(0.042)
Formerly Treated	-0.011	-0.012	-0.034***	-0.032***	-0.063	0.032
	(0.012)	(0.014)	(0.010)	(0.012)	(0.049)	(0.054)
Observations	105,557	105,205	59,567	59,438	10,790	5,178
Pre-Treat DV Mean (18-20)	0.187	0.151	0.089	0.100	0.806	0.621
Pre-Treat DV Mean (12-17)	0.026	0.042	0.019	0.033	0.766	0.641

Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3: The Effect of Tobacco 21 Laws on Cigarette and E-Cigarette Use by Gender

	Smoking Participation		Vaping Participation	
	Males	Females	Males	Females
Panel A. DiD Models				
Tobacco 21 State Law	-0.016**	0.010	-0.016*	0.004
	(0.007)	(0.006)	(0.008)	(0.008)
Observations	42,573	40,340	42,460	40,215
Pre-Treat DV Mean (12-20)	0.080	0.062	0.083	0.063
Panel B. DiD Models by Age				
T21 × 18-20 yr old	-0.041***	0.005	-0.036***	0.005
	(0.011)	(0.008)	(0.010)	(0.019)
T21 × 12-17 yr old	-0.001	0.014**	-0.004	0.003
	(0.006)	(0.006)	(0.010)	(0.007)
Observations	42,573	40,340	42,460	40,215
Panel C. DDD Models				
T21 × 18-20 yr old	-0.047***	-0.003	-0.053**	-0.027
	(0.014)	(0.014)	(0.020)	(0.029)
T21 × 12-17 yr old	-0.002	0.006	-0.020	-0.032*
	(0.010)	(0.012)	(0.012)	(0.016)
Tobacco 21 State Law	-0.004	-0.002	0.016	0.023
	(0.008)	(0.009)	(0.016)	(0.017)
Formerly Treated	0.025*	-0.047**	-0.032*	0.000
	(0.014)	(0.020)	(0.017)	(0.020)
Observations	53,561	51,748	53,382	51,575
Pre-Treat DV Mean (18-20)	0.219	0.156	0.181	0.121
Pre-Treat DV Mean (12-17)	0.027	0.025	0.044	0.039

Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4: The Effect of Tobacco 21 Laws on the Methods of Purchasing Cigarettes

	Purchasing Own Cigarettes	Buy Cigarettes in Own State
Panel A. DiD Models		
Tobacco 21 State Law	-0.314**	-0.382***
	(0.133)	(0.122)
Observations	5,663	5,663
Pre-Treat DV Mean (18-21)	0.694	0.665
Panel B. DiD Models by Age		
T21 × 18-20 yr old	-0.332**	-0.443***
	(0.134)	(0.120)
T21 × 12-17 yr old	-0.230	-0.097
	(0.165)	(0.176)
Observations	5,663	5,663
Panel C. DDD Models		
T21 × 18-20 yr old	-0.332***	-0.439***
	(0.106)	(0.105)
T21 × 12-17 yr old	-0.228*	-0.090
	(0.122)	(0.139)
Tobacco 21 State Law	0.014	0.018
	(0.025)	(0.025)
Formerly Treated	-0.015	-0.062
	(0.081)	(0.079)
Observations	12,646	12,646
Pre-Treat DV Mean (18-20)	0.890	0.858
Pre-Treat DV Mean (12-17)	0.242	0.224

Notes: The sample in column (1) includes only individuals who were reported as smokers and the sample in column (2) is made up of individuals who reported they bought their own cigarettes. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 5: The Effect of Tobacco 21 Laws on Biomarker Measures

	All Participants Sample		Wave 1 Non-Users Sample		Wave 1 Users Sample	
	NNAL	Cotinine	NNAL	Cotinine	NNAL	Cotinine
Panel A. DiD Models						
Tobacco 21 State Law	-0.042*	-337.948**	-0.023	-31.885	-0.017	-316.305
	(0.023)	(124.183)	(0.023)	(102.425)	(0.044)	(234.732)
Observations	2,177	2,176	1,034	1,033	1,142	1,142
Pre-Treat DV Mean (18-20)	0.035	414.290	0.017	104.361	0.082	1,240.922
Panel B. DDD Models						
T21 $\times$ 18-20 yr old	0.001	-173.998*	-0.014	-134.702*	0.013	-310.136
	(0.009)	(99.206)	(0.008)	(72.582)	(0.025)	(206.359)
Tobacco 21 State Law	-0.015**	-44.354	-0.007	4.068	-0.027*	-81.951
	(0.007)	(52.074)	(0.007)	(47.570)	(0.015)	(125.779)
Formerly Treated	0.049***	600.569***	-0.013	-133.742	0.110***	1,475.819***
	(0.013)	(113.207)	(0.011)	(81.980)	(0.023)	(198.310)
Observations	8,742	8,742	3,570	3,567	5,167	5,170
Pre-Treat DV Mean (18-20)	0.033	400.406	0.015	91.815	0.077	1,154.597

Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize biomarker sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 6: The Effect of Tobacco 21 Laws on Cigarette and E-Cigarette Use (Biomarkers Sample)

	All Participants Sample		Wave 1 Non-Users Sample		Wave 1 Users Sample	
	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation
Panel A. DiD Models						
Tobacco 21 State Law	-0.015	0.017	-0.025	-0.006	-0.070	0.086*
	(0.056)	(0.041)	(0.063)	(0.060)	(0.185)	(0.044)
Observations	2,176	2,166	1,034	1,032	1,006	2,125
Panel B. DDD Models						
T21 × 18-20 yr old	0.024	0.004	-0.069***	-0.039	-0.066	0.392***
	(0.025)	(0.027)	(0.021)	(0.040)	(0.075)	(0.062)
Tobacco 21 State Law	-0.043***	0.010	0.018	0.014	-0.130**	0.065*
	(0.016)	(0.022)	(0.018)	(0.038)	(0.052)	(0.038)
Observations	8,742	8,679	3,571	3,562	4,711	2,285
Pre-Treat DV Mean (18-20)	0.261	0.137	0.051	0.031	0.851	0.666

