2020

EXAMINING THE EFFECTS OF PUBLIC POLICIES AND ADDICTION ON PURCHASE OF TOBACCO PRODUCTS WITH CAUSAL INFERENCE AND MACHINE LEARNING METHODS

Xueting Deng
University of Kentucky, xueting.deng@uky.edu
Author ORCID Identifier:
https://orcid.org/0000-0002-3939-900X
Digital Object Identifier: https://doi.org/10.13023/etd.2020.461

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Xueting Deng, Student

Dr. Yuqing Zheng, Major Professor

Dr. Tyler Mark, Director of Graduate Studies

EXAMINING THE EFFECTS OF PUBLIC POLICIES AND ADDICTION ON PURCHASE OF TOBACCO PRODUCTS WITH CAUSAL INFERENCE AND MACHINE LEARNING METHODS

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By

Xueting Deng

Lexington, Kentucky

Director: Dr. Yuqing Zheng, Professor of Agricultural Economics

Lexington, Kentucky

2020

https://orcid.org/0000-0002-3939-900X

ABSTRACT OF DISSERTATION

EXAMINING THE EFFECTS OF PUBLIC POLICIES AND ADDICTION ON PURCHASE OF TOBACCO PRODUCTS WITH CAUSAL INFERENCE AND MACHINE LEARNING METHODS

My three essays explore the effects of tobacco policies and addiction on the consumption of e-cigarettes and other tobacco products. Recently, jurisdictions imposed taxes and other regulations on e-cigarettes, with the hope to raise tax revenues and address health concerns regarding e-cigarette use, especially youth addiction. My first essay in Chapter 1 focuses on the effects of e-cigarette taxes on sales of e-cigarettes. It compares the two types of tax policies on sales of e-cigarettes, cigarettes, and smoking-cessation products. This comparison provides information for lawmakers on decisions of taxes regarding the perspectives of revenue generation and tobacco control. Second, after exploring the tax effects on sales of these tobacco products at an aggregated level, it would be interesting to examine if the tax policy has diverse effects on different groups of consumers of the three tobacco products. My second essay in Chapter 2 provides answers to this question. Since most e-cigarettes contain nicotine, my third essay in Chapter 3 tests if e-cigarettes are addictive from the perspective of economics. The results provide policy implications for future regulations of e-cigarette use.

The first essay investigates the effects of two types of e-cigarette tax policies on sales of e-cigarettes using time-series cross-sectional weekly purchases from Nielsen Retail Scanner Data between 2011 and 2017. The first type of taxes is ad valorem taxes, which tax e-cigarettes on a percentage of the wholesale or retail price. The second type of tax is specific excise taxes, which collect taxes according to tax rates per milliliter (ml) of the consumable liquid. With a generalized synthetic control (GSC) identification strategy, my first essay measures the average tax effects of multiple treated regions in various treated periods against the untreated control regions and the untreated periods. The results show an estimate of -3.567 for the own-price elasticity of e-cigarette demand and an estimate of 0.433 for the pass-through rate of e-cigarette taxes to price in all treated regions.

With these estimates, one can infer the tax revenues generated and the sales effects of the two types of tax policies. The inference indicates that ad valorem taxes are more effective on tobacco control. In comparison, the specific volumetric excise taxes are more for tax revenue generation. Additionally, the ad valorem taxes show larger average effects but smaller marginal effects than the specific volumetric excise taxes. The results in this essay also indicate that cigarettes and SCP are economic substitutes for e-cigarettes; however, increasing e-cigarette taxes would not raise sales of cigarettes but would increase sales of SCP, when the tax-to-price ratio of e-cigarettes is below or similar to that of cigarettes after tax increases.

The second essay examines the policy responses of different groups of consumers of the three tobacco products with the Nielsen Consumer Panel Data between 2012 and 2018. This essay identifies seven groups of consumers according to the data. Some of them consume exclusively on one product while others consume two products or all three products in the meantime. With a generalized difference-in-differences identification strategy, results do not find that ad valorem taxes bring health concerns to any of the seven investigated subgroups of purchasers. In comparison, specific excise taxes increase e-cigarette purchases by subgroups of e-cigarette purchasers except for triple purchasers of the three products. Additionally, the average results for all these groups are that e-cigarette taxes decrease their SCP purchases but do not influence cigarette purchases. Comparing the effects of two types of e-cigarette taxes, though both negatively influence purchases of SCP, specific excise taxes increase purchases of cigarettes and e-cigarettes while ad valorem taxes do not have such effects.

The third essay examines the role of addiction in influencing the demand for e-cigarettes using the Nielsen Retail Scanner Data between 2012 and 2017. With a comparison of a myopic addiction model, a forward-looking model, and a rational addiction model, this essay tests whether consumption of e-cigarettes is addictive and rational. Results provide evidence that consumers are rationally addicted to e-cigarettes. The long-run price elasticity estimates are larger than the estimates of the short-run price elasticity. Estimates of both long-run and short-run elasticities are greater than one, -1.50 and -1.05, indicating e-cigarette demand is elastic in both the long-run and short-run. Additionally, the data show evidence that e-cigarettes are less addictive than cigarettes on average because the addictiveness coefficient estimate for e-cigarettes is smaller.

These three essays aim to provide insights to policymakers on the effectiveness of tax policies regarding revenue generations and tobacco control. The general findings of the three essays are e-cigarette taxes influence purchases, consumers are rationally addicted to the product but they respond differently to the tax policy. Different responses of the seven groups of consumers provide information for lawmakers to weigh the cons and pros of the two types of policies regarding which groups are the policies mainly targeted for tobacco control. Moreover, addiction could influence tax effects. In the long run, e-cigarette taxes have larger cumulative effects on tobacco control than in the short run. Findings from these essays provide evidence to facilitate future regulations on e-cigarettes. Additionally, they also contribute the literature on applying methods of causal inference and machine learning in exploring e-cigarettes policy regulations.

KEYWORDS: E-Cigarettes, Cigarettes, Excise Tax, Addiction, Policy, Causal Inference

Xueting Deng

12/04/2020

Date

EXAMINING THE EFFECTS OF PUBLIC POLICIES AND ADDICTION ON PURCHASE OF TOBACCO PRODUCTS WITH CAUSAL INFERENCE AND MACHINE LEARNING METHODS

By
Xueting Deng

Yuqing Zheng
Director of Dissertation

Tyler Mark
Director of Graduate Studies

12/04/2020
Date

DEDICATION

To my parents and sisters. Thank you for your love and support. Thank you so much for being my family!

ACKNOWLEDGMENTS

The following dissertation, while an individual work, benefited from the insights and direction of several people. First, my Dissertation Chair, Yuqing Zheng provided instructive comments and evaluation at every stage of the dissertation process, allowing me to complete this project on schedule. Next, Dr. J.S. Butler exemplifies the high quality scholarship to which I aspire. I appreciate a lot for his guidance and encouragement when I struggled in my graduate study.

Moreover, I wish to thank the complete Dissertation Committee, and outside reader, respectively: Michael Reed, J. S. Butler, Aaron Yelowitz, Charles Courtemanche, and Ana María Herrera. Each individual provided insights that guided and challenged my thinking, substantially improving the finished product. Furthermore, I would like to thank the research group of Chad D. Cotti, Charles J. Courtemanche, Johanna Catherine Maclean, Erik T. Nesson, Michael F. Pesko, and Nathan Tefft for providing research data.

In addition to the technical and instructional assistance above, I received equally important assistance and support from family and friends.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. ESTIMATING THE EFFECTS OF E-CIGARETTE TAXES: A GENERALIZED SYNTHETIC CONTROL APPROACH

1.1 Introduction

Many U.S. states and local governments have begun taxing e-cigarette manufacturers or retailers since 2013. By the end of 2017, eight jurisdictions taxed e-cigarettes including California, Kansas, Louisiana, Minnesota, North Carolina, Pennsylvania, West Virginia, and the District of Columbia. Some local governments in the remaining states, such as Alaska, Illinois, and Maryland, also began taxing e-cigarettes. As a result, the number of states that taxed e-cigarette taxes quickly expanded to nineteen by February 2020. Similar to cigarette taxes, tax revenues generated from e-cigarette taxes can fund activities such as health research, anti-smoking campaigns, and preschool education (Fiore et al., 2004, Marr and Huang, 2014).

Understanding the effects of e-cigarette taxes on the price and purchase of e-cigarettes and those of related tobacco products provides essential information for governments to regulate them. A myriad of studies has investigated how tobacco product taxes influence their own and related tobacco product sales (Evans et al., 1999, Wasserman et al., 1991) and recommend tax as an effective strategy to control tobacco product consumption. Most of them are on cigarettes. For example, Amato et al. (2015) provides evidence that a $1.75 increase of cigarette tax in Minnesota reduced the number of packs purchased by 12.1%. Ohsfeldt et al. (1997) show that cigarette excise taxes are associated with an increased probability of using smokeless tobacco products.

As to e-cigarettes, several researchers have examined their price elasticities and find them to be elastic, including Huang et al. (2014) and Zheng et al. (2017). Increasing attention has been paid to the impacts of e-cigarette taxes, such as those on prenatal smoking (Abouk et al., 2019), teenage smoking (Pesko and Warman, 2017), and adult smoking (Saffer et al., 2020). Amato and Boyle (2016) conduct the very first research on how taxes affect e-cigarette sales, showing mixed results of a tax increase in Minnesota. In the post-tax periods, their results show that a short-period spike has occurred in e-cigarette sales purchased from convenience stores before a sales decline; a decrease of cigarette sales has co-occurred with an e-cigarette sales increase. Note that they evaluate the consumption trends graphically and thus do not address the causal impact of the taxes.

There is a critical need in analyzing the magnitudes of e-cigarette tax effects on sales and prices using causal inference methods. Several recent studies tackle this issue using the differences-in-differences (DID) method such as Saffer et al. (2020) and Cotti et al., (2020), at the state and national levels respectively. In contrast, I employ a generalized synthetic control (GSC) approach to investigate the effects of e-cigarette taxes in multiple treated regions on sales quantities, prices, and revenues of e-cigarettes, cigarettes, and smoking cessation products (SCP). This method, developed by Xu (2017), relaxes the often-violated parallel-trend assumption and expands the regular synthetic control approach to multiple treatment units at various treatment periods (in my case, multiple states and local jurisdictions started taxing e-cigarettes at various points). It has been recently adopted by many researchers in the fields of marketing, political science, economics, etc. I aim to provide the first attempt to apply this approach to the research of tobacco tax. I obtain an estimate of -3.567 for the own-price elasticity of e-cigarettes and an estimate of 43.3% for the average pass-through of e-cigarette taxes to price in all treated regions. Similarly, I obtain the corresponding estimates for cigarettes at -0.629 and 101.5%, respectively.

I further investigate the heterogeneities of e-cigarette tax effects by examining whether these taxes differ by how they are imposed. Currently, e-cigarette taxes are mainly implemented in two types: ad valorem taxes on a percentage of the wholesale or retail price and specific volumetric excise taxes on milliliters of the liquid. These two types of tax collections could reflect different underlying motivations: tax revenue generation or tobacco control (World Health Organization, 2010). I use the GSC regressions as the main results to identify the average overall effects of each type of e-cigarette tax. My results show that the two types of e-cigarette taxes realize their corresponding underlying policy motivations.

Moreover, I display two ways for conversions of e-cigarette taxes into one comparable measurement. The first conversion uses calculations of the wholesale price. The second conversion uses tax rates for e-cigarettes and cigarettes in the District of Columbia (DC) as e-cigarette taxes are matched 100% to cigarette excise taxes at the municipal level in DC. The second conversion is not new in existing working papers as those by Cotti et al., (2020) and Allcott and Rafkin (2020); however, I improve this conversion by adjusting the changes over time. Though I reach similar results from these two completely different conversions, my results use the first conversion as a lower bound. This conversion provides a valid tool for future research regarding wholesale price calculations as supported by data.

To my knowledge, I am among the first few to evaluate the causal effects of e-cigarette taxes. My research shares a similar overall objective with two concurrently conducted studies but employs a different empirical method. Allcott and Rafkin (2020) explore the relationship between e-cigarette taxes and prices in an instrumental variable (IV) model and estimate the price elasticity of demand for use in welfare calculations. Cotti et al., (2020) use a standard two-way fixed effects model (DID) mostly to measure the pass-through rate of e-cigarette taxes. In comparison, using both the above methods as comparisons to my main results, I rely on the GSC strategy to investigate the heterogeneity of e-cigarette taxes, without the need to assume taxes impact sales only via price or a parallel trend assumption as in the IV and DID methods. I also show the dynamics of the tax effects over time, complementing other existing research on this aspect.

1.2 E-Cigarette Taxing Approach

Regions implemented the two tax policies (ad valorem and specific excise taxes) likely under different backgrounds and motivations. Regions seem to impose a specific e-cigarette excise tax with the main goal of raising revenues, which was initially proposed and lobbied by tobacco companies to reduce losses from declining sales of traditional cigarettes. In comparison, regions could have used ad valorem taxes on e-cigarettes to control the consumption of tobacco products. These differences, combined with the different imposition mechanisms, sizes, and pass-through rates of the taxes, could lead to tax heterogeneous effects. This section introduces the laws, motivations, and backgrounds of regions implementing these two types of taxes in the order of effective policy dates.

The first state-level e-cigarette tax was enacted in 2010 when Minnesota (MN) combated the prevalence and consumption of tobacco products through the conduction of mass media campaigns on a statewide tobacco control program (Centers for Disease Control and Prevention, 2019a). This program included a comprehensive statewide smoking ban, tobacco tax increases in 2005 and 2013, and local outdoor smoke-free laws. With this context, MN updated the definition of tobacco products so that e-cigarettes were subject to excise taxes and other tobacco control regulations, including restrictions on the minimum age to purchase the product. In this update, MN taxed all non-cigarette tobacco products at a percentage of the wholesale price at which distributors purchased a tobacco product. In July 2013, MN increased excise taxes for both cigarettes and non-cigarette tobacco products (including e-cigarettes). The tax rate of e-cigarettes increased to 95% of the wholesale price.

The second state to impose an e-cigarette tax was North Carolina (NC). In June 2015, NC levied a tax of $0.05 on each milliliter of the nicotine liquid that e-cigarettes use. At this time, sales of e-cigarettes had grown dramatically while the market was largely unregulated. Large tobacco companies including NC based Reynolds American Inc, supported this tax as they sought to replace the declining market for traditional cigarettes. This tax helped NC, which had begun to lose tax revenues as people switched from traditional to electronic cigarettes, by generating around $2 and $5 million in the first two years. Revenues would be lower if NC taxed e-cigarettes as traditional cigarettes or as other tobacco products. Since 2009, NC has taxed cigarettes at $0.45 per pack, currently ranked 47th in the U.S.; and other tobacco products are taxed at 12.8% of the wholesale price, according to data from the American Lung Association (2020a and 2020b) and the Campaign for Tobacco-Free Kids (2020a and 2020b).

As the market of e-cigarettes grows and the consumption of traditional cigarettes declines, more jurisdictions have imposed e-cigarette taxes, weighing revenue, public health, and other considerations. They mainly have followed the examples of MN and NC. As of February 2020, 19 states and the District of Columbia[1] imposed e-cigarette taxes (Centers for Disease Control and Prevention, 2020). Aside from

[1] Among them, nine jurisdictions employed the MN approach: Minnesota, District of Columbia, Pennsylvania, California, Illinois, New York, Vermont, Nevada, and Massachusetts; eight

these jurisdictions, Puerto Rico, U.S. Virgin Islands, and local areas in Maryland, Illinois, and Alaska also tax e-cigarettes. At the federal level, the government is considering imposing an excise tax amounting to $50.33 per 1,810 mg, equivalent to the $1.01 federal levy per pack of cigarettes.

1.3 Data

My policy analysis utilizes two parts of data: policy data and sales data. The policy data is obtained from the Centers for Disease Control and Prevention's State Tobacco Activities Tracking and Evaluation (STATE) System (2019b), government websites, and consultations with designated officials for state and local jurisdictions. The policy focus of this article is e-cigarette taxes. Meanwhile, I control for changes in four other related policies at the state level. These policies include changes in cigarette excise taxes, the requirement of licensures for over-the-counter sale of e-cigarettes, Smokefree Air Laws (SFA) that restrict the use of e-cigarettes indoors, and regulations prohibiting sales of e-cigarettes to minors. The age restrictions were 18 for most states, and up to age 19 or 21 for a few states. Among these five types of policy changes, changes in cigarette excise taxes are denoted in the dollar amounts adjusted to the level of December 2017, all other policies are measured as indicator variables in my primary GSC analyses.

Table A2.a shows the amounts of taxes (with the effective starting date) in regions with e-cigarette taxes by the end of 2017. Seven states and DC imposed e-cigarette taxes at the state level. At the local level, the City of Chicago (C1) and Cook County in Illinois (C2), as well as Montgomery County in Maryland (M1), had e-cigarette taxes effective at different dates. I treat each of them as a distinct region for this reason. They comprise 11 treated regions with e-cigarette taxes during the investigation time interval. The two-letter region abbreviations representing them are C1, C2, CA, DC, KS, LA, M1, MN, NC, PA, and WV. Alaska, Puerto Rico, U.S. Virgin Islands, and Hawaii are excluded from this study because purchase data for these regions are not available in my data source. The other 41 no-tax regions thus serve as the controls for the treatment. In total, I have 52 regions over 330 weeks spanning from September 12, 2011, through December 30, 2017.[2] This makes the total number of region-week combinations 17,160.

Further, I construct two groups for the 11 treated regions based on how they tax e-cigarettes. I denote specific excise taxes on e-cigarettes according to liquid volume in milliliters (mls) as volumetric taxes (V.Tax), used in CA, DC, M1, MN, and PA. I use price taxes (P.Tax) to refer to ad valorem taxes on e-cigarettes by percentages of the wholesale or retail price, used in the remaining six regions. I first analyze the effects of e-cigarette taxes in all the treated regions and then compare effects from the two different types of taxes to evaluate the heterogeneity of the tax effects across these two treated groups. During my

states applied the NC method: NC, LA, KS, West Virginia, Delaware, Ohio, Washington, and Wisconsin; three states used a hybrid of the MN approach and the NC method: Connecticut, New Jersey, and New Mexico.

[2] I started the time span at this week because many regions did not sell e-cigarettes until this date.

chosen time interval, 40 changes happened in cigarette excise taxes, ranging from $-0.10 to $2.50, at the nominal level.

The data source of product purchases is the Nielsen Retail Scanner Data. It provides the weekly units purchased, price, and total paid dollar amounts for each product (Universal Product Code [UPC]) at participating stores, from a variety of outlets, such as convenience stores, drug stores, and mass merchandisers. I focus on analyzing sales quantities, prices, and revenues of three product categories: e-cigarettes, cigarettes, and SCP. E-cigarette sales include disposable e-cigarettes, cartridge refills, and starter kits. Cigarette sales include all brands available. SCP sales include patches, gums, lozenges, etc. I organize the purchase data to the region-week level for e-cigarettes in units, e-cigarettes in milliliters (mls), cigarettes in packs, and SCP in units. Each aggregated quantity observation in units for e-cigarettes and SCP represents the total number of the smallest units purchased for all UPCs at a particular region in a week. I also match 93.5% of the e-cigarette products by the value of sales, in units, in the Nielsen dataset to e-cigarette characteristics,[3] including the mls of liquid in each e-cigarette UPC. Furthermore, I aggregate weekly total sales revenues for all UPCs in a particular region. With the sales quantities and revenues, I then construct a sales-weighted average price for each product category in a region-week combination.