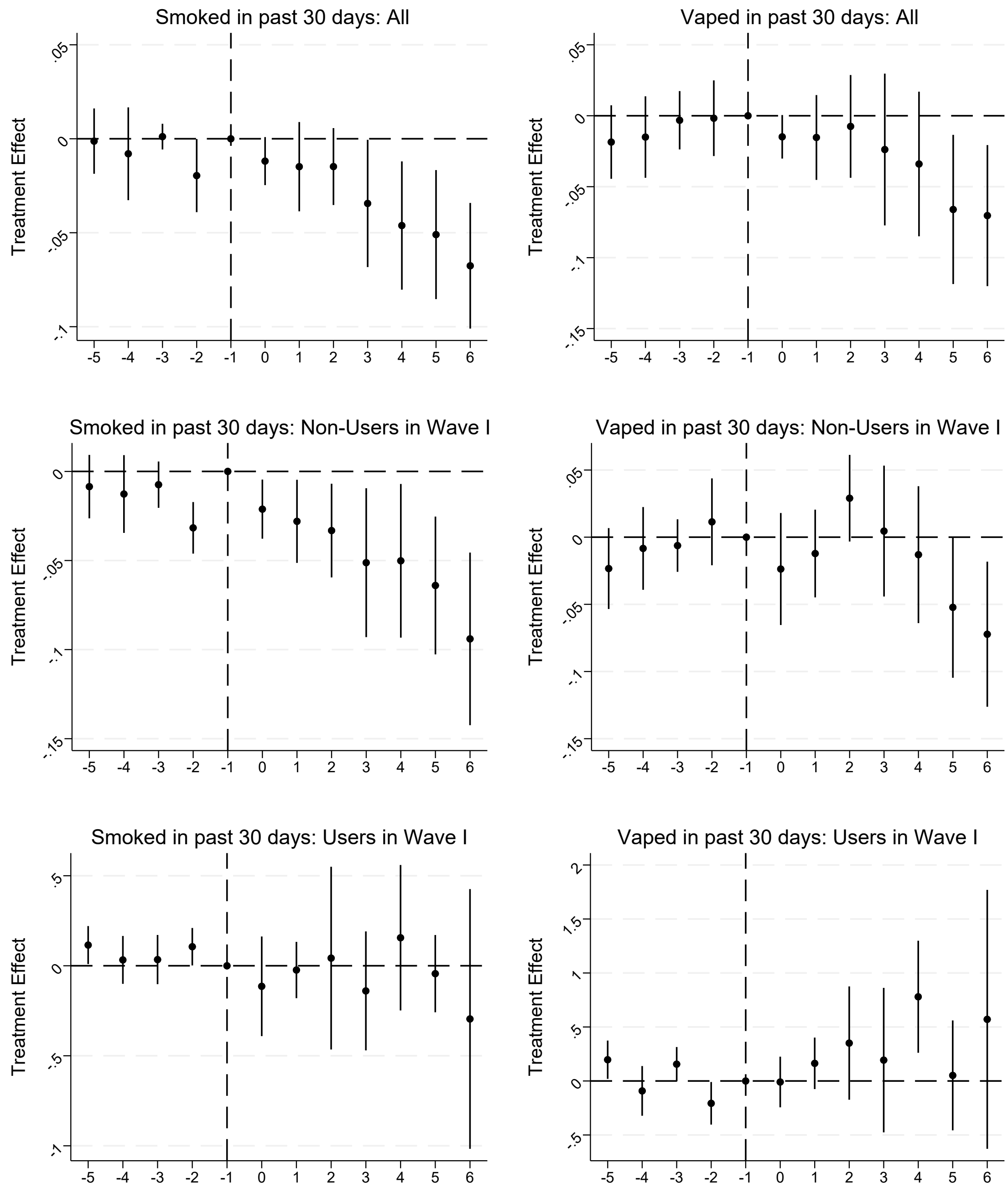
Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize biomarker sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table 7: The Effect of Tobacco 21 Laws on the Likelihood of Self-Reporting

	Smoking Participation	Vaping Participation
Panel A. DiD Models		
Tobacco 21 Law	-0.698***	0.130
	(0.094)	(1.257)
Observations	851	222
Panel B. DDD Models		
T21 $\times$ 18-20 yr old	-0.741***	0.255
	(0.065)	(0.250)
Tobacco 21 State Law	-0.083**	0.138
	(0.034)	(0.151)
Formerly Treated	-0.475***	0.197
	(0.087)	(0.167)
Observations	3,864	911
Pre-Treat DV Mean	0.807	0.426