Finally, using the available sales quantities and prices of e-cigarettes measured in mls, I convert P.Tax to dollar amounts per ml. This will unify the two types of taxes into one standard. I use two methods for completing this process. These two methods are completely different but reach similar results, suggesting either of them can be used as a valid approximation of the real taxes collected. The first method uses the average retail price per ml in a region-week combination to compute the pre-tax wholesale price, based on guidelines of cigarette minimum price laws (Department of Taxation and Finance in New York State, 2020). I assume that the markups are similar for e-cigarettes, and then multiply the computed pre-tax wholesale price with the tax rate in the corresponding region-week observation to get the tax rate for each ml.

The second method uses DC's tax to compute the dollar amounts for each percentage point of P.Tax since the e-cigarette tax rate in DC matches 100% of the cigarette excise tax. Then, based on this value, I calculate total tax revenues and the tax rate for each ml (see appendix for further details).

1.4 Empirical Strategy

1.4.1 *Selection of the Generalized Synthetic Control (GSC) Approach*

The GSC method has been recently employed in many fields of social sciences, including marketing, economics, political science, etc. I have selected the GSC approach because it requires fewer

[3] These e-cigarette characteristics are used in Cotti et al., (2018) and Cotti et al., (2020). I acknowledge their generosity for sharing the data.

assumptions and allows me to estimate the average treatment effect for multiple treatment units at various treatment periods. In comparison, DID is one of the most commonly used causal inference strategies for panel data. Its underlying assumption is "parallel trends": in the absence of the treatment, the average outcomes of the treated and control units are supposed to follow parallel paths. Due to the presence of unobserved, time-varying confounders, however, data do not support the pre-treatment trends in many cases, resulting in the violation of the parallel trends assumption. In my case, I have generated trends of e-cigarette sales quantities and prices respectively in treated regions and control regions. Figures show that the pre-treatment trends for DID are not exactly parallel (will provide upon request).

Two broadly used approaches can address this potential assumption violation, but with certain limitations. One approach, conditioning the pre-treatment observables, uses matching methods to balance the influence of time-varying confounders between the treated and control groups. For example, the synthetic control method, proposed by Abadie, Diamond, and Hainmueller (Abadie et al., 2015, 2010), matches both the pre-treatment covariates and outcomes between a treated unit and its control units in the pre-treatment periods. The method constructs a synthetic control group as the counterfactual for the treated unit by reweighting the control units. Then, it uses the post-treatment pattern of this synthetic control as the counterfactual prediction for the treated unit. However, the limitations of the synthetic control method are that it only applies to one treated unit and its uncertainty estimates are not easy to interpret.

The other approach explicitly models the unobserved, time-varying confounders, such as adding unit-specific linear or quadratic time trends to two-way fixed effects models. However, this method consumes a large number of degrees of freedom and yet may not solve the problem if the underlying confounders are not in the form of the specified trends. Another way models the unobserved, time-varying confounders semi-parametrically. For example, Bai (2009) proposes an interactive fixed effects (IFE) model by incorporating unit-specific intercepts with time-varying coefficients. This method interactively estimates the IFE model in a factor analysis of residuals. In the analysis of the IFE model, (latent) factors refer to unit-specific intercepts and factor loadings denote time-varying coefficients.

The GSC relaxes the often-violated parallel trend assumption and generalizes the synthetic control method from a single treated unit and a single treatment period. It allows me to estimate the average treatment effect for multiple treatment units at various treatment periods by unifying the synthetic control method with linear fixed-effects models. In my case, I have 11 treated regions with e-cigarette tax policies, and each has a different policy effective date during my investigation time interval.

Using the GSC strategy has three additional advantages for my estimations. First, the algorithm of the GSC is fast and less sensitive to idiosyncrasies of a small number of observations, because it estimates the IFE model only once and obtains the treated counterfactuals in a single run. Second, the GSC method provides frequentist uncertainty estimates, including standard errors and confidence intervals; using all observations from the control group, it also improves the efficiency of the synthetic control method. Third, this procedure avoids multiple robustness tests for model specifications, because the algorithm utilizes a cross-validation procedure in machine learning to automatically select the optimal number of factors in the IFE model, reducing the risks of overfitting.

1.4.2 *Econometric Model*

The functional form of my estimations using the GSC approach is:

$Y_{it} = \delta_{it}D_{it} + X'_{it}\beta + \lambda'_{i}f_t + \varepsilon_{it}$ (1),

where D_{it} equals 1 if region i at week t has been exposed to e-cigarette taxes, otherwise, it equals 0; δ_{it} represents the heterogeneous treatment effect in region i at week t; X_{it} is a vector of the four other, observable control policy covariates; β is a vector of unknown parameters, representing constant mean effects of each control policy over time; f_t is a vector of unobserved, common factors; λ_i is a vector of unknown factor loadings; ε_{it} has zero mean and denotes the unobserved, idiosyncratic disturbances for region i at week t.

Therefore, my identification comes from the various changes of e-cigarette taxes across different regions over time. In the estimation, taking the average of δ_{it} reaches the average treatment effect for all treated regions, across all treated weeks. I use this equation to investigate the average treatment effects of all treated regions and examine heterogeneous treatment effects across regions with the two different types of taxes.

In each of the regressions on sales quantities, Y_{it} represents a different outcome variable, including the log of the total e-cigarettes sold in units (in region i at week t), the log of the total e-cigarettes sold in mls, the log of the total cigarettes sold in packs, and the log of the total SCP sold in units. In the regressions on sales prices and revenues, Y_{it} is defined similarly with prices and revenues replacing quantities, respectively. Box-cox tests support the transformation in logs. Also, I have normalized all variables in the GSC estimations to speed up the process of cross-validation, without making assumptions about the distribution of the data.

The framework above can directly incorporate additive, two-way fixed effects, known time trends, and exogenous time-invariant covariates. In the function above, the factor component, $\lambda'_{i}f_t$, takes a linear additive form. This component covers various, unobserved heterogeneities, including the conventional additive region and week fixed effects, region-specific linear or quadratic time trends, and autoregressive components. In sum, this component captures all unobserved random confounders, as long as these confounders can be decomposed into a multiplicative form absorbed by $\lambda'_{i}f_t$; however, it cannot cover unobserved variables that are independent across regions. I include both region and week fixed-effects directly in my estimations.

In addition, to compare the results reached from the GSC regressions using indicators of e-cigarette changes, I used the continuous changes of e-cigarette taxes with the DID identification strategy. I expect the magnitudes of the e-cigarette tax effects from these DID regressions are smaller than those obtained in the GSC estimations as shown by Xu (2017).

Specifically, I estimate:

$$Y_{it} = \alpha E_{it} + X'_{it}\beta + r_i + w_t + \nu_{it} \text{ (2)},$$

where E_{it} equals e-cigarette tax changes in dollar amounts per ml, α provides an estimate of the marginal treatment effect of e-cigarette tax changes at the average, r_i denotes region fixed effects, w_t represents week fixed effects, and ν_{it} signifies standard errors clustered at the state level.

Lastly, to address the potential concern of price endogeneity, I instrumented e-cigarette prices and cigarette prices with changes of e-cigarette taxes and cigarette taxes respectively in instrumental variable (IV) regressions of sales quantities. Compared to the main results from GSC estimations, these IV estimations pose a strong assumption that taxes influence sales quantities solely by influencing prices.

1.5 Results

This section first shows the average treatment effects of the treated regions using both the GSC and DID approaches. Next, I have explored the heterogeneity of the tax effects and calculated pass-through rates for e-cigarette taxes and various related price elasticities.

1.5.1 *Summary Statistics*

Before any regression analysis, I have conducted comparisons of summary statistics in Table 1.1 for the treated and the control groups, as well as the pre-treatment and the post-treatment periods for the treated regions. As to translating P.Tax into dollar amounts per ml, both conversions reach similar results (see details in Appendix 1). With the first conversion (conversion [a]), the average P.Tax per ml is $4.4, which is much larger than the average of $0.5 for V.Tax. The average e-cigarette tax increase per ml in all the treated regions is $2.6.

For the treated regions, all policy variables have higher values in the post-treatment period (treatment-tax), i.e. these e-cigarette and cigarette policies are stricter than those in the pre-treatment weeks. This highlights the importance of controlling for these policies to identify the effects of e-cigarette taxes. Table 1.1 also indicates that sales quantities and prices of both e-cigarettes and cigarettes are respectively lower and higher in the post-treatment period.

1.5.2 *Average Treatment Effects on the Treated (ATT) for E-Cigarette Sales*

Figure 1.1 shows the treatment status by week for all the 52 regions in my investigation period.[4] Each rectangular unit represents a region-week combination. It visualizes the length of the treatment time for each treated region and displays the various effective dates for e-cigarette tax policies, which provides excellent sources for the identification.

The GSC regressions estimate the effect of the e-cigarette tax (EET) in the post-treatment period by subtracting the time intercepts estimated from the control group and region intercepts obtained from the pre-treatment data of the treated. The predicted sales of e-cigarettes for region i at week t is the sum of region intercept i and week intercept t, plus the impact of the time-varying covariates if included. In the first eight columns of Table 1.2, I present the DID and GSC results (ATT) for e-cigarettes quantities measured by units and mls, respectively. All regressions in Table 1.2 included region and week fixed-effects. Standard errors are all generated by parametric bootstraps of 1,000 times. Based on the unit measure, I have found that the GSC estimate is much larger. Specifically, the estimated ATT of EET by DID is -35.1% and that is -63.5% by the GSC when all the controls are included. This suggests that potential violations of the "parallel trends" assumption, contrast to Figure 1.2, attenuate the estimates of the DID. Both specifications fail to report a statistically significant impact of EET when mls are used.

The top panel in Figure 1.2 visualizes the GSC results in column (4) of Table 1.2. In the left panel, the solid line shows the average actual sales of e-cigarettes in units, and the dashed line represents the counterfactual synthetic control—the average predicted sales in the absence of EET. Similar to figures generated in an event study for the DID, the GSC method generates the actual and the predicted average sales before and after EET took effect in all the treated regions. The two lines in the top left figure are almost coincident before EET took effect. The top right figure shows the gap between the solid and dashed lines in the left figure, with grey, shaded areas denoting the 95% confidence intervals. The EET effect peaked at the 175th week in the post-treatment period and declined in the weeks after. Based on the same specification, I have found that a one-dollar cigarette tax increase raised the average e-cigarette unit sales by 7.8%. This signifies a substitutive relationship among sales of e-cigarettes and cigarettes.

The GSC regressions estimate the effect of the e-cigarette tax (EET) in the post-treatment period by subtracting the time intercepts estimated from the control group and region intercepts obtained from the pre-treatment data of the treated. The predicted sales of e-cigarettes for region i at week t is the sum of region intercept i and week intercept t, plus the impact of the time-varying covariates if included. In the first eight columns of Table 1.2, I present the DID and GSC results (ATT) for e-cigarettes quantities

[4] Due to missing sales data before 2011 in most regions as controls for the first e-cigarette tax change in Minnesota, I analyze tax effects in Minnesota starting at its second e-cigarette tax increase in all the GSC regressions.

measured by units and mls, respectively.[5] All regressions in Table 1.2 included region and week fixed-effects. Standard errors are all generated by parametric bootstraps of 1,000[6] times. Based on the unit measure, I have found that the GSC estimate is much larger. Specifically, the estimated ATT of EET by the DID is -35.1% and that is -63.5% by the GSC when all the controls are included. This suggests that potential violations of the "parallel trends" assumption, contrast to Figure 1.2, attenuate the estimates of the DID. Both specifications fail to report a statistically significant impact of EET when mls are used.

In columns (9) to (12), I have investigated the heterogeneous tax effects by tax type using the GSC approach. I have found that for the unit measure, the tax impact for P.Tax is -1.01 and statistically significant (at the 5% default level) while that impact of V.Tax is not statistically significant.

1.5.3 *Average Treatment Effects on the Treated for E-Cigarette Prices and Revenues*

In Table 1.3, I apply the GSC specification in column (4) of Table 1.2 to e-cigarette prices and revenue. The variables logP(unit) and LogP(ml) represent logs of the weekly average price for all e-cigarette products per unit and per ml in each region, respectively. Each dependent variable contains three regressions, for different treated regions: P.Tax regions, V.Tax regions, and all treated regions.

In the first group, column (3) of Table 1.3 shows that the overall ATT is a 17.8% increase in e-cigarette prices for all treated regions in the post-treatment period when compared with the control. Similar to the results in Table 1.2, column (1) indicates that P.Tax has a larger effect than does V.Tax (0.305 vs. 0.046). The bottom panel of Figure 1.2 presents the counterfactual for the average of all treated regions and the ATT over time. The counterfactual indicates that the average price of e-cigarettes had been declining but the taxes reversed this declining trend. Similar to Figure 2, I show the tax effects on prices and quantities in a series of figures, Figure A2.a to Figure A2.k in Appendix 2, for each individual treated region.

The bottom panel in Figure 1.3 shows the estimated factors and factor loadings obtained in the results of column (3). The first factor captures the price decrease over time. The second factor shows the price fluctuates before the 150th week[7], then decreases throughout the remaining weeks. Tracking back to Figure 1.3 (b), I find that the second factor also negatively influences the sales quantities after the 150th week. Such unobserved factors could reflect public/regulatory perception of e-cigarettes from an alternative to smoking cessation to a tobacco product with associated risks.

In the last group of regressions for revenues, results show that EET reduces the weekly average sales revenues of e-cigarettes by 39.2%. P.Tax again shows a much stronger effect. In comparison, sales revenues in the V.Tax regions increase by 4.6%, on average, in the post-treatment period.

[5] Adjusting sales quantities by population, I reached very similar results in all the regressions.

[6] Increasing the number of bootstrap times to 5,000 or greater yielded similar results.

[7] The 150th week dates between July 7 and July 13, 2014.

1.5.4 *Impacts on Quantities, Prices, and Revenues of Cigarettes and SCP*

In Table 1.4, I investigate if EET influences sales quantities, prices, and sales revenues of cigarettes and SCP, which are closely related products to e-cigarettes. In panel A, I have found that cigarette taxes play an important role in influencing cigarette sales quantities (in packs), revenues, and prices. EET increases the weekly average price for cigarettes by 2% but does not show heterogeneities among different treated regions. In comparison, increasing cigarette taxes by one dollar increases the average cigarette price by 14%. In panel B, EET increases SCP quantities and prices, and such impacts are driven by the ad valorem taxes. This suggests that e-cigarettes and SCP are substitutes as well.

1.5.5 *Price Elasticities of Demand and Tax Pass-Through Rates*

I have calculated price elasticities using statistically significant coefficients (GSC specification) in the result tables. For example, for the own-price elasticity of demand for e-cigarettes, I divide the tax effect on quantities (-0.635 in column [4] of Table 1.2) by the tax effect on the corresponding price (0.178 in column [3] of Table 1.3) according to the chain rule, yielding an elasticity of -3.567 in all treated regions. The magnitude of this estimate is larger than those estimates in the literature with different identification strategies. For examples, Zheng et al. (2017) obtain an estimate of -2.1; Pesko et al. (2018) reach an estimate of -1.8. The estimate is -3.311 in the P.Tax regions, where the average price of e-cigarettes in the pre-tax weeks are smaller than that in all treated regions.

Similarly, I obtain an own-price elasticity of cigarette demand at -0.629, which is consistent with the consensus estimate from the literature by (the International Agency for Research on Cancer, 2011). Also, the cross-price elasticity of cigarette prices on e-cigarette demand is 0.557, and the cross-price elasticity of e-cigarette prices on SCP demand is 0.360. Such results imply that cigarettes and SCP are economic substitutes for e-cigarettes.

I also have calculated the pass-through rates for e-cigarette taxes to the price of the product with the results of column (3) in Table 1.3. I have found a $1.127 increase in price after the implementation of EET.[8] Translating into tax increases by ml, I have reached a pass-through rate of 43.3%.[9] That is, the burden of EET is split between the consumption and production sides of the market, though consumers bear slightly less of the burden. I have found a pass-through rate of 42.1%[10] in the P.Tax regions and a pass-through rate of 64.9%[11] in the V.Tax regions.

---

[8] 0.178 * $6.332(the average price of e-cigarettes per unit in the pre-tax period).

[9] [$1.127/$2.605(the average tax per ml)] *100%.

[10] (0.305*6.031/4.374) *100%

[11] (0.046*6.537/0.463) *100%

Similarly, I have calculated the pass-through rate for cigarette excise taxes to the prices of cigarettes with the results of column (6) in Table 1.4. I have reached a pass-through rate of 101.5%. My pass-through estimates for cigarette taxes are consistent with the estimates from the literature by Keeler et al. (1996), Hanson and Sullivan (2009), and DeCicca et al. (2013).

1.5.6 *Comparisons with the Results from the Tax Level Per ml*

To compare with the results from the GSC estimates, I have conducted similar regressions using the DID method and reported results in Table 1.5. Investigating the EET effect by tax per ml directly, I have replaced the EET represented by the tax indicator with that of the tax level per ml in the DID regressions. Results of EET in the V.Tax regions are statistically significant for both the price and sales quantity regressions. I have found an own-price elasticity of e-cigarette demand at -1.356[12] where quantities are in units. Similarly, I have arrived at an elasticity estimate of -1.183[13] where quantities are in ml. These estimates are both smaller than the estimate of -3.567 from the GSC regressions.

As to price, EET increases the average price of e-cigarettes per unit by 3.6%, represented in column (6); it increases the average price of e-cigarettes per ml by 4.8%, as shown in column (12). I have obtained the pass-through rates of EET to e-cigarette prices per unit and per ml at 22.8% and 51.3%, respectively. Regarding heterogeneities of tax effects, I have obtained pass-through rates on the average e-cigarette price per unit at 19.3% in the P.Tax regions and 77.1% in the V.Tax regions. Likewise, the pass-through rates on the average e-cigarette price per ml are 47.7% in the P.Tax regions and 117.5% in the V.Tax regions. Consistent with my findings in the GSC models, these results show that pass-through rates are larger in the V.Tax regions, where the tax rates are lower. Also, these DID regressions show that pass-through rates are higher for e-cigarette prices measured in ml than in units. Note that not all e-cigarette units, unlike the liquid, were taxed in the treated regions.

To further compare with the GSC estimates, I have applied EET and cigarette excise taxes as instrumental variables (IV) for the corresponding prices of the products in demand estimations, using the fixed-effects method. The first and second rows of Table 1.6 provide estimates of own-price elasticities and cross-price elasticities, as both prices and sales quantities are in logs. As shown in the table, the estimates of own-price elasticity of e-cigarette demand ranged between -0.179 to -1.286 in columns (1) to (6); the magnitudes of these are smaller than the estimate in the GSC regressions. The estimates for the own-price elasticity of cigarette demand ranged between -0.955 to -1.072; the magnitudes of these are larger than those estimated in the GSC regressions. These IV regressions support the findings of my main results from the GSC models, though with different magnitudes for similar estimates.