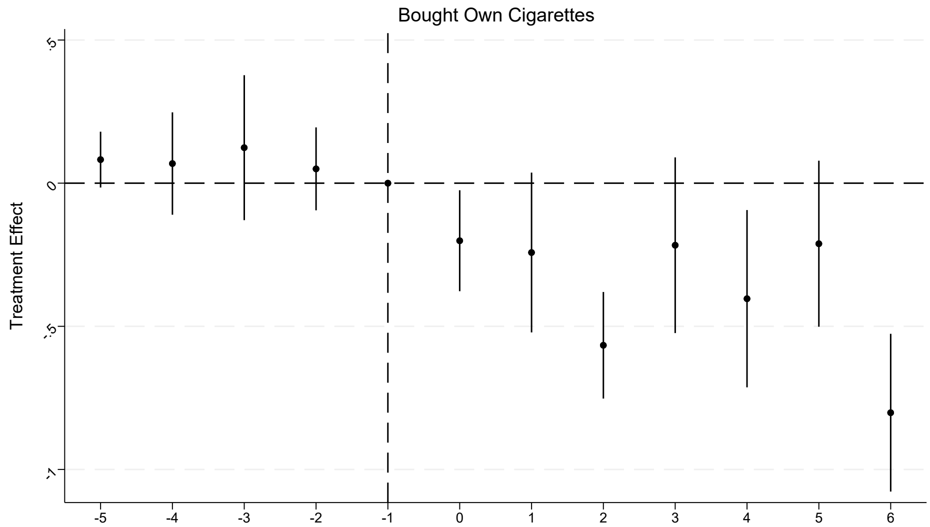
Notes: The sample in column (1) includes only participants who had a urine NNAL level of greater than or equal to 0.030 ng/ml. The sample in column (2) includes only participants who had a urine cotinine level of greater than or equal to 25 ng/ml but NNAL levels below 0.025 ng/ml.The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize biomarker sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

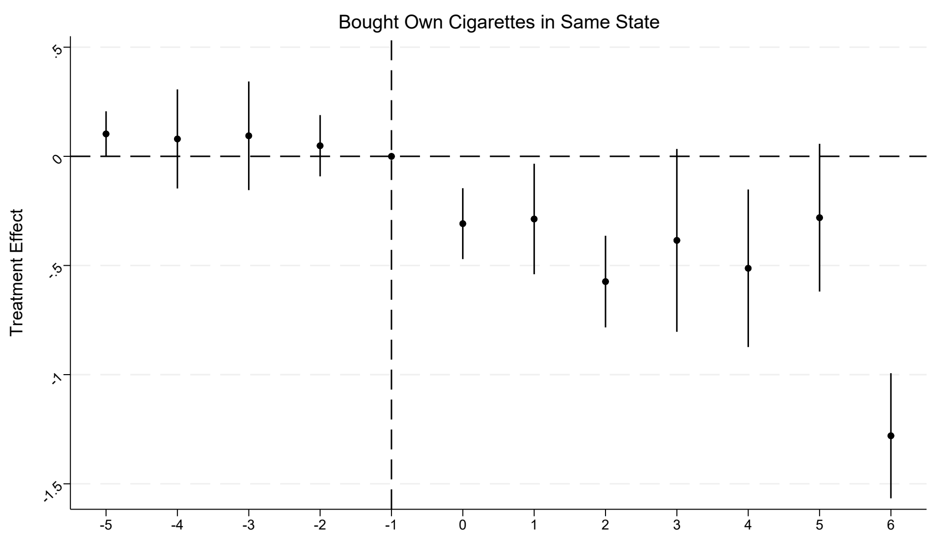
Figure 1: Event Studies of Effect of Tobacco 21 Laws on Self-Reported Use



Notes: The figures show coefficients and 95% confidence intervals for the six-month intervals leading up to and following T21 laws, with the half-year before the policy as the excluded category. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). The event studies are estimated over the sample of individuals under age 21 and all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize sample weights.

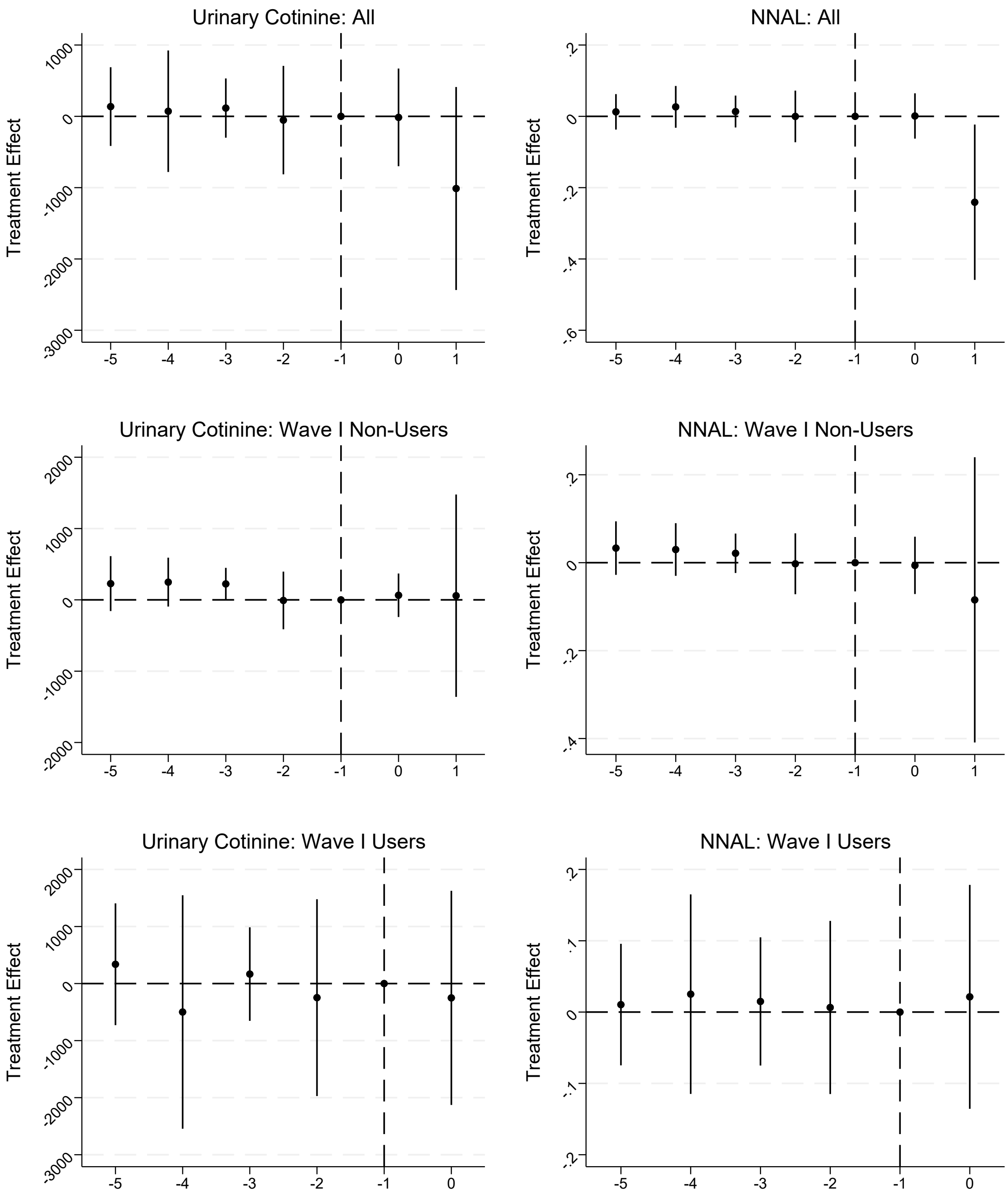
Figure 2: Event Studies of Effect of Tobacco 21 Laws on Methods of Cigarette Purchasing