[12] -0.160/0.118 (in column of (2) and (5) of Table 1.5)

[13] -0.136/0.115 (in columns of (8) and (11) of Table 1.5)

Similar results are shown for alcohol control policies by Sharma et al. (2014), as they indicate that volumetric taxation is less effective than a price policy instrument when comparing volumetric taxation with minimum unit pricing on the consumption of alcohol.

1.6 Conclusions

In this article, I have estimated the effects of e-cigarette taxes on sales quantities, prices, and revenues of e-cigarettes, cigarettes, and SCP respectively. I have used the weekly Nielsen Retail Scanner Data for purchases of these products from various stores in the U.S. My article is the first to apply the GSC strategy to tobacco control and estimations of tax effects. Such estimates are more accurate when the assumption of "parallel trends" is violated.

In my main results regarding all treated regions, I find that e-cigarettes are price-elastic, and cigarettes and SCP are economic substitutes for e-cigarettes. As for pass-through, I reach an estimate of 43.3 for EET% and 101.5% for cigarette excise taxes, averaged in all treated regions. Meanwhile, I observe the heterogeneities of tax effects. Estimates of EET on sales quantities and prices of e-cigarettes have larger average effects in the P.Tax regions but smaller effects in the V.Tax regions, when the tax is measured as indicators of different tax types. In contrast, when taxes are measured as dollars per ml, estimates of EET on sales and prices of e-cigarettes have smaller marginal effects in the P.Tax regions, but larger marginal effects in the V.Tax regions. As to heterogeneities in estimates of elasticities, my results show larger magnitudes for estimates of own-price elasticities of e-cigarette demand when the average price of the product is smaller. Regarding estimates of pass-through, my results demonstrate that pass-through rates for EET are larger in the V.Tax regions, where the average tax rate is lower. Moreover, pass-through rates are higher for e-cigarettes measured in mls than in units.

These heterogeneities show that the effects of P.Tax and V.Tax are different. These two types of taxes are reflections of two different underlying policy motivations: tobacco control or tax revenue generation. The average effects of these two different taxes are that sales quantities and sales revenues of e-cigarettes decrease in the P.Tax regions. In contrast, the average sales revenues of e-cigarettes increase in the V.Tax regions but EET does not show statistically significant results on sales revenues of cigarettes in my main results. This indicates that these two different types of tax policies reach their corresponding policy objectives.

Results from my DID regressions show that the marginal tax effects of each additional dollar increase in P.Tax increase sales quantities and sales revenues of cigarettes, but the average effects of P.Tax do not increase sales quantities nor sales revenues of cigarettes. In contrast, I observe that each additional dollar increase in V.Tax affects neither sales quantities nor sales revenues of cigarettes but increases sales quantities of SCP. This is to say, raising tax rates in the V.Tax regions or control regions would better achieve the objective of tobacco control if the major policy motivation were tobacco control. At the same time, raising tax rates in the P.Tax regions would still contribute to the objective of tobacco control as far as the overall tax to price ratio for e-cigarettes is lower than or similar to that for cigarettes. As my analyses indicated, the average tax-to-price ratio at the state/region level for e-cigarettes is smaller than that of cigarettes in the V.Tax regions, with 5% and 24% respectively. In contrast, the average ratios are 36.8% and 35.1% for e-cigarettes and cigarettes respectively in the P.Tax regions. However, additional federal level excise taxes and local taxes on cigarettes make the total tax-to-price ratio for cigarettes higher in the P.Tax regions.

If increases in e-cigarette tax rates expand to all the states in the U.S., these increases would make the average e-cigarette tax-to-price ratio equal to the current state-level cigarette excise tax-to-price ratio at 26.2%[14]. Since the ratios of tax-to-price for e-cigarettes and cigarettes in the P.Tax regions are almost equal, this is similar to the scenario of tax expansion in all the states. Accordingly, I would use the estimates[15] of own-price elasticity of e-cigarette demand and pass-through rates for e-cigarette taxes in the P.Tax regions in the following calculations. This means the average increases of e-cigarette taxes per ml across the U.S. would be $2.674[16]. This makes the average tax rate and the price of e-cigarettes $2.862 per ml and $10.997 per ml respectively. When -3.311 is used as the own-price elasticity of e-cigarette demand, sales quantities of e-cigarettes would reduce 89.7%[17]. The yearly sales quantities of e-cigarettes in ml would reduce from 181,118[18] to 18,552[19], if the sales price is kept constant. Yearly e-cigarette tax revenues would increase from $34,050[20] to $53,096[21].

According to my estimates from the main results, sales quantities and revenues of cigarettes would not change when ratios of taxes to price for cigarettes and e-cigarettes are similar. Sales quantities and revenues of SCP would increase after the tax increases of e-cigarettes. The average yearly sales units of SCP would increase by 1,890,142[22]; this would generate additional sales revenues of SCP by $882,212[23]. If the average state-level sales tax rate in the U.S. were 6%, the additional state-level sales tax collected from SCP in each region would be $52,933. The yearly state sales taxes collected from e-cigarettes would

14 (1.790/6.836)*100%

15 These values are -3.311 and 0.421.

16 If 100%*(0.188+x)/(9.871+2.674*0.421)=26.2%, then x= 2.674.

17 (3.311*2.674/9.871)*100%

18 3,463.80*52

19 181,118*(1-0.897)

20 0.188*181,118

21 2.862*18,552

22 335,452.43*0.400*(2.674/9.871)*52

23 1,271,653*0.435

reduce from $107,269[24] to $12,241[25]. The total changes in state tax revenues collected from e-cigarettes and SCP would reduce $22,989, from $141,319[26] to $118,330[27]. In reality, the sales price of e-cigarettes on the supply side would decline over time, if no taxes have been added. This reality means the equilibrium sales quantities would be much greater than the estimate from the demand side at 18,552. As indicated in the P.Tax regions, the sales reduction of e-cigarettes is 58.8% instead of 89.7% in reality. That means the real sales quantities of e-cigarettes could be 74,621[28] ml. The real equilibrium price for e-cigarettes could be lower than $10.997 per ml after the tax change across the U.S. In this case, my calculations can be used as a lower bound of the practice. That means the total annual reduction in tax revenues collected could be much smaller than $22,989. Considering the health benefits generated from using more SCP without increasing usage of cigarettes, the revenue decrease should be acceptable.

Similarly, House Bill H.R. 4742 would tax e-cigarettes at $0.0278 per milligram (mg) of nicotine at the federal level, equivalent to the $1.01 federal levy per pack of cigarettes on tobacco alternatives. For instance, the average Juul pod contains nicotine at 59 mg/ml. A particular Juul pod contains 0.7 ml of liquid and costs $4.5 on average. Each pod would face an e-cigarette tax of $1.148[29]. This tax would raise e-cigarette prices by $0.691[30] per ml. This also means that the tax would raise the price of a Juul pod by 10.7%[31]. This price increase would cause sales quantities to reduce by 35.6%[32] if Juul maintains the current price. After the tax, the federal tax-to-price ratio for each pod would be 25.5%[33]. Adding the average state/region e-cigarette taxes at $0.188 per ml, the ratio would be 28.4%[34]. In contrast, the current cigarette federal and state excise taxes to price ratio in all the regions is 41%[35]. According to my results, sales of cigarettes would not change when the tax-to-price ratio of e-cigarettes is similar to or below that of cigarettes.

Thus, my research provides evidence that adjusting tax rates of e-cigarettes similar to the tax-to-price ratio of cigarettes is both effective in regulating sales of e-cigarettes and economically affordable from

[24] 181,118*9.871*0.06

[25] 18,552*10.997*0.06

[26] $34,050+$107,269

[27] $53,096+$12,241+$52,933

[28] 181,118*(1-0.588)

[29] $0.0278*59*0.7

[30] $0.0278*59*0.421

[31] $0.691*0.7/$4.5

[32] 10.7*3.311

[33] ($1.148/$4.5)*100%

[34] (($0.188*0.7+$1.148)/$4.5)*100%

[35] (($1.01+$1.790)/6.836)*100%

the perspective of tax revenues. Therefore, it is feasible to expand e-cigarette taxes to all the states in the U.S., if the goal is to curb nicotine addiction from e-cigarettes and cigarettes. One limitation of our research is that the Nielsen Retail Scanner Data does not cover vaping stores, and has limited coverage of sales from online stores, liquor stores, and convenience stores. However, the rich weekly sales data covering many years at the product level could balance this limitation to some degree. Additionally, because the public cares about youth addiction to e-cigarettes, an expansion of e-cigarette taxes, together with the recent Tobacco 21 laws and flavor bans for e-cigarettes (US Food & Drug Administration, 2020a & 2020b), could curb both the initiation of e-cigarette use and the switch back to cigarettes. For adult smokers, the expansion policies would not encourage them to switch to cigarettes nor use more e-cigarettes, but rather possibly increase their use of SCP to quit smoking, as taxes for cigarettes and e-cigarettes would make these products less affordable than before, if the expansion happens.

Last but not least, my estimates of the own-price elasticity of cigarette demand are consistent with the consensus estimate by hundreds of studies from a thorough review of the literature. Using the same method, I reach an estimate of the own-price elasticity of e-cigarette demand larger than the absolute magnitude of -1.3, which is resulted from the DID by Cotti et al., (2020). Also, consistent with the literature, my estimate of the pass-through rate of cigarette excise taxes shows that the tax is a little more than fully passed on to consumers. With the same methods, my results show that consumers partially bear the burden of e-cigarette taxes while Cotti et al., (2020) reach an estimate of the pass-through[36] rate of 1.5 and indicate the e-cigarette industry is moderate to highly concentrated. Conditioning on the market structures for cigarettes and e-cigarettes are not perfectly competitive, but they are oligopolistic, to be specific. I believe the different magnitudes of the pass-through rates for e-cigarette and cigarette taxes I reached could be because e-cigarettes are price elastic but cigarettes are inelastic, as well as the average tax rate of cigarettes is higher than that of e-cigarettes.

[36] Pass-through measures the rate of the tax burden carried by consumers on tax incidence (when a new tax is introduced or changed magnitudes). Under perfect competition, the parties with inelastic supply or demand bear more taxes. Under imperfect competition, pass-through rate also depends on the tax rate and mark-up. When mark-up is higher, pass-through rate is also higher. Keeping mark-up constant, raising tax rates increases pass-through or the tax burden carried by consumers. (See Weyl and Fabinger, 2013 for more information.)

Table 1.1 Variable Means in the Treated and Control Regions of E-Cigarette Taxes

Variables	Control	Treated-Pre	Treated-Tax	All Regions
Cig Taxes($/pack)	0.232	0.392	0.973	0.308
Ecig SFA Laws	0.088	0.018	0.080	0.078
R.Licensure	0.095	0.208	0.460	0.137
R.to Minors	0.550	0.394	0.897	0.553
Q_Ecig(unit)	6,276.75	6,054.34	5,551.26	6,193.41
P_Ecig($/unit)	5.986	6.332	6.798	6.093
Q_Ecig(ml)	3,538.00	3,499.19	2,584.49	3,463.80
P_Ecig($/ml)	9.649	10.685	10.725	9.871
R_Ecig($)	37,180.23	35,975.26	33,956.66	36,779.70
Q_Cig(pack)	382,107.03	376,328.93	251,284.32	371,863.45
P_Cig($/pack)	6.682	7.247	7.735	6.836
R_Cig($)	2,506,434.44	2,278,791.58	1,644,891.367	2,412,546.82
Q_SCP(unit)	312,293.56	427,119.67	411,439.14	335,452.43
P_SCP($/unit)	0.435	0.447	0.416	0.435
R_SCP($)	135,224.22	186,109.65	162,080.09	144,254.77
Population (thousands)	5,701.17	8,494.07	5,753.75	6,094.27
Cig Taxes Level ($/pack)	1.760	1.678	2.341	1.790
Observations	13,530	2,392	1,238	17,160
Ecig Tax Conversion Based on Wholesale Price Calculations (a)				
Ecig Taxes($/ml): P.Tax Regions			4.374	
Ecig Taxes($/ml): V.Tax Regions			0.463	
Ecig Taxes($/ml): All Treated			2.605	0.188
Ecig Tax Conversion Based on DC Taxes (b)				
Ecig Taxes($/ml): P.Tax Regions			4.879	
Ecig Taxes($/ml): V.Tax Regions			0.463	
Ecig Taxes($/ml): All Treated			2.882	0.208
Additional Variables for Calculations				
P_Ecig($/unit): P.Tax Regions		6.031	7.535	
P_Ecig($/unit): V.Tax Regions		6.537	5.906	
P_Ecig($/ml): P.Tax Regions		11.368	11.870	
P_Ecig($/ml): V.Tax Regions		10.218	9.337	
P_Cig($/pack): P.Tax Regions		7.425	8.015	
P_Cig($/pack): V.Tax Regions		7.125	7.397	
Q_Ecig(unit): P.Tax Regions		9424.65	5613.19	
Q_Ecig(unit): V.Tax Regions		3747.34	5476.28	
Q_Ecig(ml): P.Tax Regions		5106.95	2003.49	
Q_Ecig(ml): V.Tax Regions		2398.67	3287.92	
Q_Cig(pack): P.Tax Regions		490,693.20	183,326.43	
Q_Cig(pack): V.Tax Regions		298,045.78	333,561.90	
Cig Taxes($/pack): P.Tax Regions		0.009	0.871	
Cig Taxes($/pack): V.Tax Regions		0.654	1.097	
Cig Taxes Level($/pack): P.Tax Regions		1.971	2.810	
Cig Taxes Level($/pack): V.Tax Regions		1.479	1.772	

Source: Authors' calculations from the Nielsen Retail Scanner Data in weeks from September 12, 2011, to December 30, 2017. All prices, revenues, and taxes are inflation-adjusted to 2017 December. Cig means cigarette. SFA denotes smoke-free air laws. R.Licensure means retail licensure on e-cigarettes (Ecig). R.to refers to restrictions on Ecig sales to minors.

Table 1.2 E-Cigarette Tax Impact on the Quantities of E-Cigarettes: by Tax Indicator

	LogQ_Ecig (unit)				LogQ_Ecig (ml)				LogQ_Ecig (unit)		LogQ_Ecig (ml)	
	DID		GSC		DID		GSC		GSC			
	Overall	Overall	Overall	Overall	Overall	Overall	Overall	Overall	P.Tax	V.Tax	P.Tax	V.Tax
Policy Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ecig Taxes	-0.045	-0.351*	-0.580**	-0.635**	0.137	-0.032	-0.069	-0.064	-1.010**	-0.172	-0.101	0.082
	(0.143)	(0.188)	(0.186)	(0.197)	(0.090)	(0.144)	(0.100)	(0.106)	(0.381)	(0.183)	(0.142)	(0.101)
Cig Taxes ($)		0.363**		0.078*		0.209		-0.021	0.078*	0.078*	-0.021	-0.021
		(0.184)		(0.061)		(0.134)		(0.046)	(0.045)	(0.048)	(0.047)	(0.049)
Ecig SFA Laws		0.217		-0.049		0.018		-0.003	-0.049	-0.049	-0.003	-0.003
		(0.176)		(0.051)		(0.126)		(0.067)	(0.058)	(0.050)	(0.054)	(0.053)
R.Licensure		0.212*		-0.033		0.069		-0.019	-0.033	-0.033	-0.019	-0.019
		(0.114)		(0.032)		(0.085)		(0.035)	(0.032)	(0.032)	(0.034)	(0.035)
R.to Minors		-0.148**		-0.034		-0.119**		-0.016	-0.034	-0.034	-0.016	-0.016
		(0.073)		(0.024)		(0.058)		(0.017)	(0.024)	(0.024)	(0.018)	(0.018)
Observations	17,160	17,160	17,160	17,160	17,160	17,160	17,160	17,160	15,180	15,510	15,180	15,510
Treated Regions	11	11	11	11	11	11	11	11	5	6	5	6

Note: Regressions include region fixed effects (FE), week FE, and 41 control regions. Regressions with the GSC have five unobserved factors but DID has none. Robust errors in parentheses are based on parametric bootstraps of 1,000 times. Asterisks ***, **, and * are significant levels at 1%, 5%, and 10% respectively. LogQ(unit) are logs of the total e-cigarette (Ecig) products sold in the smallest units; LogQ (ml) are logs of the total Ecig vaping liquid sold in ml. Regions with price taxes (P.Tax) include CA, DC, M1, MN, PA. Regions with volumetric taxes (V.Tax) include C1, C2, KS, LA, NC, and WV. C1 is the city of Chicago, C2 is the rest of Cook County in IL, and M1 is Montgomery County in MD. R.Licensure means retail licensure on Ecig. R.to refers to restrictions on Ecig sales to minors. Cig means cigarette.

Table 1.3 E-Cigarette Tax Impact on Prices and Revenues of E-Cigarettes: by Tax Indicator

	LogP_Ecig(unit)			LogP_Ecig(ml)			LogR_Ecig		
	P.Tax	V.Tax	Overall	P.Tax	V.Tax	Overall	P.Tax	V.Tax	Overall
Policy Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ecig Taxes	0.305***	0.046*	0.178***	0.107	0.027	0.068	-0.588**	0.046*	-0.392**
	(0.040)	(0.021)	(0.022)	(0.112)	(0.082)	(0.073)	(0.226)	(0.021)	(0.122)
Cig Taxes ($)	-0.002	-0.002	-0.002	-0.050	-0.050	-0.050	0.050	0.050	0.050
	(0.017)	(0.016)	(0.016)	(0.036)	(0.038)	(0.033)	(0.045)	(0.043)	(0.046)
Ecig SFA Laws	0.007	0.006	0.006	-0.085*	-0.085*	-0.085*	-0.010	-0.010	-0.010
	(0.059)	(0.028)	(0.027)	(0.049)	(0.048)	(0.047)	(0.052)	(0.048)	(0.052)
R.Licensure	0.012	0.012	0.012	-0.013	-0.013	-0.013	-0.005	-0.005	-0.005
	(0.014)	(0.014)	(0.013)	(0.025)	(0.025)	(0.024)	(0.029)	(0.031)	(0.029)
R.to Minors	-0.006	-0.006	-0.006	0.003	0.003	0.003	-0.008	-0.008	-0.008
	(0.008)	(0.007)	(0.008)	(0.013)	(0.014)	(0.013)	(0.020)	(0.020)	(0.020)
Observations	15,180	15,510	17,160	15,180	15,510	17,160	15,180	15,510	17,160
Treated Regions	5	6	11	5	6	11	5	6	11

Note: All regressions use the GSC strategy; all include region fixed effects (FE), week FE, and have five unobserved factors. Each regression has 41 control regions. Robust errors in parentheses are based on parametric bootstraps of 1,000 times. Asterisks ***, **, and * are significant levels at 1%, 5%, and 10% respectively. In a particular region, LogP(unit) refers to logs of the weekly average price for e-cigarettes(Ecig) at the unit level; LogP(ml) means logs of the weekly average price for Ecig liquid at the ml level; LogR is logs of total weekly sales revenues. All prices and revenues are inflation-adjusted with CPI to the level of 2017 December. Regions with price taxes (P.Tax) include CA, DC, M1, MN, and PA. Regions with volumetric taxes (V.Tax) include C1, C2, KS, LA, NC, and WV. C1 is the city of Chicago, C2 is the rest of Cook County in IL, and M1 is Montgomery County in MD. R.Licensure means retail licensure on Ecig. R.to refers to restrictions on Ecig sales to minors. Cig means cigarette. EET refers to Ecig taxes.