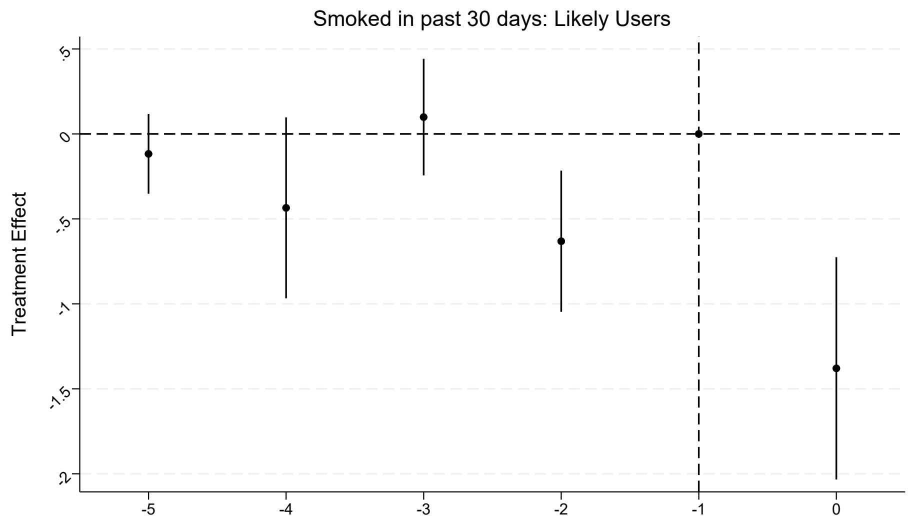
Notes: The sample in the top figure includes only individuals who were reported as smokers and the sample in the bottom figure is made up of individuals who reported they bought their own cigarettes. The figures show coefficients and 95% confidence intervals for the six-month intervals leading up to and following T21 laws, with the half-year before the policy as the excluded category. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). The event studies are estimated over the sample of individuals under age 21 and all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize sample weights.

Figure 3: Event Studies of Effect of Tobacco 21 Laws on Biomarkers



Notes: The figures show coefficients and 95% confidence intervals for the six-month intervals leading up to and following T21 laws, with the half-year before the policy as the excluded category. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). The event studies are estimated over the sample of individuals under age 21 and all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize biomarker sample weights.

Figure 4: Event Studies of Effect of Tobacco 21 Laws on Likelihood of Self-Reporting Among Clinical Users



Notes: The sample includes only participants who had a urine NNAL level of greater than or equal to 0.030 ng/ml. The figures show coefficients and 95% confidence intervals for the six-month intervals leading up to and following T21 laws, with the half-year before the policy as the excluded category. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). The event studies are estimated over the sample of individuals under age 21 and all models also include indicators for age and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include individual and year-by-quarter fixed effects and utilize biomarker sample weights.

Appendices

Table A1: Effective Dates of State Tobacco 21 Laws

State	Effective Date	Meaningful contribution to the PATH Survey	Presence of pre-existing sub-state T21 laws
Hawaii	1/1/2016	Y	Y
California*	6/9/2016	Y	N
District of Columbia*	2/18/2017	Y	N
New Jersey	11/1/2017	Y	Y
Oregon*	1/1/2018	Y	N
Maine*	7/1/2018	Y	N
Massachusetts	12/31/2018	Y	Y
Illinois	7/1/2019	Y	Y
Virginia*	7/1/2019	Y	N
Delaware	7/16/2019	N	N
Arkansas*	9/1/2019	Y	N
Texas*	9/1/2019	Y	N
Vermont	9/1/2019	N	N
Connecticut*	10/1/2019	Y	N
Maryland*	10/1/2019	Y	N
Ohio	10/16/2019	Y	Y
New York	11/13/2019	Y	Y

Source: Preventing Tobacco Addiction Foundation, available at: https://tobacco21.org/. * Treatment states included in the analytical sample.

Table A2: Callaway and Sant'Anna Models (Self-Reports)

	All		Wave I Non-Users		Wave I Users	
	Smoking Particpation	Vaping Particpation	Smoking Particpation	Vaping Particpation	Smoking Particpation	Vaping Particpation
Tob 21 ATT	-0.005	-0.022 **	-0.026 **	-0.042 ***	-0.126	0.308 **
	(0.009)	(0.011)	(0.012)	(0.015)	(0.111)	(0.130)
Observations	83,141	82,903	47,466	47,370	3,557	2,125

Notes: This table shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Table A3: Callaway and Sant'Anna Models (Purchasing)

	Bought Own Cigarettes	Bought Own Cigarettes in Same State
Tob 21 ATT	-0.140 **	-0.213 ***
	(0.061)	(0.061)
Observations	5,546	5,546

Notes: This table shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Table A4: Callaway and Sant'Anna Models (Biomarkers)

	All		Wave I Non-Users		Wave I Users	
	NNAL	Cotinine	NNAL	Cotinine	NNAL	Cotinine
Tob 21 ATT	-0.042	-216.283	0.002	107.776	0.038	125.149
	(0.070)	(447.245)	(0.027)	(170.788)	(0.081)	(651.613)
Observations	2,177	2,176	1,034	1,033	1,142	1,142

Notes: This table shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Table A5: Callaway and Sant'Anna Models (Likelihood of Self-Reporting)

	Self-Reported Smoking	Self-Reported Vaping
Tob 21 ATT	-1.217 ***	-0.300
	(0.080)	(0.250)
Observations	851	221

Notes: This table shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Table A6: The Effect of Tobacco 21 Laws on Cigarette and E-Cigarette Use (State Fixed Effects)

	All Participants Sample		Wave 1 Non-Users Sample		Wave 1 Users Sample	
	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation	Smoking Participation	Vaping Participation
Panel A. DiD Models						
Tobacco 21 State Law	0.012*	-0.001	-0.015*	-0.011	-0.131***	0.054
	(0.006)	(0.007)	(0.008)	(0.010)	(0.031)	(0.040)
Observations	80,657	80,437	46,500	46,408	3,515	2,113
Pre-Treat DV Mean (12-20)	0.079	0.076	0.044	0.056	0.812	0.648
Panel B. DiD Models by Age						
T21 $\times$ 18-20 yr old	-0.030***	-0.002	-0.006	-0.002	-0.132***	0.067*
	(0.009)	(0.011)	(0.009)	(0.012)	(0.030)	(0.038)
T21 $\times$ 12-17 yr old	0.031***	-0.000	-0.023***	-0.020*	-0.128*	-0.030
	(0.008)	(0.010)	(0.008)	(0.011)	(0.072)	(0.092)
Observations	80,657	80,437	46,500	46,408	3,515	2,113
Panel C. DDD Models						
T21 $\times$ 18-20 yr old	0.014	-0.036**	-0.025***	-0.005	-0.037	-0.094***
	(0.011)	(0.015)	(0.006)	(0.011)	(0.031)	(0.031)
T21 $\times$ 12-17 yr old	0.074***	-0.035***	-0.041***	-0.031***	-0.005	-0.184**
	(0.012)	(0.007)	(0.005)	(0.006)	(0.041)	(0.089)
Tobacco 21 State Law	-0.024***	0.027**	0.009	0.007	-0.052**	0.154***
	(0.008)	(0.011)	(0.007)	(0.010)	(0.024)	(0.038)
Formerly Treated	0.003	-0.027***	-0.007	0.009	0.010	-0.125***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.019)	(0.035)
Observations	102,927	102,596	58,525	58,401	10,709	5,156
Pre-Treat DV Mean (18-20)	0.191	0.151	0.086	0.096	0.819	0.643
Pre-Treat DV Mean (12-17)	0.026	0.041	0.018	0.032	0.779	0.663

Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for gender, age, race and ethnicity, family income categories, and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include state and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A7: The Effect of Tobacco 21 Laws on the Methods of Purchasing Cigarettes (State Fixed Effects)

	Purchasing Own Cigarettes	Buy Cigarettes in Own State
Panel A. DiD Models		
Tobacco 21 State Law	-0.273***	-0.330***
	(0.045)	(0.046)
Observations	5,570	5,570
Pre-Treat DV Mean (18-21)	0.670	0.639
Panel B. DiD Models by Age		
T21 × 18-20 yr old	-0.342***	-0.417***
	(0.054)	(0.057)
T21 × 12-17 yr old	-0.022	-0.018
	(0.061)	(0.058)
Observations	5,570	5,570
Panel C. DDD Models		
T21 × 18-20 yr old	-0.335***	-0.417***
	(0.022)	(0.029)
T21 × 12-17 yr old	0.009	0.007
	(0.022)	(0.024)
Tobacco 21 State Law	-0.015	-0.009
	(0.020)	(0.021)
Formerly Treated	-0.122***	-0.154***
	(0.034)	(0.033)
Observations	12,511	12,511
Pre-Treat DV Mean (18-20)	0.839	0.808
Pre-Treat DV Mean (12-17)	0.224	0.193

Notes: The sample in column (1) includes only individuals who were reported as smokers and the sample in column (2) is made up of individuals who reported they bought their own cigarettes. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for gender, age, race and ethnicity, family income categories, and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include state and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A8: The Effect of Tobacco 21 Laws on Biomarker Measures (State Fixed Effects)