Table 1.4 E-cigarette Tax Impact on the Quantities, Prices, and Revenues of Cigarettes and SCP: by Tax Indicator

	LogQ			LogP			LogR		
	P.Tax	V.Tax	Overall	P.Tax	V.Tax	Overall	P.Tax	V.Tax	Overall
Policy Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Cig									
Ecig Taxes	0.202	-0.166	0.022	0.016	0.023	0.020**	0.148	-0.093	0.030
	(0.118)	(0.101)	(0.066)	(0.012)	(0.013)	(0.009)	(0.118)	(0.100)	(0.070)
Cig Taxes ($)	-0.088***	-0.088***	-0.088***	0.140***	0.140***	0.140***	0.056**	0.056***	0.056**
	(0.013)	(0.014)	(0.015)	(0.002)	(0.002)	(0.002)	(0.015)	(0.014)	(0.015)
Panel B: SCP									
Ecig Taxes	0.122**	0.004	0.064*	0.033***	-0.010	0.010*	0.082*	0.022	0.052
	(0.035)	(0.033)	(0.025)	(0.011)	(0.008)	(0.007)	(0.037)	(0.032)	(0.025)
Cig Taxes ($)	0.014	0.014	0.014	0.001	0.003	0.003	0.012	0.012	0.012
	(0.010)	(0.010)	(0.010)	(0.001)	(0.005)	(0.005)	(0.010)	(0.009)	(0.009)
Observations	15,180	15,510	17,160	15,180	15,510	17,160	15,180	15,510	17,160
Treated Regions	5	6	11	5	6	11	5	6	11

Note: All regressions use the GSC strategy, include both region fixed effects (FE) and week FE, and have five unobserved factors. Each regression has 41 control regions. Standard errors in parentheses are based on parametric bootstraps of 1,000 times. Asterisks ***, **, and * are significant levels at 1%, 5%, and 10% respectively. In a particular region, LogQ is logs of the total cigarette (Cig) packs or SCP units sold; LogP is logs of the weekly average price for each pack of Cig or each unit of SCP; LogR is logs of total weekly sales revenues. All prices and revenues are inflation-adjusted with CPI to the level of 2017 December. Regions with price taxes (P.Tax) include CA, DC, M1, MN, and PA. Regions with volumetric taxes (V.Tax) include C1, C2, KS, LA, NC, and WV. C1 is the city of Chicago, C2 is the rest of Cook County in IL, and M1 is Montgomery County in MD. R.Licensure means retail licensure on e-cigarettes (Ecig). R.to refers to restrictions on Ecig sales to minors. EET refers to Ecig taxes.

Table 1.5 The Effects of EET on the Sales Quantities, Prices, and Revenues of E-Cigarettes (in Logs): by Tax Per ml

	LogQ (unit)			LogP (unit)			LogQ(ml)			LogP(ml)		
	P.Tax	V. Tax	Overall	P.Tax	V. Tax	Overall	P.Tax	V. Tax	Overall	P.Tax	V. Tax	Overall
Policy Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ecig Taxes ($)	-0.009	-0.160***	-0.009	0.032*	0.118***	0.036**	-0.021	-0.136***	-0.021	0.042**	0.115***	0.048**
	(0.021)	(0.032)	(0.019)	(0.016)	(0.009)	(0.015)	(0.029)	(0.017)	(0.029)	(0.020)	(0.009)	(0.019)
Cig Taxes ($)	0.164	0.158*	0.106	0.019	-0.044**	0.0005	0.182**	0.115**	0.120**	0.037	-0.018	0.013
	(0.122)	(0.082)	(0.066)	(0.063)	(0.019)	(0.040)	(0.069)	(0.044)	(0.053)	(0.027)	(0.023)	(0.022)
		LogR										
	(13)	(14)	(15)									
Ecig Taxes ($)	0.023	-0.042	0.027*									
	(0.015)	(0.027)	(0.016)									
Cig Taxes ($)	0.184**	0.114*	0.106*									
	(0.074)	(0.067)	(0.053)									

Note: All regressions use the generalized DID identification strategy. Regressions include region fixed effects (FE) and time FE. Time FE includes year FE, quarter FE, month FE, week FE, and their interactions. Standard errors are in parentheses, clustered at the state level. Asterisks ***, **, and * are significant levels at 1%, 5%, and 10% respectively. Overall regressions include 11 treated regions, 41 control regions, and 17,160 observations. Price tax (P.Tax) regressions include 5, 41, and 15,180 for these items. Volumetric tax (V.Tax) regressions include 6, 41, and 15,510 respectively. In a particular region, LogQ(unit) means logs of the total e-cigarette products purchased in the smallest units; LogQ(ml) denotes logs of the total e-cigarette vaping liquid purchased in ml. LogP(unit) represents logs of the weekly average price for e-cigarette at the unit level. LogP(ml) refers to logs of the weekly average prices for e-cigarette liquid at the ml level. All prices, Ecig taxes per ml, and Cig tax increases are inflation-adjusted with CPI to the level of 2017 December. Regions with P.Tax include CA, DC, M1, MN, and PA. Regions with V.Tax include C1, C2, KS, LA, NC, and WV. C1 is the city of Chicago, C2 is the rest of Cook County in IL, and M1 is Montgomery County in MD. Cig means cigarette. EET is e-cigarette taxes. Results for other policy variables are not shown.

Table 1.6 The Effects of EET on Sales Quantities of E-Cigarettes, Cigarettes, and SCP: Instrumenting Prices with Taxes

	LogQ(unit)_Ecig			LogQ(ml)_Ecig			LogQ(unit)_Cig			LogQ(unit)_SCP		
	P.Tax	V. Tax	All	P.Tax	V. Tax	All	P. Tax	V. Tax	All	P.Tax	V. Tax	All
Policy Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ecig Price ($)	-0.174	-1.286***	-0.179**	-0.397***	-1.107***	-0.382***	1.006***	-0.119***	0.903***	0.189***	0.125***	0.203***
	(0.143)	(0.117)	(0.090)	(0.102)	(0.125)	(0.059)	(0.106)	(0.056)	(0.044)	(0.031)	(0.042)	(0.021)
Cig Price ($)	1.041***	0.815***	0.767***	1.219***	0.768***	0.905***	-0.955***	-0.988***	-1.072***	0.040*	-0.117***	-0.083***
	(0.124)	(0.075)	(0.059)	(0.130)	(0.072)	(0.052)	(0.083)	(0.032)	(0.038)	(0.022)	(0.024)	(0.019)
Ecig SFA Laws	0.260***	0.292***	0.276***	0.174***	0.288***	0.184***	-0.198***	-0.0002	-0.164***	-0.034***	-0.035***	-0.035***
	(0.024)	(0.015)	(0.015)	(0.031)	(0.031)	(0.018)	(0.026)	(0.014)	(0.013)	(0.009)	(0.010)	(0.007)
R.Licensure	0.158***	0.129***	0.128***	0.102***	0.123***	0.086***	-0.068***	0.036***	-0.004	0.014***	0.008**	0.018***
	(0.014)	(0.010)	(0.009)	(0.017)	(0.012)	(0.009)	(0.016)	(0.005)	(0.007)	(0.005)	(0.004)	(0.003)
R.to Minors	-0.106***	-0.118***	-0.107***	-0.116***	-0.124***	-0.109***	0.020***	0.024***	0.026***	-0.013***	-0.013***	-0.012***
	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.006)	(0.003)	(0.005)	(0.002)	(0.003)	(0.002)
Observations	15,180	15,510	17,160	15,180	15,510	17,160	15,180	15,510	17,160	15,180	15,510	17,160
Treated Regions	5	6	11	5	6	11	5	6	11	5	6	11

Note: All regressions use the generalized DID identification strategy. FE means fixed-effects. Time FE includes year FE, quarter FE, month FE, week FE, and their interactions. Robust standard errors are in parentheses, clustered at the state level. Asterisks ***, **, and * are significant levels at 1%, 5%, and 10% respectively. In a particular region, LogQ(unit) is logs of the total products sold in the smallest units; LogQ(ml) is logs of the total e-cigarette vaping liquid purchased in ml. E-cigarette (Ecig) prices and cigarette (Cig) prices are instrumented with Ecig tax changes per ml and Cig tax changes per pack; all are inflation-adjusted with CPI to the level of 2017 December. Regions with price taxes (P.Tax) include C1, C2, CA, DC, M1, MN, and PA. Regions with volumetric taxes (V.Tax) include KS, LA, NC, and WV. C1 is the city of Chicago, C2 is the rest of Cook County in IL, and M1 is Montgomery County in MD. EET means e-cigarette taxes.

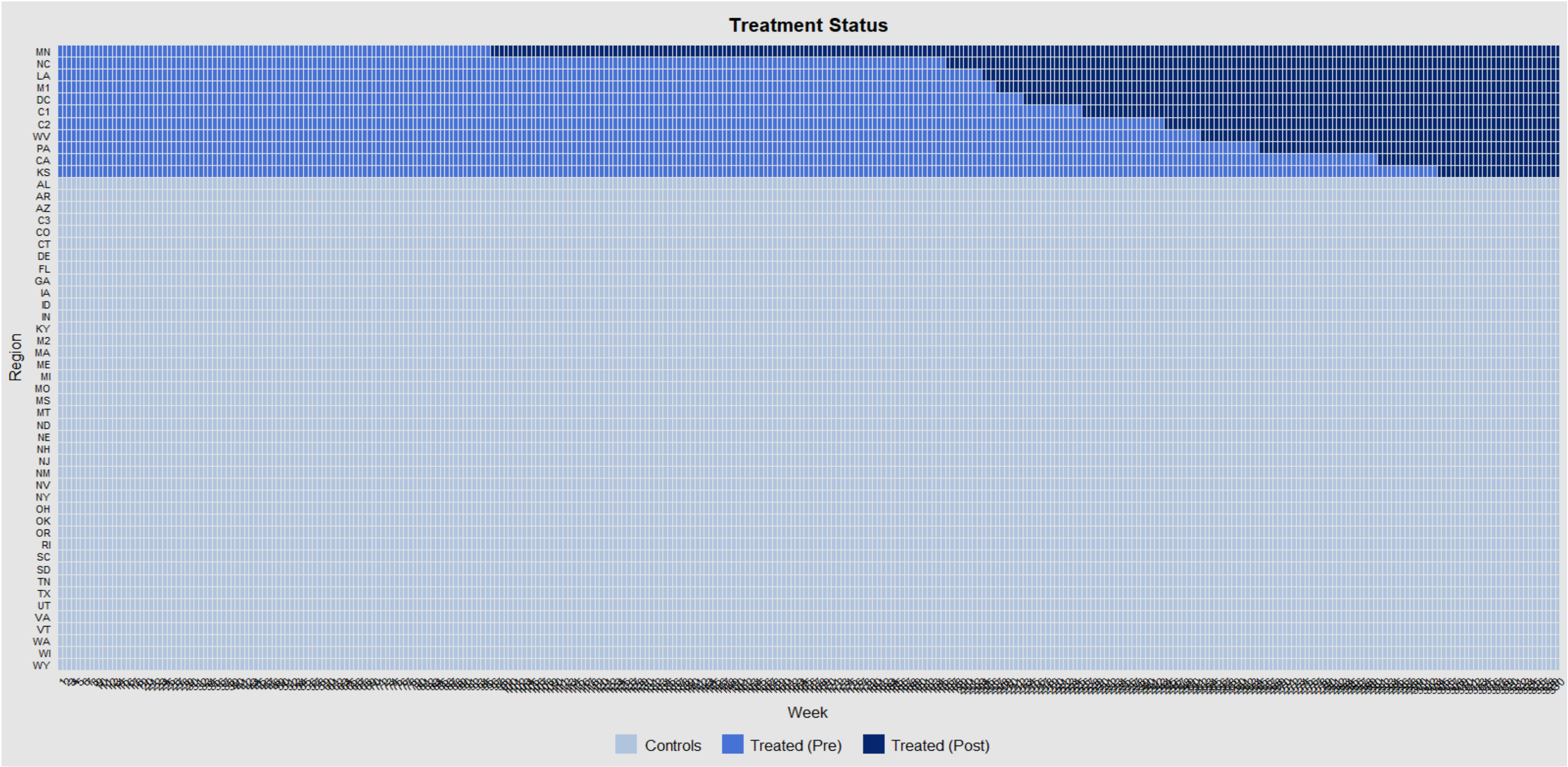


Figure 1.1 Treatment Status by Week for September 12, 2011, through December 30, 2017

Note: C1 is the city of Chicago, C2 is the rest of Cook County, C3 is the rest of the counties in IL; M1 is Montgomery County, M2 is the rest of the counties in MD.

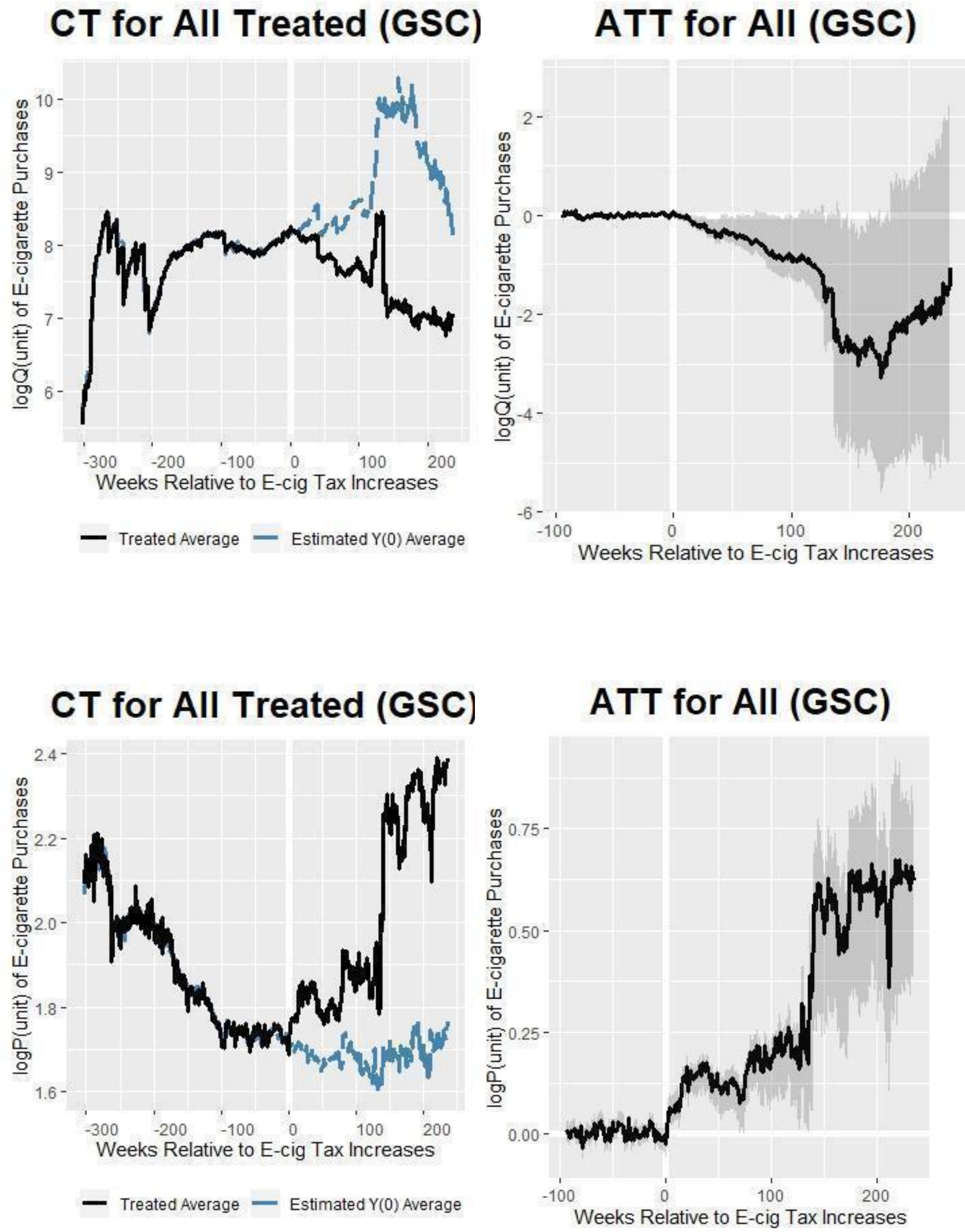
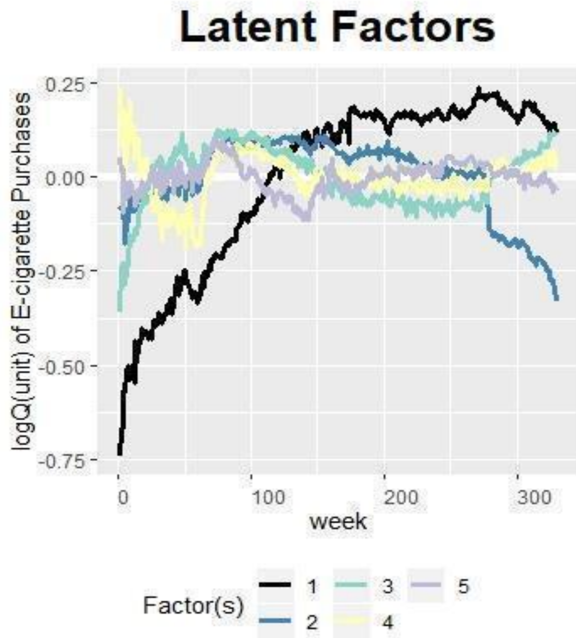


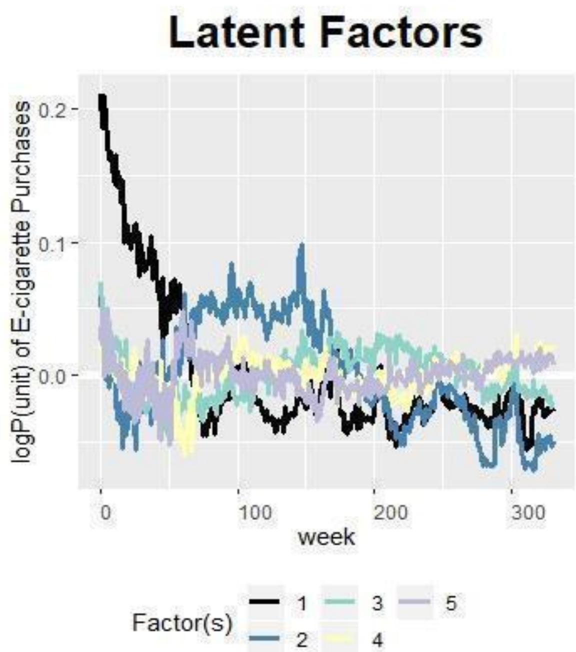
Figure 1.2 E-Cigarette Tax Impact on Sales and Price of E-Cigarettes: Counterfactual and ATT

Note: The top panels are for sales quantity and the bottom panels are for prices. The shaded area in the right figures is 95% confidence intervals for the estimated average treatment effect on the treated (ATT). CT stands for counterfactual.



(a) Factors for logQ(unit)

(b) Loadings for logQ(uni



(c) Factors for logP(unit)

(d) Loadings for logP(unit)

Figure 1.3 E-Cigarette Tax Impacts on Sales and Price of E-Cigarettes: Factors and Loadings

Note: Figures (b) and (d) show the first two important factor loadings.