	All Participants Sample		Wave 1 Non-Users Sample		Wave 1 Users Sample	
	NNAL	Cotinine	NNAL	Cotinine	NNAL	Cotinine
Panel A. DiD Models						
Tobacco 21 State Law	-0.029	-274.396	-0.025	-72.032	-0.055	-969.131***
	(0.023)	(187.168)	(0.020)	(81.670)	(0.042)	(341.365)
Observations	2,165	2,164	1,026	1,025	1,138	1,138
Pre-Treat DV Mean (18-20)	0.035	416.957	0.014	89.602	0.084	1,179.220
Panel B. DDD Models						
T21 $\times$ 18-20 yr old	-0.012	-160.540	-0.022**	-112.179*	-0.035	-764.849***
	(0.015)	(113.510)	(0.011)	(57.970)	(0.026)	(243.603)
Tobacco 21 State Law	-0.001	99.444	-0.005	-2.668	-0.026	-42.596
	(0.010)	(97.647)	(0.009)	(53.634)	(0.021)	(195.941)
Formerly Treated	0.048***	640.520***	-0.025*	-136.372*	0.064***	784.987***
	(0.012)	(96.356)	(0.015)	(70.486)	(0.022)	(284.791)
Observations	8,702	8,702	3,545	3,542	5,152	5,155
Pre-Treat DV Mean (18-20)	0.035	411.072	0.014	87.823	0.084	1,179.220

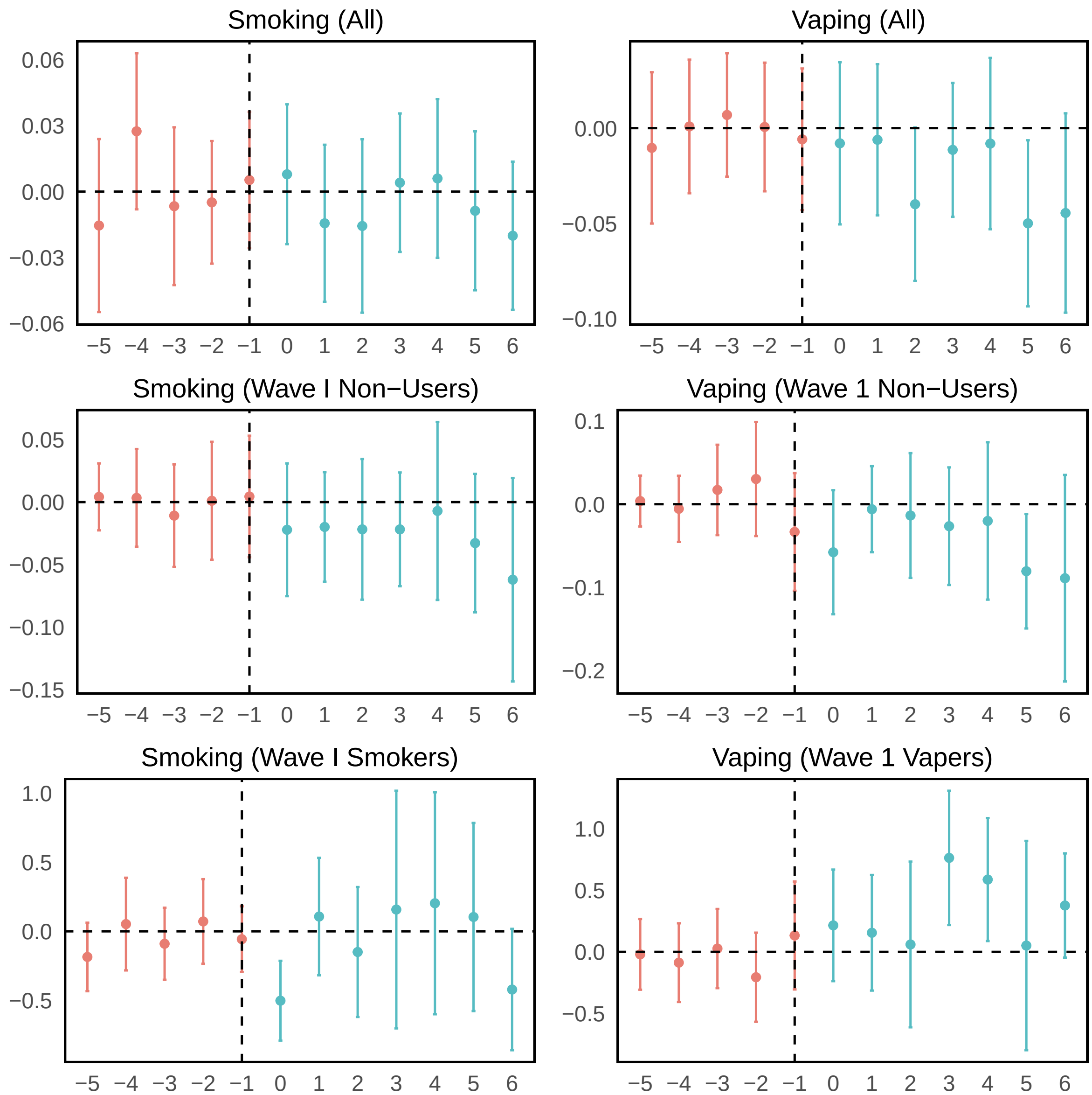
Notes: The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for gender, age, race and ethnicity, family income categories, and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include state and year-by-quarter fixed effects and utilize biomarker sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

Table A9: The Effect of Tobacco 21 Laws on the Likelihood of Self-Reporting (State Fixed Effects)

	Smoking Participation	Vaping Participation
Panel A. DiD Models		
Tobacco 21 Law	-0.726***	0.431
	(0.067)	(0.317)
Observations	847	220
Panel B. DDD Models		
T21 $\times$ 18-20 yr old	-0.664***	0.106
	(0.050)	(0.186)
Tobacco 21 Law	0.026	0.016
	(0.040)	(0.079)
Formerly Treated	-0.263***	0.254**
	(0.054)	(0.115)
Observations	3,844	908
Pre-Treat DV Mean	0.794	0.428

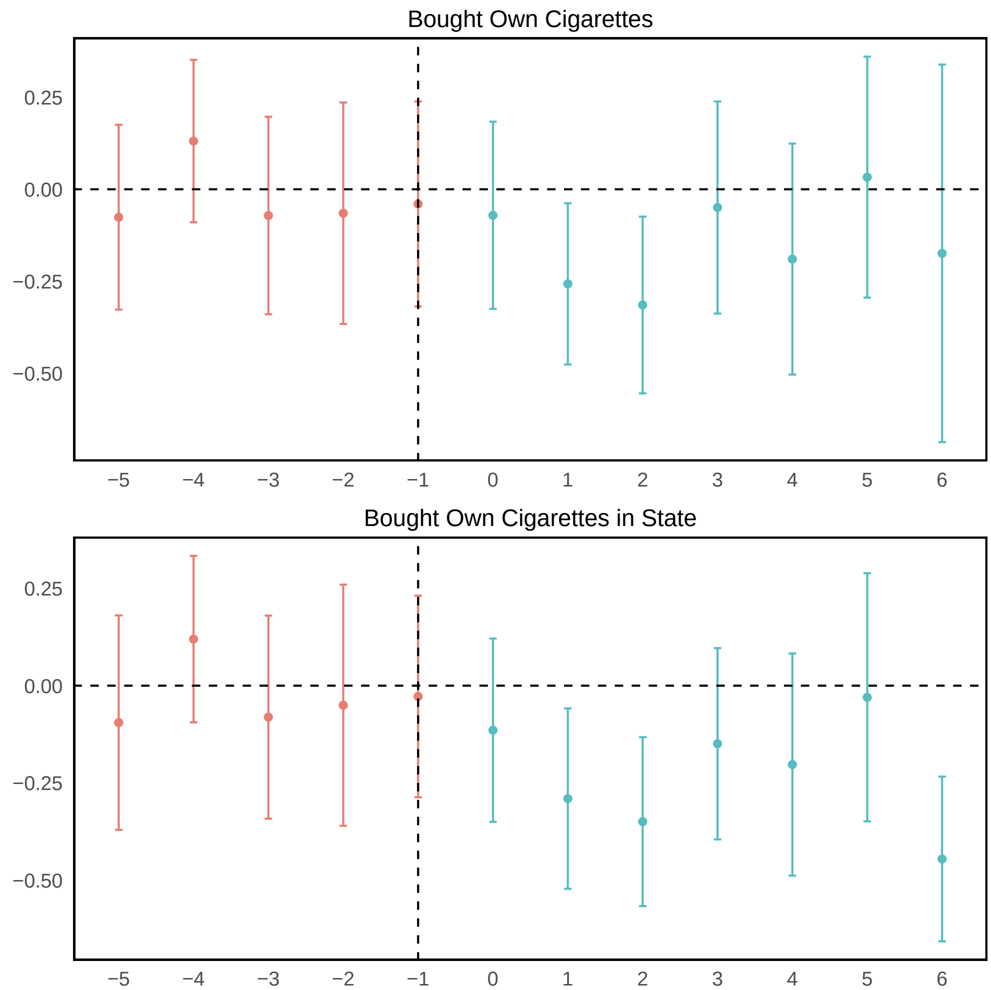
Notes: The sample in column (1) includes only participants who had a urine NNAL level of greater than or equal to 0.030 ng/ml. The sample in column (2) includes only participants who had a urine cotinine level of greater than or equal to 25 ng/ml but NNAL levels below 0.025 ng/ml. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). Aside from the variables in the table, all models also include indicators for gender, age, race and ethnicity, family income categories, and also include measures of per-pack excise tax on cigarettes, an indicator for the presence of a minimum legal purchasing age for e-cigarettes (if below 21 years old), standardized e-cigarette taxes, an indicator for the legalization of recreational marijuana, measures of the population covered by smoke-free air laws, and the state unemployment rate. Additionally, all models include state and year-by-quarter fixed effects and utilize sample weights. Robust standard errors clustered by state are in parentheses. Stars denote statistical significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure A1: Callaway and Sant'Anna (2021) Event Studies of Effect of Tobacco 21 Laws on Self-Reported Use