CHAPTER 2. EXAMINING THE EFFECTS OF E-CIGARETTE TAXES AND REGULATIONS ON THE DEMAND FOR TOBACCO PRODUCTS

2.1 Introduction

Manufacturers advertise e-cigarettes as a better alternative to cigarettes (Dave et al., 2019b, Farsalinos and Polosa, 2014); however, public health advocates are concerned with their health consequences, especially on youth addiction (Counotte et al., 2009, Dwyer et al., 2009, Slawecki et al., 2005). Recently, a growing number of state and local legislatures in the U.S. have passed laws to regulate sales of e-cigarettes with taxes, concerning public health and generating tax revenues. As of February 2020, 19 states and the District of Columbia imposed e-cigarette taxes (Centers for Disease Control and Prevention, 2020). Some of these jurisdictions use ad valorem taxes while others use specific excise taxes. At the federal level, though a tax policy on e-cigarettes is still not in place, House Bill H.R. 4742 would tax e-cigarettes at $0.0278 per milligram (mg) of nicotine, equivalent to the $1.01 federal levy per pack of cigarettes.

As e-cigarette taxes attract the attention of lawmakers and the public, researchers are also motivated to study the effects of e-cigarette taxes from different perspectives. On purchases of tobacco products, Amato and Boyle (2016) qualitatively evaluate an e-cigarette tax in Minnesota on purchases of e-cigarettes, reaching mixed results. Applying a two-way fixed-effects model, Cotti et al., (2020) find that e-cigarettes taxes reduce flavored e-cigarette sales and cause large substitution toward mentholated traditional cigarettes. Utilizing a different identification strategy, generalized synthetic control for causal inference, my first essay (2020) shows that e-cigarette taxes reduce sales of e-cigarettes; I also indicate that changes in e-cigarette taxes do not raise sales of cigarettes when the tax-to-price ratio of e-cigarettes is below or similar to that of cigarettes after tax increases.

On prenatal tobacco use, Abouk et al. (2019) find that e-cigarette taxes reduce pre-pregnancy e-cigarette use, increase pre-pregnancy smoking and prenatal smoking, as well as lower smoking cessation during pregnancy. On teenage tobacco use, Pesko and Warman (2017) show that higher e-cigarette taxes reduce youth e-cigarette use and may increase youth smoking intensity while youth may switch back to e-cigarettes from cigarettes when cigarette tax increases. On adult smoking and smoking cessation, Saffer et al. (2020) find that the e-cigarette tax in Minnesota increases adult smoking and reduces smoking cessation.

Aside from research regarding e-cigarette taxes, a myriad of studies have investigated the effects of other tobacco product restrictions on the demand for tobacco products. For example, Amato et al. (2015) provide evidence that cigarette taxes negatively affect cigarette sales in Minnesota. Similarly, Cotti et al. (2018) show that higher cigarette excise taxes decrease both cigarette and e-cigarette purchases, cigarette smoke-free air (SFA) laws decrease cigarette purchases, e-cigarette SFA laws do not affect cigarette or e-cigarette purchases. Likewise, Tauras (2006) discovers that more restrictive cigarette SFA laws decrease the average smoking amount by adult smokers. Furthermore, when investigating the effects of e-cigarette regulations on the demand for e-cigarettes, Pesko et al. (2016) find that proposed taxes on e-cigarettes, warning labels, and restrictions on e-cigarette flavors are associated with reducing the number of adult smokers who would switch to e-cigarettes.

Additionally, researchers reach mixed results of policy effects, which may be related to different data, various investigated samples, and diverse identification strategies. For example, Friedman (2015), Dave et al. (2019a), and Pesko et al. (2016) find evidence that e-cigarette regulations may increase the uses of cigarettes; while Abouk and Adams (2017) find that restricting youth access to e-cigarettes reduce both conventional cigarettes uses and e-cigarette sales.

However, a research gap in the literature exists in investigating the heterogeneous effects of the two types of e-cigarette taxes—ad valorem taxes and specific excise taxes—on individual household purchases. Also, examining causal responses of tobacco-user subgroups based on usage of different tobacco product types is essential as these subgroups may respond differently to policy changes (Nesson, E., 2017; Robertson et al., 2019). Results from these investigations would provide information for policymakers on the decisions of e-cigarette taxes in the next step. I aim to fill this research gap and contribute to the literature by investigating the causal effects of e-cigarette taxes on the demand for e-cigarettes, cigarettes, and smoking-cessation products (SCP) among U.S. adults. Meanwhile, I incorporate influences of other related tobacco policies and regulations[37] on the demand for these products. To the author' knowledge, little to no research exists exploring the effects of U.S. laws requiring licenses for over-the-counter sales of e-cigarettes and e-cigarette packaging regulations on the demand for tobacco products in the current literature, though articles are available discussing the access of e-cigarettes through medical prescriptions in Australia (Fraser et al., 2015, Gartner and Hall, 2015).

To fulfill these research purposes, I use a generalized difference-in-differences identification strategy supporting a causal interpretation of policy effects on demand. The data that I have utilized is a large panel of adult households from the Nielsen Consumer Panel (NCP) Data

[37] The second section of this paper discusses these policies and regulations.

from 2012 to 2018[38]. The limitation of this data is that it does not cover purchases from tobacco and vape shops which might influence the generalization of the results obtained. However, to my knowledge, NCP data includes the most comprehensive adult e-cigarette purchases from a longer timespan than other datasets. Moreover, NCP data offers representative prices for application in tobacco price research (Lusk and Brooks, 2011, Opazo Breton et al., 2018). Since purchases by the household are scanned and recorded immediately after each shopping trip, on the precision of price and quantities provided, unlike retrospective self-reported data, no evidence shows that NCP data contains meaningful measurement errors (Einav et al., 2010).

My results show that, on average, e-cigarette taxes do not influence cigarette purchases while decreasing SCP purchases. Comparing the effects of two types of e-cigarette taxes, ad valorem taxes have a larger average tax rate than that of specific excise taxes after converting them in the same unit. In terms of effects on the demand, ad valorem taxes do not increase purchases of cigarettes nor e-cigarettes but negatively influence purchases of SCP; specific excise taxes increase purchases of cigarettes and e-cigarettes, as well as have larger negative effects on SCP purchases than do ad valorem taxes. Furthermore, investigating heterogeneous effects of e-cigarette taxes on seven subgroups of ever-purchasers of the three products, I find that these subgroups respond differently to the two types of e-cigarette taxes. From the perspective of tobacco control, it seems that specific excise taxes bring negative health externalities to all subgroups of e-cigarette purchasers except for triple purchasers of the three products by increasing e-cigarette purchases if e-cigarettes are considered with health risks. In comparison, no evidence shows that ad valorem taxes cause health concerns to any subgroups of purchasers.

The rest of this essay exhibits as follows. The next section provides an introduction to e-cigarette taxes and related policies in the U.S. The third section describes data. The empirical strategy section describes empirical methodologies. The next two sections review the results and investigate heterogeneous effects. The last section concludes the essay.

2.2 E-Cigarette Taxes and Related Policies in the U.S.

The main focus of the policies is e-cigarette taxes in this essay. The following is an introduction to e-cigarette taxes and related policies I control for in my analysis. In 2010, Minnesota (MN) started to tax e-cigarettes at a percentage of the wholesale price. As the second state in the

38 I use data in these years is because the latest data available in Nielsen is from 2018 and the earliest meaningful e-cigarette purchase data starts in 2012 (lots of purchase data is missing before 2012 as e-cigarette sales was new).

U.S. to tax e-cigarettes, North Carolina (NC) implemented a specific excise tax on e-cigarettes at \$0.050 for each milliliter(ml) of the nicotine liquid contained in 2015. Since then, more states and local jurisdictions have imposed e-cigarette taxes (Centers for Disease Control and Prevention, 2019a; Cammenga, 2019), following the models of MN or NC. I use regions to refer to these state and local jurisdictions. By the end of 2018, e-cigarette taxes have two types: ad valorem taxes and specific excise taxes. An ad valorem tax, as that in MN, is a percentage of the wholesale or retail price of e-cigarettes. In contrast, a specific excise tax, as the one in NC, is based on the milliliters (mls) of the consumable liquid volume contained in products.

In this essay, I refer to ad valorem taxes as price tax (P.Tax) and specific excise taxes as a volumetric tax (V.Tax). Accordingly, regions with P.Tax are P.Tax regions while regions with V.Tax are denoted as V.Tax regions. Regions that are not P.Tax (V.Tax) regions include the V.Tax (P.Tax) regions and the control regions which never implement e-cigarette taxes. In my investigation time interval, five regions are P.Tax regions including California (CA), District of Columbia (DC), Montgomery county (M1) in Maryland, Minnesota (MN), and Pennsylvania (PA). Eight regions that have applied V.Tax are Chicago (C1) in Illinois (IL), Cook County (C2) in IL, Louisiana (LA), North Carolina (NC), Kansas (KS), West Virginia (WV), Delaware (DE), and New Jerse (NJ). Additionally, Alaska, Puerto Rico, U.S. Virgin Islands, and Hawaii also imposed e-cigarette taxes but purchase data in these regions are not available in my purchase data source. Therefore, policies in these regions are not included in my analyses if any exists.

E-cigarette taxes are measured differently for P.Tax and V.Tax because one is based on price and the other one is based on volume. To compare the effects of these two types of taxes, one needs to unify them with the same unit. In my case, I have converted the P.Tax from a percentage of the price to the same unit as V.Tax, dollars per ml (\$/ml). I have achieved the conversion[39] in three steps. First, I have converted e-cigarette prices from dollars per unit to dollars per ml. To fulfill this task, I have matched[40] the e-cigarette purchase data in NCP with characteristics[41] of e-cigarettes, specifically the ml content for each e-cigarette unit. Second, I have calculated the approximations of wholesale price from the retail price obtained in the first step. Third, I have

[39] See Appendix1 in Deng (2020) for details of the conversion.

[40] The match rate is over 85%.

[41] These e-cigarette characteristics are from Cotti et al., (2018) and Cotti et al., (2020). The authors of this paper would like to acknowledge their generosity for sharing the data.

multiplied wholesale prices with the tax rates in percentages, then divided the result by the total ml contained, to get the tax rates in the unit of dollars per ml.

Compared with e-cigarette taxes, cigarette excise taxes are not new. All U.S. states, the District of Columbia, and the territories had implemented cigarette taxes by 1969. The unit of these taxes are dollars per pack. In my investigated period, 2012-2018, 23 states had multiple changes in the rates of cigarette taxes, varying from decreasing $0.010 to increasing $2.500 per pack (Campaign for Tobacco-Free Kids, 2020a). In the three local jurisdictions with e-cigarette taxes, Chicago and Cook County also changed cigarette taxes in the period. In all the tax changes, except for one tax decrease, all other changes are tax increases. Aside from taxes, another important e-cigarette regulation is e-cigarette packaging regulations. Since 2014, jurisdictions have started to regulate e-cigarettes to be sold in child-resistant packaging, excluding e-cigarette products sold in sealed, pre-filled, or disposable replacement cartridges that are not intended to be opened by the consumer. Such packaging is required to protect children from serious personal injury or serious illness resulting from the handling, using, or ingesting such substances.

As to retail licensure, states typically require retailers to obtain a license or permit from the state or local government for selling cigarettes or other tobacco products. On e-cigarettes particularly, by 2018, sixteen states and the District of Columbia had laws effective on requiring e-cigarette retailers and vape shops to obtain a license or a permit. Concerning the SFA laws, they prohibit the use of e-cigarettes or cigarettes in indoor areas of private worksites, restaurants, and bars by the corresponding SFA laws on e-cigarettes or cigarettes. On the age restrictions of e-cigarette sales to minors, 18 was for most states, and up to age 19 or 21 for a few states. Recently, on December 20, 2019, the Tobacco 21 Act (FDA, 2020) raised the federal minimum age of sale of tobacco products from 18 to 21 years, effective immediately. This act is also applicable to e-cigarettes as they are classified as tobacco products by the FDA (2016). If a state chooses to continue with current age laws, it may face the risk of losing federal funding.

Additionally, the Affordable Care Act (ACA) gives states the option of expanding their standard Medicaid program. States that adopted the expansion could extend coverage to large numbers of adult smokers who are not eligible for traditional Medicaid cessation coverage, thereby increasing the potential impact of Medicaid cessation coverage. The status of the Medicaid expansion for states could be not adopted, adopted but not implemented, as well as adopted and implemented. I am interested in the policy effects of status change for implementation so I have used whether a state’s status was adopted and implemented as the measure for this policy change.

2.3 Data

Data mainly contains two parts: policy data and purchase data. I use these data to investigate the causal effects of policies on the purchase of e-cigarettes, cigarettes, and SCP. The policy data come from government websites of jurisdictions, Centers for Disease Control and Prevention (CDC)'s State Tobacco Activities Tracking and Evaluation (STATE) System (2019b), the Campaign for Tobacco-Free Kids (2020a, 2020b), and Public Health Law Center (2020). The timespan of my research is from 2012 to 2018. My focus of the policies is on e-cigarette taxes. I also control for related policies and regulations including cigarette excise taxes, e-cigarette packaging regulations, the requirement of licenses for over-the-counter (OTC) sales of e-cigarettes, laws restricting sales of e-cigarettes to minors, SFA laws that restrict uses of e-cigarettes, SFA laws that restrict uses of cigarettes, and implementation status of a state for Medicaid expansion with tobacco cessation treatments via the Affordable Care Act.

To recover the causal effects of these policies, my policy data use changes in these policies. This is because policy changes are required in causal inference to compare the treated regions and quarters with the control regions and quarters. If a region in a quarter had a change for a particular policy, this region is treated, and this quarter is a treated quarter for this policy. Otherwise, in the selected time interval, regions that never had a change of such policy serve as controls for regions that had. Similarly, if a region had a change of such policy in a certain quarter, the quarters before the effective date for this region serve as controls for the treated quarters.

The policy changes possess two types in my investigation. The first type is for e-cigarette taxes and cigarette taxes. This type is a change of tax rates from zero or non-zero level to a different level. I use continuous variables to show changes in dollar amounts for e-cigarette taxes and cigarette taxes. For example, the nominal change of e-cigarette tax was \$0.050 per ml in KS in 2017Q3, and all quarters after, as no other changes happened in KS after that. Similarly, the nominal change of cigarette tax in KS was \$0.500 per pack in 2015Q3 and all quarters after. The second type of policy change is for all other policies. This type is policy change from no implementation to implementation of a particular policy. I use indicator variables (equal to one) to represent a state in a particular quarter had a policy in place. If a particular policy was not implemented in a state at a quarter, the corresponding policy variable would be zero for this state and quarter combination.

Table 2.1 shows changes in policies and regions where these policies were effective between 2012 and 2018. It displays three core policies including e-cigarette taxes, cigarette taxes, and e-cigarette packaging regulations. Moreover, I have calculated tax changes and tax rate levels for e-cigarettes and cigarettes in the P.Tax regions and the V.Tax regions. All taxes and tax changes are adjusted with CPI to the level of 2018Q4 (the fourth quarter of 2018). In the P.Tax regions, the average change of e-cigarette taxes is $1.543 per ml and the average change of cigarette taxes is $0.597 per pack. Similarly, in V.Tax regions, the average change of e-cigarette taxes is $0.056 per ml and the average change of cigarette taxes is $0.275 per pack.

Furthermore, a particular pod, like Juul, contains 0.7 ml of liquid. With this considered, with tax changes included, the average tax rates for an e-cigarette pod and a pack of cigarettes would be $1.080 and $1.978 (not including federal excise taxes for cigarettes) in P.Tax regions. Similarly, the average tax rate for an e-cigarette pod would be $0.039, and that for a pack of cigarettes would be $1.598. This shows that the average tax rates are higher for both e-cigarettes and cigarettes in the P.Tax regions than in the V.Tax regions. The average changes in tax rates for the two products are also higher in the P.Tax regions. That means e-cigarettes and cigarettes are cheaper in V.Tax regions on the tax perspective. Additionally, from the tax perspective, e-cigarettes are cheaper than cigarettes in all regions, and this tax gap is even larger in V.Tax regions.

The purchase data for tobacco-related product purchases in 2012-2018 are from the NCP data collected from 48 states. Since C1, C2, and M1 imposed e-cigarette taxes at the local level, to investigate the tax effects in these jurisdictions, I break down IL into three regions: C1, C2, and the rest of the state (C3). Similarly, I separate M1 in Maryland from the rest of the state (M2). As such, C3 and M2 would serve as control regions. The local and state jurisdictions compose 52 regions. The NCP data provides household demographic characteristics including income, education, whether the households have children, etc. This dataset contains approximately sixty thousand American households annually. About 80% of the households continue participation in the following year.

The tobacco products collected from the NCP data include cigarettes, e-cigarettes, and SCP (nicotine patches/gums/tablets, etc.) from a variety of outlets such as convenience stores, drug stores, and mass merchandisers. Among these purchases, e-cigarettes include all related products such as disposable e-cigarettes, starter kits, and refill cartridges. The NCP data records purchase information for each shopping trip. The amount of e-cigarette purchases is relatively trivial, so I have aggregated the weekly purchase data for each household to the quarter level. Then, I have created indicator variables to show whether a household purchased that product category, which is cigarettes, e-cigarettes, or SCP, in each quarter. Furthermore, I have calculated the total quantity number of a product that a household purchased over each quarter, specifically, cigarettes in packs, e-cigarettes in units, and SCP in units.

With the aggregation above, the full sample includes over 1.6 million household-quarter observations from 117,817 households. From this full sample, I have extracted samples of "ever-purchasers" which are households that have ever purchased the relevant product at least once from 2012 to 2018. In this way, I have generated samples of ever-purchasers respectively for cigarettes, e-cigarettes, and SCP. In all households of the full sample, 21.4% (25,225 households) are ever-purchasers of cigarettes, 2.0% (2,373 households) are ever-purchasers of e-cigarettes, and 3.1% (3,636 households) are ever-purchasers of SCP. In a quarter, on average, approximately 8% of households purchased cigarettes, 0.4% purchased e-cigarettes, and 0.6% purchased SCP. Table 2.2 shows the summary statistics of the full sample and samples of ever-purchasers regarding purchases and corresponding policies.

Samples of ever-purchasers provide some insight into consumer behaviors. In terms of ever-purchasers of e-cigarettes, about 80.9% of the households that have ever purchased e-cigarettes purchased cigarettes, suggesting that cigarette purchases might be a strong predictor of e-cigarette purchases. This is consistent with findings from Dutra and Glantz (2014): the use of e-cigarettes is associated with higher odds of ever or current cigarette smoking. In contrast, 17.2% of ever-purchasers of e-cigarettes purchased SCP. As to ever-purchasers of cigarettes, 9.4% of the households purchased e-cigarettes and 8.8% of the households purchased SCP. Furthermore, comparing ever-purchasers of cigarettes and e-cigarettes, the average number of cigarettes purchased by ever-purchasers of e-cigarettes is about four times of that purchased by ever-purchasers of cigarettes. This is consistent with results from Jorenby et al. (2017): dual users do not smoke fewer cigarettes than smoke-only users. Additionally, regarding ever-purchasers of SCP, 60.8% of them purchased cigarettes and 13.9% of them purchased e-cigarettes.

Following the overview of ever-purchasers of the three products, I further break them down into seven distinct groups without overlaps of one another in Figure 2.1. Policies may have different effects on different groups so I would investigate heterogeneous effects of policies for these groups in the section of heterogeneous effects. These groups represent differences in sourcing nicotine and show in three types for purchases. The first type is single product purchasers. Of this type, group 1 is cigarette only purchasers, that means, these households did not purchase e-cigarettes nor SCP. Similarly, group 2 is SCP only purchasers, and group 3 is e-cigarette only purchasers. The second type is dual purchaser exclusive groups, which means they purchased the two indicated products but did not purchase the third product. Group 4 is dual purchasers of cigarettes and SCP without e-cigarette purchases. Similarly, group 5 is dual purchasers of cigarettes and e-cigarettes and group 6 is dual purchasers of e-cigarettes and SCP. The third type of purchaser is triple purchasers, i.e., they are ever-purchasers of all three products. The respective numbers of households in group 1 to group 7 are 21,092; 1,371; 503; 1,760; 1,924; 56; and 449.

2.4 Empirical Strategy

I match the policy data with the purchase data by quarters (in which purchases were made) and residing regions of households. With this combined data, I estimate the causal effects of policies on purchases of tobacco products. My policy focus is on e-cigarette taxes. The identification strategy that I used is a generalized differences-in-differences strategy. In this identification, treated households and treated quarters of time for e-cigarette taxes are households in regions and quarters with changes in e-cigarette taxes while those households in regions or quarters without changes serve as control households and control quarters. To measures the effects of e-cigarette taxes on the treated households in the treated quarters against the untreated households in the untreated quarters, I apply the identification strategy in two empirical models.

First, I estimate the policy effects on the probability that a household would purchase a type of tobacco product in a linear probability model:

$$P\left(C_{hryq}^{j} > 0\right) = \alpha_0 + \alpha_1 ET_{ryq} + \alpha_2 CT_{ryq} + \alpha_3 P_{ryq} + \boldsymbol{\beta X}_{ryq} + \sigma_h + \tau_{yq} + \varepsilon_{hryq} \quad (1),$$

where $P\left(C_{hryq}^{j} > 0\right)$ is the purchase probability of tobacco product j for household h, in region r, year y, and quarter q. Specifically, j represents cigarettes, e-cigarettes, or SCP; ET_{ryq} is a continuous variable reflecting the change of e-cigarette tax in region r, year y, and quarter q; CT_{ryq} is a change of cigarette excise taxes in region r, year y, and quarter q; all tax changes are adjusted by CPI to the level of 2018Q4. P_{ryq} indicates whether a region in a quarter has e-cigarette packaging regulations. $\boldsymbol{X}_{ryq}$ is a vector of the five other, observable policy covariates: whether a region in a quarter requires licenses for over-the-counter sales of e-cigarettes, restricts sales of e-cigarettes to minors, has an SFA law that restricts uses of e-cigarettes, has an SFA law that restricts uses of cigarettes, and implements a Medicaid expansion; $\boldsymbol{\beta}$ is a vector of unknown parameters, representing the average mean effects of each of these policies over time. Correspondingly, α_1 and α_2 represent the average mean effects of e-cigarette tax changes and cigarette tax changes. Furthermore, σ_h is household fixed-effects, τ_{yq} is year-quarter or quarterly fixed-effects, and ε_{hryq} represents the unobserved error term. This specification clusters standard errors at the state level.

Second, I estimate the effects of these policies on the purchase quantities of each type of tobacco product using a fixed-effects model, with $logC_{hryq}^{j}$ replacing $P\left(C_{hryq}^{j} > 0\right)$ in equation

(1) as the dependent variable, where C_{hryq}^{j} is the purchased quantity of tobacco product j for household h resided in region r in year y and quarter q; all independent variables are the same as in equation (1). The purchased quantities are in logs because the magnitude of these is larger than other variables. Box-cox tests support the logarithm transformation. The interpretation of tax effects would be the percentage changes of purchased quantities by each additional dollar increased at the mean. In both specifications[42], household fixed-effects control for unobserved non-time varying differences in demand across households. They might serve as better controls for unobservable factors than broader geographic controls, such as county fixed-effects or state fixed-effects. I would test the robustness of the results by replacing household fixed-effects with state or county fixed-effects in the robustness check section. Adding state-specific linear time trends creates collinearity with the fixed-effects so they are not included in models.

Moreover, model (1) first uses all observed households to estimate purchase probabilities of cigarettes, e-cigarettes, and SCP respectively, then it uses each ever-purchaser sample to estimate the purchase probability for that same particular product category. With the same samples, the second specification estimates the demand for these products. Regressions in the full sample and ever-purchaser samples identify policy effects on demand of the pool of all consumers and ever-purchasers for the three products. Aside from identifying the average policy effects of e-cigarette taxes from both P.Tax and V.Tax, I extract two sub-samples—not in V.Tax regions and not in P.Tax regions—respectively from all households in the full sample and the ever-purchasers for each product. Using the sub-samples of not in the V.Tax regions, models measure the effects of P.Tax on purchases; while applying the sub-samples of not in the P.Tax regions, models examine the effects of V.Tax. These sub-sample regressions test if different scales of tax rates or types of e-cigarette taxes have contrasting effects on purchase.

2.5 Results

This section shows the average policy effects on the purchase probability (extensive margin) and the purchased quantity (intensive margin) of cigarettes, e-cigarettes, and SCP with a generalized difference-in-differences approach.

42 To apply fixed effects, this article uses linear fixed effects estimators in model (1) instead of Probit, Logit, Tobit, or Heckman, because applying fixed effects to other estimators would reach biased results or is not applicable in panel data.

2.5.1 *Analysis of Extensive and Intensive Purchase Habits*

Table 2.3 shows the results of regressions for purchase probabilities and purchase quantities in six panels. In terms of e-cigarette taxes, the top panels show the average effects of all e-cigarette taxes in all regions and all quarters, the middle panels exhibit the average effects of P.Tax, while the bottom panels indicate the average effects of V.Tax. Individually speaking, panel A1 displays the policy effects on purchase probabilities and amounts of cigarettes, e-cigarettes, and SCP for all households. Panel A2 displays those for all households not in the V.Tax regions. Panel A3 displays those for all households not in the P.Tax regions. Similarly, panels B1to B3 demonstrate the policy effects on the purchase of cigarettes, e-cigarettes, and SCP for the corresponding ever-purchasers in all regions, not in the V.Tax regions, and not in the P.Tax regions.

Contrasting all three panels of A1 to A3, increases of cigarette taxes decrease purchase probabilities and amounts of cigarettes, increases of e-cigarette taxes have positive effects on purchase amounts of e-cigarettes, increases of e-cigarette taxes negatively influence purchase probabilities and amounts of SCP, and implementations of e-cigarette packaging regulations increase the purchase probabilities and amounts of SCP. In comparison, V.Tax in A3 positively influences cigarette purchase probabilities and purchase amounts; it also increases purchase probabilities of e-cigarettes, has larger positive effects on e-cigarette purchase amounts than those of P.Tax in A2, as well as has larger negative effects on SCP purchase than those of P.Tax in A2.

Comparing panels of B1-B3 with panels of A1-A3, generally, the effects of policies have larger magnitudes for ever-purchasers than the pool of all households, if they have statistically significant effects on purchases. Moreover, e-cigarette taxes do not show any effects on purchase amounts of e-cigarettes for the pool of all ever-purchasers of e-cigarettes nor those not in V.Tax regions. Above all, it means that P.Tax does not increase purchases of cigarettes nor e-cigarettes but negatively influence purchases of SCP. In comparison, V.Tax increases purchases of cigarettes and e-cigarettes, as well as has larger negative effects on SCP purchases than P.Tax. Aside from taxes and e-cigarette packing regulations, other policies mostly do not show statistically effects, except e-cigarette SFA laws negatively influence SCP purchases of SCP ever-purchasers, cigarette SFA laws negatively influence e-cigarette purchases of e-cigarette ever-purchasers, and implementations of Medicaid expansion negatively affects cigarette purchase probabilities of cigarette ever-purchasers.

2.5.2 *Robustness Analysis*

After the baseline regressions, I conduct a series of robustness checks using different model specifications, focusing on the effect of e-cigarette taxes. Since e-cigarette taxes show statistically significant results in all regressions in panel B3 of Table 2.3, using the same samples would provide more evident results about robustness, so I show these results in Table 2.4. In the first robustness check, the specification adds household characteristics, keeping everything else the same as in the baseline regressions. These characteristics include household size, household income level, whether having children under 18 years old, marital status, household access to the internet, ethnicity, and characteristics regarding the male or female household head such as categories of age group, education level, hours of employment, and occupation type. Results of e-cigarette taxes in this specification are consistent with those in B3 of Table 2.3 (baseline specification) on the statistical significance and magnitude of the estimates. In the second robustness check, with these characteristics added but replacing the household fixed-effects with county fixed-effects, e-cigarette taxes show similar results on cigarette purchase and SCP purchase but they do not show statistically significant results on e-cigarette purchase anymore.

The third specification still adds the household characteristics but applies state fixed-effects; e-cigarette taxes do not have influences on cigarette purchase amounts nor e-cigarette purchase (probabilities and amounts), compared with the baseline regression results. Removing the household characteristics and replacing household fixed-effects with the county or state-fixed effects show similar results as the above. Household characteristics do not vary much over time, so adding them obtains similar results. Moreover, county fixed-effects or state fixed-effects slightly change the results of e-cigarette purchase but neither of them controls for unobserved non-time varying differences in demand across households.

Furthermore, instead of clustering at the state level, the fourth specification clusters standard errors at the county level; results are consistent with that of the baseline regressions. In another specification, replacing continuous changes of e-cigarette taxes with an indicator of e-cigarette tax changes, e-cigarette taxes do not show statistically significant results on e-cigarette purchase nor SCP purchase. This indicates that there might be differences in the average effects and marginal effects of e-cigarette tax changes reflected by the indicator and the continuous change variable. Moreover, using continuous e-cigarette tax changes (2012-2017) that I obtained from the Nielsen Retail Scanner Data, the last specification shows similar results as those of the baseline regressions. This resolves the concern of potential measurement errors for e-cigarette taxes resulted from fewer products purchased or different product compositions for households in the household panel. Additionally, I have also conducted similar robustness checks for other panels of regressions in Table 2.3; results of those are similar as the above if e-cigarette taxes show statistically significant results in the original specifications of Table 2.3; e-cigarette taxes keep non-statistical significance in the robustness check results if they are not statistically significant in the original specifications. Lastly, replacing e-cigarette purchase amounts in units with mls, the results are consistent though the magnitude is slightly larger (not shown in table).

2.6 Heterogeneous Effects

Table 2.5 examines whether heterogeneity exists in the e-cigarette tax effects across different subgroups of ever-purchasers of the three products based on Figure 2.1. Compared with B1-B3 in Table 2.3, instead of using all ever-purchasers in the regressions for purchases of the corresponding product, regressions in Table 2.5 examine purchases of all three products by each of the seven subgroups. The purpose is to test if subgroups respond differently to tax changes. The results of these regressions can provide insights into understanding heterogeneous purchase behaviors and evidence for policy implications. Generally, the results in the table show that subgroups behave differently: some subgroups show statistically significant responses while their counterpart groups do not, or subgroups show different magnitudes of responses if estimates are statistically significant for these compared subgroups.

In terms of cigarette purchase, cigarette only purchasers do not respond to changes in e-cigarette taxes in rows (1)-(3) of Table 2.5. Dual purchasers of cigarettes and e-cigarettes do not respond either in rows (13)-(15). Dual purchasers of cigarettes and SCP increase purchase probabilities of cigarettes in response to P.Tax (row (11)); such dual purchasers increase both purchase probabilities and amounts of cigarettes in response to V.Tax (row (12)). Triple purchasers of the three products increase both purchase probabilities and amounts of cigarettes in response to V.Tax (row (21)).

About e-cigarette purchase, in response to V.Tax, e-cigarette only purchasers, dual purchasers of cigarettes and e-cigarettes, as well as dual purchasers of e-cigarettes and SCP increase e-cigarette purchases in rows (9), (15), (18). In comparison, triple purchasers of the three products decrease e-cigarette purchases in response to V.Tax (row (21)). Regarding SCP purchase, in response to P.Tax, SCP only purchasers decrease SCP purchases in rows (5). Responding to V.Tax, dual purchasers of cigarettes and SCP, dual purchasers of e-cigarettes and SCP, and triple purchasers of the three products decrease SCP purchases in rows (12), (18), (21).

Since the size of the subgroup of cigarette only purchasers is broad, to further investigate the heterogeneous effects, I further break purchases of these ever-purchasers into three groups: pack-a-day purchase, intermediate purchase, and occasional purchase (less than a half pack a day purchase on average). Results indicate that these cigarette only purchasers reduce amounts of pack-a-day purchase in response to P.Tax (row (23)), but increase occasional cigarette purchases in response to P.Tax (row (30)). Similarly, I also break down cigarette purchases of other subgroups (results not shown in table): triple purchasers, dual purchasers of cigarettes and SCP, and dual purchasers of cigarettes and e-cigarettes. In most cases, P.Tax does not influence cigarette purchases; if it does, P.Tax is likely to increase occasional purchases and reduces intermediate purchases. In comparison, V.Tax mostly has statistically significant effects on cigarette purchases: it is likely to increase occasional cigarette purchases but decrease intermediate and pack-a-day purchases.

To sum up, results indicate that P.Tax bearly influences purchases of the three products at least does not increase sales of e-cigarettes for any of the users who use e-cigarettes. Occasionally, P.Tax influences other subgroups who do not purchase e-cigarettes: it increases occasional cigarette purchases but decreases intermediate purchases of dual purchasers of cigarettes and SCP; it decreases SCP purchases of SCP only purchasers. In comparison, V.Tax influences purchases of the three products in most of the subgroups except for SCP only purchasers. Specifically, V.Tax influences cigarette purchases mostly by increasing occasional cigarette purchases but decreasing intermediate and pack-a-day purchases. For those who use e-cigarettes, V.Tax increases e-cigarette purchases but does not increase purchases of the other two products, except for the triple purchasers who decrease purchases of e-cigarette and SCP, as well as pack-a-day and intermediate cigarette purchases but increase occasional cigarette purchases.

2.7 Conclusions

I use detailed household purchase data to examine the policy effects of e-cigarette taxes from 2012 to 2018. The investigation controls for purchase changes caused by related policies and regulations including cigarette excise taxes, e-cigarette packaging regulations, the requirement of licensure for e-cigarette OTC sales, restrictions of e-cigarette sales to minors, SFA laws that restrict uses of e-cigarettes, SFA laws that restrict uses of cigarettes, and implementation of Medicaid expansion.

The policy focus is on e-cigarette taxes. In the investigation time interval, jurisdictions implemented two types of e-cigarette-taxes: ad valorem taxes (P.Tax) and specific excise taxes

(V.Tax). P.Tax is based on a percentage of the wholesale or retail price while V.Tax is collected according to the liquid volume contained in the product. Regions with P.Tax (V.Tax) implemented are P.Tax (V.Tax) regions. Regions that are not P.Tax (V.Tax) regions are the control regions and the V.Tax (P.Tax) regions. The tax rates for e-cigarettes and cigarettes are both lower in the V.Tax regions than in the P.Tax regions. The tax rates for e-cigarettes are lower than cigarettes in all regions; V.Tax regions have the largest tax gap between e-cigarettes and cigarettes.

Regarding policy effects on ever-purchasers' purchase on corresponding products, on average, e-cigarette taxes do not influence cigarette purchases while decrease SCP purchases. Comparing the effects of two types of e-cigarette taxes, P.Tax does not increase purchases of cigarettes nor e-cigarettes but negatively influences purchases of SCP; V.Tax increases purchases of cigarettes and e-cigarettes, as well as has larger negative effects on SCP purchases than P.Tax. As to the effects of other policies and regulations, cigarette excise taxes decrease cigarette purchases, e-cigarette packaging regulations increase SCP purchases, e-cigarette SFA laws negatively influence SCP purchases, cigarette SFA laws have negative effects on e-cigarette purchases, and implementations of Medicaid expansion decrease cigarette purchase probabilities. Moreover, I conduct a series of robustness checks and obtain robust results.

Aside from the main results above, I conduct investigations of heterogeneous effects of e-cigarette taxes on the seven subgroups of ever-purchasers: cigarette only purchasers, SCP only purchasers, e-cigarette only purchasers, dual purchasers of cigarettes and SCP, dual purchasers of cigarettes and e-cigarettes, dual purchasers of e-cigarettes and SCP, and triple purchasers of the three products. Meanwhile, I compare the effects of P.Tax and V.Tax. Results indicate that these subgroups respond differently to P.Tax and V.Tax. From the perspective of tobacco control, it seems that V.Tax brings negative health effects to e-cigarette only purchasers, dual purchasers of cigarettes and e-cigarettes, and dual purchasers of e-cigarettes and SCP by increasing e-cigarette purchases if e-cigarettes are considered with health risks. It seems that V.Tax does not cause health concerns to other subgroups of purchasers; P.Tax does not cause health concerns to any subgroups of purchasers.

The different effects of P.Tax and V.Tax are probably because of the different tax rates of e-cigarettes and cigarettes in the P.Tax and V.Tax regions. As the gap between e-cigarette taxes and cigarette taxes is larger in the V.Tax regions than in the P.Tax regions, in most cases, households in the V.Tax regions are likely to increase e-cigarette purchases if they are e-cigarette purchasers. These results suggest that implementing e-cigarette taxes at a higher rate, at least as the average rate of P.Tax and without making the rates higher than tax rates for cigarettes, probably can curb e-cigarette purchases without increasing cigarette purchases.

Table 2.1 Summary of Core Policies Related to Cigarettes and E-Cigarettes by Year

Changes in E-Cigarette Taxes ($/ml)

Year	Num. States w/ Changes	Average Nominal Change	States with E-Cigarette Taxes
2012	1	$1.025	MN
2013	1	$1.909	MN
2014	1	$2.840	MN
2015	4	$2.221	MN, NC, DC, LA,
2016	6	$2.303	MN, DC, NC, LA, WV, PA
2017	8	$2.364	MN, DC, NC, LA, WV, PA, CA, KS
2018	10	$2.626	MN, DC, NC, LA, WV, PA, CA, KS, DE, NJ

Changes in Cigarette Excise Taxes ($/pack)

Year	Num. States w/ Changes	Average Nominal Changes	States with Cigarette Excise Tax Changes
2012	9	$1.070	CT, NH, NM, NY, RI, SC, UT, VT, WA
2013	11	$1.124	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN
2014	12	$1.139	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN, OR
2015	17	$1.111	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN, OR, AL, KS, LA, NV, OH
2016	19	$1.073	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN, OR, AL, KS, LA, NV, OH, WV, PA
2017	20	$1.089	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN, OR, AL, KS, LA, NV, OH, WV, PA, CA
2018	23	$1.105	CT, NH, NM, NY, RI, SC, UT, VT, WA, MA, MN, OR, AL, KS, LA, NV, OH, WV, PA, CA, DC, KY, OK

E-Cigarette Packaging Regulations

Year	Num. States w/ Policy	States with E-Cigarette Packaging Regulations
2014	4	MN, NY, OH, SD
2015	19	MN, NY, OH, SD, AR, IL, ID, MA, MO, NM, NC, ND, OR, RI, TX, UT, VT, VA, WY
2016	24	MN, NY, OH, SD, AR, IL, ID, MA, MO, NM, NC, ND, OR, RI, TX, UT, VT, VA, WY, ME, NJ, PA, TN, WA
2017	25	MN, NY, OH, SD, AR, IL, ID, MA, MO, NM, NC, ND, OR, RI, TX, UT, VT, VA, WY, ME, NJ, PA, TN, WA, NH,

Source: CDC's STATE System, the Campaign for Tobacco-Free Kids, and the Public Health Law Center. Timespan is 2012 to 2018. Policy changes are relative to the year 2009. Some states had multiple tax changes in the timespan. No states had e-cigarette packaging regulations before 2014, and there were no newly added states for changes in 2018.