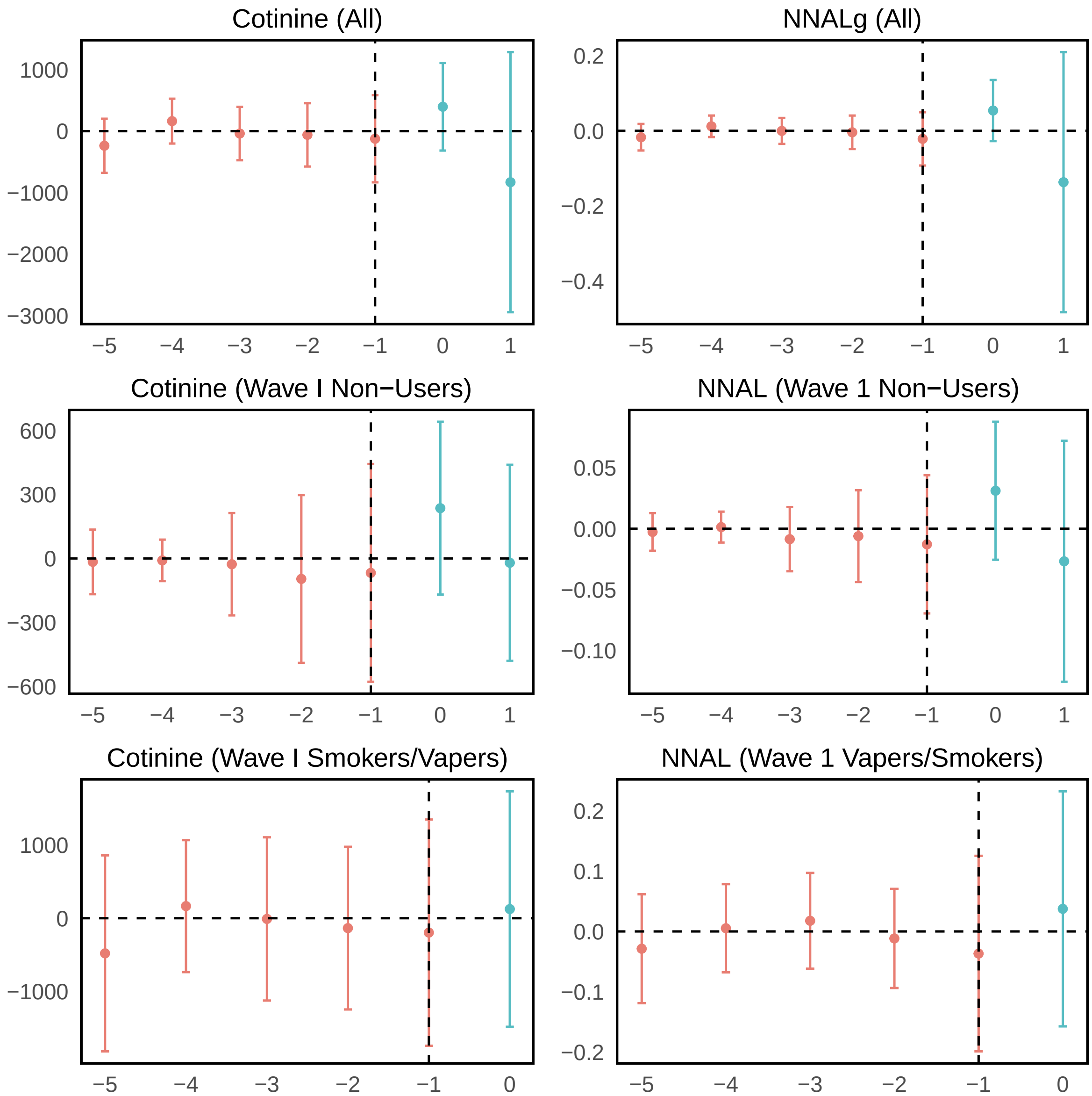
Notes: This figure shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Figure A2: Callaway and Sant'Anna (2021) Event Studies of Effect of Tobacco 21 Laws on Methods of Cigarette Purchasing



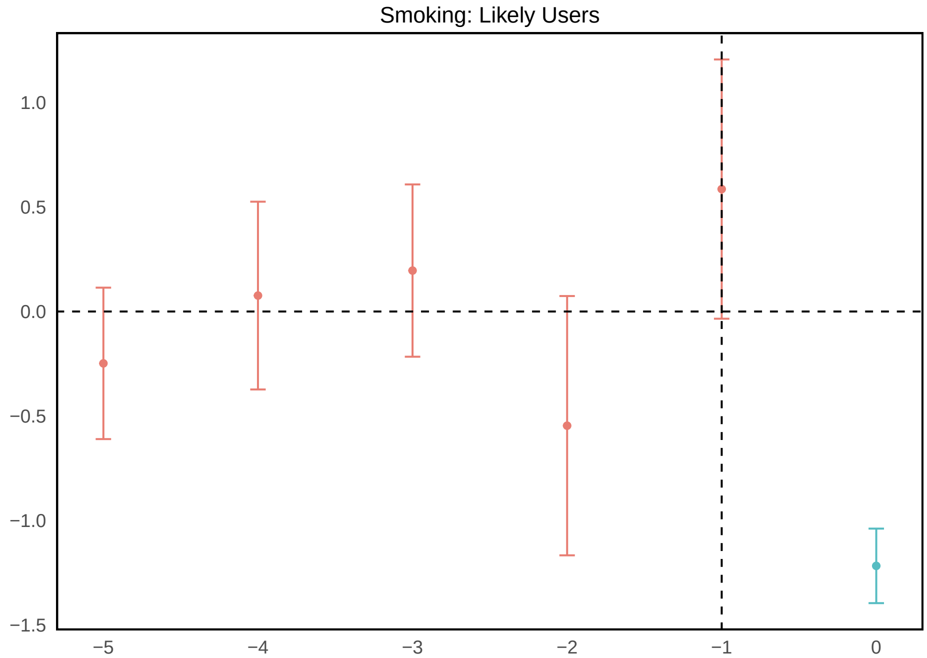
Notes: The sample in the top figure includes only individuals who were reported as smokers and the sample in the bottom figure is made up of individuals who reported they bought their own cigarettes. This figure shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Figure A3: Callaway and Sant'Anna (2021) Event Studies of Effect of Tobacco 21 Laws on Biomarkers



Notes: This figure shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Figure A4: Callaway and Sant'Anna (2021) Event Studies of Effect of Tobacco 21 Laws on Likelihood of Self-Reporting Among Clinical Users



Notes: The sample includes only participants who had a urine NNAL level of greater than or equal to 0.030 ng/ml. This figure shows results from estimating regressions following the methods outlined in Callaway and Sant'Anna (2021) and using the R-package `did`. The sample includes 35 states and the District of Columbia, among which nine states implemented a T21 law during the estimation period (see Appendix Table A1). All models are run on individuals below age 21.

Figure A5: State T21 Law Heterogeneity as of December 2019