Table 2.2 Summary Statistics

Variables	Full Sample (N= 1,625,911)		Samples of Ever-Purchasers: Cigarettes (N= 378,332)		E-Cigarettes (N= 50,606)		SCP (N= 63,413)	
Dependent Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Any Cigarette Purchase (Yes)	0.084	0.277	0.360	0.480	0.495	0.500	0.315	0.464
Any E-Cigarette Purchase (Yes)	0.004	0.061	0.013	0.114	0.119	0.324	0.020	0.140
Any SCP Purchase (Yes)	0.006	0.077	0.015	0.120	0.027	0.161	0.152	0.359
Number of Cigarette Purchase (packs)	3.266	19.821	14.037	39.208	27.856	55.961	14.592	40.414
Number of E-Cigarette Purchase (units)	0.054	2.127	0.170	3.564	1.743	11.936	0.371	5.7891
Number of SCP Purchase (units)	1.882	45.213	3.317	56.358	6.450	77.442	48.244	224.004
Policy Variables								
Changes in E-Cigarette Taxes ($/ml)	0.264	1.221	0.245	1.182	0.201	1.045	0.309	1.359
Changes in Cigarette Excise Taxes ($/pack)	0.360	0.658	0.315	0.618	0.304	0.602	0.332	0.625
E-Cigarette Packaging Regulations (Yes)	0.267	0.442	0.257	0.437	0.256	0.437	0.281	0.450
Retail Licensure on E-Cigarettes (Yes)	0.113	0.317	0.105	0.306	0.102	0.302	0.114	0.318
E-Cigarette Restrictions on Sales to Minors (Yes)	0.568	0.495	0.565	0.496	0.567	0.496	0.587	0.492
E-Cigarette SFA Laws (Yes)	0.081	0.273	0.066	0.249	0.061	0.240	0.058	0.234
Cigarette SFA Laws (Yes)	0.683	0.465	0.663	0.473	0.663	0.473	0.667	0.471
Medicaid Cover Tobacco (Yes)	0.420	0.494	0.402	0.490	0.407	0.491	0.414	0.493
C. Ecig Taxes Not in V.Tax Regions ($/ml)	0.287	1.281	C. Cig Taxes Not in V.Tax Regions ($/pack)				0.369	0.655
C. Ecig Taxes Not in P.Tax Regions ($/ml)	0.007	0.097	C. Cig Taxes Not in P.Tax Regions ($/pack)				0.312	0.598

Source: Author's calculations for data from the Nielsen Consumer Panel Data, the CDC STATE System, state government websites, and others. Note: Timespan is 2012 through 2018. Summary statistics are for all households or all ever-purchasers of a particular product. Changes in e-cigarette taxes and cigarette taxes are compared to 2009; all taxes are inflation-adjusted by CPI to the level of 2018Q4. SCP denotes smoking-cessation products. Ecig means e-cigarette. C. means changes in.

Table 2.3 Results of Purchase Probability and Purchase Amount

Panel A1 (Sample: All HHs in All Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.0001 (0.0004)	0.001 (0.005)	0.0001 (0.0001)	0.002* (0.001)	-0.0002** (0.0001)	-0.003*** (0.001)
Changes in Cig Taxes ($/pack)	-0.003* (0.002)	-0.052** (0.024)	0.0001 (0.0003)	0.001 (0.004)	0.0003 (0.0003)	0.005 (0.005)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.0008*** (0.0003)	0.013*** (0.004)
Observations	1,624,373	1,624,373	1,624,373	1,624,373	1,624,373	1,624,373

Panel A2 (Sample: All HHs Not in V.Tax Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.0002 (0.0004)	0.002 (0.005)	0.0001 (0.0001)	0.002* (0.001)	-0.0001* (0.0001)	-0.002* (0.001)
Changes in Cig Taxes ($/pack)	-0.004** (0.002)	-0.062** (0.030)	0.0001 (0.0003)	0.001 (0.004)	0.0002 (0.0003)	0.003 (0.005)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.0009*** (0.0003)	0.016*** (0.004)
Observations	1,465,147	1,465,147	1,465,147	1,465,147	1,465,147	1,465,147

Panel A3 (Sample: All HHs Not in P.Tax Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.002*** (0.001)	0.029*** (0.010)	0.0005*** (0.0002)	0.007*** (0.002)	-0.0007*** (0.0002)	-0.012*** (0.003)
Changes in Cig Taxes ($/pack)	-0.008*** (0.003)	-0.110*** (0.040)	0.0002 (0.0005)	0.002 (0.007)	-0.00002 (0.0005)	0.00001 (0.008)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.0006** (0.0002)	0.010*** (0.004)
Observations	1,352,022	1,352,022	1,352,022	1,352,022	1,352,022	1,352,022

Source: Author's calculations from the Nielsen Consumer Panel Data and policies. Timespan is 2012-2018. Regressions are purchase probabilities and amounts of a product by all households. Compared to A1, A2 removes households who resided in the V.Tax regions, and A3 deletes those who were in the P.Tax regions. Regressions include household fixed-effects (FE) and year by quarter time FE. Robust standard errors in parentheses are clustered by state. NS means not statistically significant; results are not displayed. Levels of statistical significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 2.3 Results of Purchase Probability and Purchase Amount (Continued)

Panel B1 (Sample: Ever-Purchasers in All Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.001 (0.002)	0.012 (0.025)	0.004 (0.003)	0.066 (0.048)	-0.005*** (0.001)	-0.080*** (0.023)
Changes in Cig Taxes ($/pack)	-0.013** (0.006)	-0.204** (0.087)	0.005 (0.010)	0.056 (0.130)	0.004 (0.008)	0.073 (0.124)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.018*** (0.006)	0.291*** (0.091)
Observations	378,103	378,103	50,595	50,595	63,393	63,393

Panel B2 (Sample: Ever-Purchasers Not in V.Tax Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.001 (0.002)	0.018 (0.027)	0.004 (0.003)	0.061 (0.046)	-0.004** (0.002)	-0.065** (0.025)
Changes in Cig Taxes ($/pack)	-0.015** (0.008)	-0.246** (0.107)	0.006 (0.011)	0.081 (0.149)	0.0003 (0.009)	0.006 (0.145)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.020*** (0.006)	0.342*** (0.092)
Observations	338,997	338,997	45,630	45,630	57,978	57,978

Panel B3 (Sample: Ever-Purchasers Not in P.Tax Regions)

	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Changes in Ecig Taxes ($/ml)	0.010** (0.004)	0.114** (0.056)	0.014*** (0.004)	0.199*** (0.048)	-0.018*** (0.005)	-0.306*** (0.073)
Changes in Cig Taxes ($/pack)	-0.028*** (0.009)	-0.407*** (0.131)	0.008 (0.015)	0.103 (0.202)	-0.001 (0.010)	0.016 (0.158)
Ecig Packaging Regulations (Yes)	NS	NS	NS	NS	0.016*** (0.005)	0.262*** (0.088)
Observations	317,501	317,501	43,572	43,572	53,439	53,439

Source: Author's calculations from the Nielsen Consumer Panel Data and policies. Timespan is 2012-2018. Ever-purchasers are households that purchased the particular product at least once. Regressions are purchase amounts of a product by the ever-purchasers of the corresponding product. Regressions include household fixed-effects (FE) and year by quarter time FE. Robust standard errors in parentheses are clustered by state. NS means not statistically significant; results are not displayed. Levels of statistical significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 2.4 Robustness Estimates (Ever-Purchasers Not in P.Tax Regions)

	Cig Ever-Purchasers		Ecig Ever-Purchasers		SCP Ever-Purchasers	
Effects of E-Cigarette Taxes ($/ml)	Cig Purchase		Ecig Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
Add HH Charicteristics (HH Fixed Effects)	0.010**	0.120**	0.016***	0.215***	-0.017***	-0.289***
	(0.004)	(0.058)	(0.004)	(0.056)	(0.005)	(0.076)
N	317,501	317,501	43,572	43,572	53,439	53,439
Add HH Charicteristics (County Fixed Effects)	0.048***	0.705***	-0.001	-0.037	-0.059***	-1.031***
	(0.013)	(0.202)	(0.008)	(0.112)	(0.011)	(0.199)
N	317,686	317,686	43,581	43,581	53,456	53,456
Add HH Charicteristics (State Fixed Effects)	0.007*	0.067	-0.001	-0.001	-0.029***	-0.487***
	(0.004)	(0.053)	(0.005)	(0.006)	(0.005)	(0.082)
N	317,686	317,686	43,801	43,801	53,456	53,456
Standard Errors Clustered at County	0.010**	0.114	0.014***	0.199**	-0.018***	-0.306***
	(0.005)	(0.070)	(0.004)	(0.058)	(0.005)	(0.078)
N	317,501	317,501	43,572	43,572	53,439	53,439
E-Cigarette Tax Indicator (Yes)	0.012**	0.182**	0.009	0.124	0.007	0.085
	(0.005)	(0.072)	(0.007)	(0.085)	(0.012)	(0.201)
N	317,501	317,501	43,572	43,572	53,439	53,439
E-Cigarette Tax Based on Nielsen	0.015***	0.147***	0.015***	0.185***	-0.022***	-0.351***
Retail Scanner Data (2012-2017)	(0.003)	(0.045)	(0.003)	(0.046)	(0.004)	(0.060)
N	277,942	277,942	38,366	38,366	46,571	46,571

Source: Author's calculations from the Nielsen Consumer Panel Data and policies. Timespan is 2012-2018. Ever-purchasers are households that purchased the particular product at least once. Regressions are purchase amounts of a product by the ever-purchasers of the corresponding product. All regressions include household and year by quarter fixed-effects. Unless indicated, regressions do not control for household characteristics. State-specific linear time trends are not included because of redundancy with the two-way fixed effects. Robust standard errors clustered by state or county are in parentheses. Levels of statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5 Heterogeneity Estimates

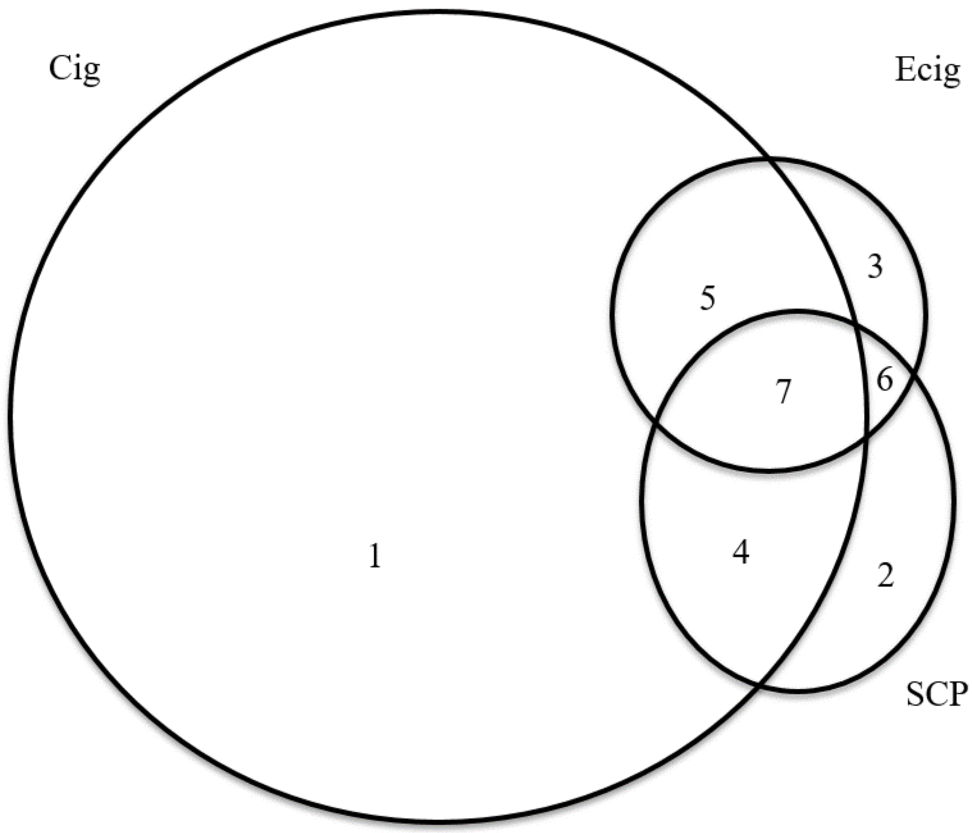
Heterogeneity Estimates for Effects of E-Cigarette Taxes	**Cigarette Purchase**		**E-Cigarette Purchase**		**SCP Purchase**	
	Probability	Amount	Probability	Amount	Probability	Amount
(1) Cig Only Purchasers	0.001	0.010	/	/	/	/
in All Regions	(0.002)	(0.030)				
N	304,964	304,964				
(2) Cig Only Purchasers	0.001	0.017	/	/	/	/
Not in V.Tax Regions	(0.002)	(0.032)				
N	273,029	273,029				
(3) Cig Only Purchasers	0.006	0.066	/	/	/	/
Not in P.Tax Regions	(0.005)	(0.076)				
N	254,843	254,843				
(4) SCP Only Purchasers	/	/	/	/	-0.007***	-0.120***
in All Regions					(0.002)	(0.037)
N					21,915	21,915
(5) SCP Only Purchasers	/	/	/	/	-0.008***	-0.123***
Not in V.Tax Regions					(0.003)	(0.040)
N					20,237	20,237
(6) SCP Only Purchasers	/	/	/	/	-0.014	-0.322
Not in P.Tax Regions					(0.012)	(0.198)
N					18,219	18,219
(7) Ecig Only Purchasers	/	/	0.009*	0.131*	/	/
in All Regions			(0.005)	(0.068)		
N			7,466	7,466		
(8) Ecig Only Purchasers	/	/	0.005	0.085	/	/
Not in V.Tax Regions			(0.005)	(0.064)		
N			6,661	6,661		
(9) Ecig Only Purchasers	/	/	1.150***	14.660***	/	/
Not in P.Tax Regions			(0.201)	(2.742)		
N			6,493	6,493		
(10) Dual Purchasers of Cig & SCP	0.007	0.089	/	/	-0.003	-0.041
No Ecig in All Regions	(0.004)	(0.065)			(0.002)	(0.034)
N	31,112	31,112			31,112	31,112
(11) Dual Purchasers of Cig & SCP	0.008*	0.102	/	/	-0.002	-0.026
No Ecig Not in V.Tax Regions	(0.004)	(0.066)			(0.002)	(0.033)
N	28,056	28,056			28,056	28,056
(12) Dual Purchasers of Cig & SCP	0.026***	0.354***	/	/	-0.005	-0.120**
No Ecig Not in P.Tax Regions	(0.009)	(0.130)			(0.004)	(0.061)
N	26,512	26,512			26,512	26,512
(13) Dual Purchasers of Cig & Ecig	-0.011	-0.153	0.004	0.073	/	/
No SCP in All Regions	(0.007)	(0.102)	(0.004)	(0.055)		
N	32,763	32,763	32,763	32,763		
(14) Dual Purchasers of Cig & Ecig	-0.012	-0.162	0.004	0.067	/	/
No SCP Not in V.Tax Regions	(0.007)	(0.104)	(0.004)	(0.055)		
N	29,284	29,284	29,284	29,284		
(15) Dual Purchasers of Cig & Ecig	0.001	0.038	0.020***	0.299***	/	/
No SCP Not in P.Tax Regions	(0.008)	(0.123)	(0.005)	(0.065)		
N	28,371	28,371	28,371	28,371		

Table 2.5 Heterogeneity Estimates (Continued)

Heterogeneity Estimates for Effects of E-Cigarette Taxes	Cigarette Purchase		E-Cigarette Purchase		SCP Purchase	
	Probability	Amount	Probability	Amount	Probability	Amount
(16) Dual Purchasers of Ecig & SCP	/	/	-0.003	-0.054	-0.011	-0.151
No Cig in All Regions			(0.009)	(0.123)	(0.025)	(0.398)
N			1,102	1,102	1,102	1,102
(17) Dual Purchasers of Ecig & SCP	/	/	-0.017	-0.236	-0.001	-0.018
No Cig Not in V.Tax Regions			(0.013)	(0.191)	(0.024)	(0.393)
N			1,057	1,057	1,057	1,057
(18) Dual Purchasers of Ecig & SCP	/	/	0.081***	1.089***	-0.111***	-1.607***
No Cig Not in P.Tax Regions			(0.015)	(0.216)	(0.029)	(0.446)
N			933	933	933	933
(19) Triple-Purchasers of Cig &	0.010	0.143	0.002	0.022	-0.007	-0.133*
Ecig & SCP in All Regions	(0.006)	(0.094)	(0.007)	(0.090)	(0.005)	(0.072)
N	9,264	9,264	9,264	9,264	9,264	9,264
(20) Triple-Purchasers	0.006	0.100	0.003	0.040	-0.004	-0.078
Not in V.Tax Regions	(0.006)	(0.091)	(0.007)	(0.089)	(0.005)	(0.074)
N	8,628	8,628	8,628	8,628	8,628	8,628
(21) Triple-Purchasers	0.118***	1.484***	-0.070***	-1.020***	-0.038***	-0.621*
Not in P.Tax Regions	(0.019)	(0.305)	(0.010)	(0.144)	(0.019)	(0.308)
N	7,775	7,775	7,775	7,775	7,775	7,775
(22) Cig Only Pack-a-Day	/	-0.032***	/	/	/	/
in All Regions		(0.004)				
N		10,752				
(23) Cig Only Pack-a-Day	/	-0.033***	/	/	/	/
Not in V.Tax Regions		(0.005)				
N		9,709				
(24) Cig Only Pack-a-Day	/	-0.014	/	/	/	/
Not in P.Tax Regions		(0.012)				
N		9,376				
(25) Cig Only Intermediate	/	-0.004	/	/	/	/
in All Regions		(0.004)				
N		11,908				
(26) Cig Only Intermediate	/	-0.002	/	/	/	/
Not in V.Tax Regions		(0.004)				
N		10,631				
(27) Cig Only Intermediate	/	-0.006	/	/	/	/
Not in P.Tax Regions		(0.006)				
N		10,337				
(28) Cig Only Occasional	0.0004	0.003	/	/	/	/
in All Regions	(0.002)	(0.031)				
N	280,104	280,104				
(29) Cig Only Occasional	0.001	0.004	/	/	/	/
Not in V.Tax Regions	(0.002)	(0.033)				
N	250,769	250,769				
(30) Cig Only Occasional	0.008**	0.102**	/	/	/	/
Not in P.Tax Regions	(0.004)	(0.049)				
N	233,190	233,190				

Table 2.5 Heterogeneity Estimates (Continued)

Source: Author's calculations from the Nielsen Consumer Panel dataset and policies from the CDC STATE database and state government websites. Timespan is 2012-2018. Purchasers are households that have purchased the particular product at least once. Cig means cigarettes; Ecig stands for e-cigarettes; SCP refers to smoking-cessation products. All regressions include household fixed effects (FE) and year by quarter time FE. Robust standard errors clustered by the state are in parentheses. Levels of statistical significance: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.



1: Cig Only Purchasers
2: SCP Only Purchasers
3: Ecig Only Purchasers
4: Dual Purchasers of Cig & SCP but No Ecig
5: Dual Purchasers of Cig & Ecig but No SCP
6: Dual Purchasers of Ecig & SCP but No Cig
7: Triple Purchasers of Cig & Ecig & SCP

Figure 2.1 Dissection of Purchases by Ever-Purchasers of the Three Products

Source: Author's calculations of purchase data from the Nielsen Consumer Panel Data.
Note: Cig denotes cigarettes. Ecig refers to e-cigarettes. SCP symbolizes smoking-cessation products. N denotes the number of observations for the household by quarter combinations.

CHAPTER 3. AN EMPIRICAL ANALYSIS OF E-CIGARETTE ADDICTION

3.1 Introduction

Most e-cigarettes contain nicotine, a highly addictive substance (U.S. Department of Health and Human Services, 2016). Nicotine is also toxic and harmful, especially for youth and pregnant women. However, e-cigarettes are the most commonly used tobacco product among youth now. According to the Centers for Disease Control and Prevention (2020a), about one in three high school students reported current e-cigarette use in 2019; average monthly sales of e-cigarettes increased 122 percent from 2014 to 2020 as price falls. It is of interest to ask whether the addictive nature of this relatively new tobacco product is apparent addictive from data on consumption.

Becker and Murphy (1988) propose a rational addiction model incorporating the influences of past and current consumption for lifetime utility-maximizing consumers. In their model, past consumption is reinforcing for addictive goods: high levels of past consumption reinforces the desire for current consumption and increases the marginal utility of current consumption. Their model also indicates that consumers are rational or forward-looking in that they anticipate the expected future consequences of their current actions. This feature differs their model from myopic models of addictive behavior which ignoring the effect of future consumption when consumers make consumption decisions. Therefore, the rational addiction model of Becker and Murphy (1988) suggests that the consumption of an addictive good will depend on both future and past consumptions. It has the inter-temporal, dependent demand structure or "adjacent complementarity" (Ryder and Heal, 1973). This rational addiction model is also a type of the rational choice model (Calvert, 1985), which focuses on the dynamics of current consumption in response to future prices of addictive goods.

Tests of addiction have been applied to several different goods. However, there is no research investigating the role of addiction in influencing the demand for e-cigarettes. Since most e-cigarettes contain nicotine, a highly addictive substance, it is worth evaluating how addiction to e-cigarettes influences the demand. Thus, this essay aims to fill the literature gap. Evidence from this research can facilitate policymakers' decisions on regulating the consumption of e-cigarettes and provide evidence to address concerns of public health.

Regarding empirical research on addiction, several researchers test cigarette addiction and find evidence of that. Among them, using aggregated state-level yearly purchase data in 1955-1985 and fixed-effects two-stage least squares (2SLS) estimations, Becker and Murphy (1994) reach an estimate of -0.78 for the long-run price elasticity of cigarette consumption and an estimate of -0.44 for the short-run price elasticity. With similar data, Baltagi and Griffin (2001) revisit the estimation of Becker and Murphy (1994) but use a forward-filter first-difference 2SLS and a generalized method of moment estimator. They find evidence that is consistent with rational addiction but reach different estimates from different estimators: the short-run price elasticity ranges between -0.28 and -0.86 and the long-run price elasticity varies from -0.56 to -2.55. Instead of using aggregated data, Chaloupka (1991) applies a micro data set and finds a long-run price elasticity of cigarette consumption ranging between -0.48 and -0.27.

Other researchers also evaluate cigarette taxation and demand using a dynamic model that incorporates consumers' rational addiction. For example, Gordon and Sun (2015) use Nielsen Household Panel Data from two submarkets in a large Midwestern city over 118 weeks; they reach a long-run price elasticity of cigarette consumption at -0.63 and a short-run price elasticity of -0.35. Sung et al. (1994) investigate the effects of cigarette taxes on cigarette yearly consumption of 11 western states and find evidence of rational addiction; they obtain a short-run demand elasticity of -0.40 and an estimate of -0.48 for the long-run demand elasticity. The results of these articles show that a model incorporating addiction is valid and a tax-increase reduces consumption more in the long-run than in the short-run.

Moreover, researchers have also empirically analyzed rational addiction to other goods in numerous research. For example, Grossman and Chaloupka (1998) show evidence of rational addiction to cocaine by young adults and find an estimate of -1.35 for the long-run price elasticity of consumption. On alcohol rational addiction, Baltagi and Griffin (2002) get a short-run price elasticity of -0.10 and a long-run price elasticity of -1.24; Grossman et al. (1998) show that alcohol is less addictive than are cigarettes, and they get an average short-run price elasticity of -0.41 and an average long-run price elasticity of -0.65. Additionally, Olekalns and Bardsley (1996) test caffeine addiction in coffee consumption; Cameron (1999) has examined rational addiction and the demand for cinema; Cawley (2000) examines the rational addiction to calorie consumption regarding eating patterns; Mobilia (1993) provides evidence of rational addiction in gambling; Kwon et al. (2016) suggest that consumers are rationally addicted to mobile social apps. Richards et al. (2007) show evidence of carbohydrate addiction.

Many of this literature uses ordinary least squares (OLS) and fixed-effects 2SLS methods to estimate aggregate data. In comparison, the results of 2SLS are more variable than the OLS estimates. Although typically the coefficients on the lag and lead of consumption are positive, some specifications present negative or not statistically significant coefficient estimates for past and future consumptions. This might be due to the good is not addictive or consumers cannot anticipate future price movements. Lastly, estimates of the discount factor are highly variable and in some cases negative.

This essay uses Nielsen Retail Scanner Data for weekly e-cigarette purchases throughout 2012-2017 in each region[43]. The purchase data are used to approximate the consumption of a representative consumer. This limitation may affect the generalization of the results. This essay starts with a myopic model to test addiction and shows that consumers are addicted to e-cigarettes. Then, with a forward-looking model, this essay finds evidence that consumers consider the future for their current e-cigarette consumption. With this evidence, I test both the elements of addiction and rationality in a rational model using the strategy of fixed-effects 2SLS. In the estimations, I compare results of OLS with 2SLS using different sets of IVs, including policies, prices, and taxes. Results in all these models are consistent with the rational model predictions. I reach a short-run price elasticity of demand around -1.05 and a long-run price elasticity estimate of -1.50 from the 2SLS estimations. These results could not provide a precise estimate for the discount factor, nevertheless, I show that restricting the discount factor to different numbers would not influence estimates of the elasticities. Additionally, compared to cigarette addiction, I find evidence that e-cigarettes are less addictive.

The rest of this essay presents as follows. The next section introduces the theory behind the model and the model specification in my empirical analysis. The data section explains the data source and variables in the model. The last two sections review the results and conclude the essay.

3.2 Model Specification

According to the nature of addiction, consumption is dynamic. Utility in the current period depends on the consumption in the same period and that in the previous period. Following Becker, Grossman, & Murphy (1994) (BGM), the consumer's problem is to maximize the lifetime utility

$$\max \sum_{t=1}^{\infty} \beta^{t-1} \, \mathrm{U}(Y_t \, , C_t \, , C_{t-1}, e_t) \tag{1}$$

$$\text{such that } C_0 = C^0 \text{ and } \sum_{t=1}^{\infty} \beta^{t-1} (Y_t + P_t \, C_t) = A^0 \tag{2}$$

[43] In most cases, a region is the same as a state, except for adjusting local jurisdictions with e-cigarette taxes; accordingly, Illinois and Maryland become five regions including Chicago, Cook County in Illinois, the rest of Illinois, Montgomery County in Maryland, and the rest of Maryland.

where $\beta = 1/(1 + \mathrm{r})$ assuming the rate of interest is equal to the rate of time preference, C_t and C_{t-1} are the quantities of e-cigarettes consumed in period t and period $\mathrm{t} - 1$. Furthermore, Y_t is the consumption of a composite commodity in period t and is taken as the numeraire, e_t denotes the impact of unmeasured life-cycle variables on utility, C_0 measures the initial level of e-cigarette consumption in period zero, P_t is the price of e-cigarettes in period t, and A^0 is the present value of wealth, ignoring any effect of C on earnings or wealth.

This two goods model assumes the utility function is quadratic in Y_t , C_t, and e_t . Solving the first-order conditions for Y_t , and substituting the result into the first-order condition for C_t, BGM gets a first-difference equation, in which the current e-cigarette consumption is a function of the past and future e-cigarette consumption, the current price of e-cigarettes, and the shift variables e_t and e_{t+1}:

$$C_t = \theta C_{t-1} + \beta\theta C_{t+1} + \theta_1 P_t + \theta_2 e_t + \theta_3 e_{t+1} \quad (3).$$

In this equation, θ measures the effect of changes in past or future consumption on current consumption depending on the sign of this term. The definition that a good is addictive is when $\theta > 0$. The larger is θ, the larger is the degree of addiction. See (Becker et al., 1994, pp. 398–399) for the restrictions on the coefficients. Recognizing that e_t is serially correlated affecting utility in each period and consumption at all periods through the optimizing behavior, BGM treat C_{t-1} and C_{t+1} as endogenous. To resolve the issue of potential inconsistent parameter estimates by OLS estimations, they use past and future prices as instrument variables (IVs) for C_{t-1} and C_{t+1}, if the unobservables are uncorrelated with prices in these periods. Also, BGM includes other exogenous variables such as income, short and long-distance smuggling indexes, and taxes. Alternatively, Olekalns and Bardsley (1996) provide a rational addiction model including leads and lags of prices as independent variables.

For my empirical estimation, I write a variant of (3) for a representative consumer as follows:

$$C_{i,y,t} = \gamma_0 + \theta C_{i,y,t-1} + \beta\theta C_{i,y,t+1} + \theta_1 P_{i,y,t} + \gamma_1 Y_{i,y} + \boldsymbol{\delta X}_{i,y,t} + \sigma_i + \tau_{y,t} + \varepsilon_{i,y,t} \quad (4)$$

where the subscript i denotes the ith region and the subscript t denotes the tth week in year y. $C_{i,y,t}$ is the log of the total consumption of e-cigarettes (measured as total units of e-cigarettes purchased) for region i at week t in year y. Similarly, $C_{i,y,t-1}$ denotes the log of the e-cigarette consumption in the previous week; and $C_{i,y,t+1}$ represents the e-cigarette consumption in the one-period following week. $P_{i,y,t}$ is the log of the purchase weighted average weekly retail price of e-cigarettes per unit. $Y_{i,y}$ indicates the per capita income in region i and year y. As in BGM, θ measures the addictiveness of e-cigarettes; β is the rate of time preference assuming it is equal to the rate of interest. Positive coefficient estimates for $C_{i,y,t-1}$ and $C_{i,y,t+1}$ indicate that e-cigarettes are economically addictive and consumers are forward-looking for e-cigarettes consumption, respectively.

Furthermore, $\boldsymbol{X}_{i,y,t}$ is a matrix of related observable policy covariates. These policies contain a continuous change in cigarette excise taxes per pack compared to 2009 in region i, year y, and week t; whether a region in a week of a year requires licenses for over-the-counter sales of e-cigarettes, restricts sales of e-cigarettes to minors, and has an SFA law that restricts uses of e-cigarettes. $\boldsymbol{\delta}$ is a vector of unknown parameters, representing the average mean effects of each of these policies over time. Moreover, σ_i is region fixed-effects, controlling for unobserved non-time varying differences in demand across regions, for example, the marginal utility of wealth for a region in a model with perfect foresight; $\tau_{y,t}$ is year-week or weekly fixed-effects, controlling for unobserved differences in demand over time that are commonly shared by regions; and $\varepsilon_{i,y,t}$ represents the unobserved time and region varying error term. With these fixed-effects applied in the model, γ_1 reflects forces associated with region-specific changes in the marginal utility of wealth over time.

This model does not directly estimate the effects of e-cigarette taxes on the current period of consumption but infers their effects indirectly when these taxes are used as IVs for the lagged and future consumptions if these consumptions are endogenous. In that case, the results section further discusses variables, in addition to e-cigarette taxes, used as IVs in regressions. Moreover, prices, taxes, and income are inflation-adjusted to the level of 2018 December with the monthly consumer price index (CPI)[44] obtained from the Bureau of Labor Statistics. Furthermore, this model does not capture smuggling indexes. This is because, unlike cigarette taxes, current e-cigarette taxes are newly imposed and have lower rates on average if a region has a tax in place. As a result, e-cigarette taxes may not cause sizable "border purchasing effects" or smuggling effects as that of cigarettes (Becker et al., 1994), or alcohol (Baltagi and Griffin,1995).

44 I apply non-cigarette tobacco CPI for e-cigarette prices and taxes, cigarette CPI for cigarette excise taxes, and all goods CPI for per capita income.

Also, following BGM, solving the second-order condition of equation (4) would obtain the roots of the following quadratic equation:

$$-\theta\phi^2 + \phi - \theta\beta = 0. \tag{5}$$

The two roots are

$$\phi_1 = \frac{1-(1-4\theta^2\beta)^{1/2}}{2\theta} \qquad \phi_2 = \frac{1+(1-4\theta^2\beta)^{1/2}}{2\theta}, \tag{6}$$

with $4\theta^2\beta < 1$ by concavity. Both of these roots are real and positive if and only if e-cigarettes are addictive ($\theta > 0$). These estimates can be used to derive derivatives of consumption changes with respect to e-cigarette price changes (see Appendix A in Becker et al., 1994 for a series of consumption responses to price changes). As the prices and consumptions in equation (4) are in log forms, the derivatives obtained represent elasticities in this case.

These elasticity estimates contain short- and long-run demand elasticities for e-cigarettes, own-price anticipated effects and unanticipated effects, future-price unanticipated effects, as well as past-price unanticipated effects on the current consumption, $C_{i,y,t}$. The cross-price elasticities between e-cigarette consumption levels at different spots of time reflects the importance of addiction to aggregate e-cigarette consumption. In the model, when $P_{i,y,t}$ decreases, it will increase e-cigarette consumption in the current period, $C_{i,y,t}$, and that in the next period, $C_{i,y,t+1}$, if e-cigarettes are addictive. If this price decrease is anticipated, the rise in the current period consumption also stimulates the consumption in the previous period, $C_{i,y,t-1}$. By accumulating decreases in the current price and future prices, a permanent decrease in e-cigarette price has a larger effect on current consumption than that does by a temporary fall in price.

3.3 Data

The data of e-cigarette weekly purchase quantities and prices are from the Nielsen Retail Scanner Data between January 1, 2012, and December 30, 2017[45], in the U.S. The earliest and usable[46] data for e-cigarette purchases in this dataset begins in 2012. E-cigarette sales include total e-cigarette starter kits, refill cartridges, and disposables for a variety of outlets such as convenience

45 The latest data available when I started this article was the 2017 data. Later, Nielsen has the 2018 data available. Adding additional data from one more year would not change much of my results, as when I removed the data in 2012 or 2017, results are similar to that with the data included.

46 Some e-cigarette purchases happened before 2012 are missing because many states did not sell e-cigarettes then.

stores, drug stores, and mass merchandisers. The total number of regions is 52, including all states and the District of Columbia, except for Illinois and Maryland; these two states are represented by five regions: Chicago, Cook County in Illinois, the rest of Illinois, Montgomery County in Maryland, and the rest of Maryland. Purchases for Alaska, Puerto Rico, U.S. Virgin Islands, and Hawaii are not available in the Nielsen data set so they are not included in the list of regions. There are 313 weeks in total. Overall, these regions and weeks constitute 16,276 observations of e-cigarette purchases in region-week combinations. Regions do not have gaps in purchases in time.

Aside from the purchase data from Nielsen, the population data for each region in each year estimated on July 1, in thousands of persons, is from the U.S. Census Bureau. Adjusting purchases of e-cigarettes with these population data obtain purchases of e-cigarettes by per thousand of persons. The per capita personal income in a region and a year is from the Bureau of Economic Analysis. It is total personal income divided by the total midyear population. The policy data is from the Centers for Disease Control and Prevention's State Tobacco Activities Tracking and Evaluation (STATE) System (2020b), the Campaign for Tobacco-Free Kids (2020a, 2020b), and Public Health Law Center (2020), government websites, and consultations with designated officials of state and local jurisdictions.

In the models of this paper, e-cigarette taxes are in dollars per milliliter ($/ml). If a region-week combination has an e-cigarette tax, the tax variable indicates the dollar amounts per ml; otherwise, the tax variable is zero. This paper converts the original policy data of e-cigarette taxes into this measurement by first matching the purchase data with e-cigarette characteristics[47] (See Appendix1 in my first essay, Deng (2020), for details of the conversion). The reason for the conversion is because the original policy data for e-cigarette taxes are not in the same measurement; some jurisdictions apply ad valorem taxes by percentages of wholesale or retail prices, other jurisdictions tax e-cigarettes by specific excise taxes on per ml of the liquid contained in the product. For example, Minnesota taxed e-cigarettes at 95% of the wholesale price in 2013 March and after; North Carolina imposed an e-cigarette tax at $0.050 per ml of the liquid in 2015 October and after. Aside from e-cigarette taxes, changes in cigarette excise taxes are dollars per pack compared to 2009 with zeroes indicate no tax changes; for other policies, if a region-week combination has a particular policy in place, the corresponding policy variable equals to one, otherwise, it equals to zero. Additionally, prices, income, and taxes are all inflation-adjusted by

---

[47] These e-cigarette characteristics are from Cotti et al., (2018) and Cotti et al., (2020). These authors are acknowledged for their generosities of sharing the data.

CPI to the level of 2017 December. Table 3.1 shows a descriptive analysis of the variables in this paper.

3.4 Results

I start my estimation strategy with a myopic addiction model then continue with a forward-looking model in Table 3.2. With these results as a foundation, I test a rational addiction model in Table 3.3. Table 2 shows the results of myopic addiction behaviors and forward-looking behaviors separately. An addiction model predicts that the previous consumption reinforcing the current consumption. If the goods were addictive, the coefficient of previous consumption would be positive. Since the previous price ($P_{i,y,t-1}$) is a strong predictor of the previous consumption ($C_{i,y,t-1}$), using an OLS estimation, column (1) provides some evidence that e-cigarettes are economically addictive as the coefficient for $P_{i,y,t-1}$ is negative. Similarly, incorporating the previous consumption directly without the previous-period price, I have found the coefficient of $C_{i,y,t-1}$ is positive (not shown in table). However, as the model indicates, OLS estimates with the past consumption incorporated directly are inconsistent as $C_{i,y,t-1}$ depends on $e_{i,y,t}$ through the optimizing behavior implied in the first-order conditions. To resolve the endogenous variable problem for past consumption, following the literature, I obtain 2SLS estimates of myopic models of addiction.

In column (2), past price and other explanatory variables in equation (4) consist of the instruments for past consumption. On top of column (2), column (3) adds the one-period lag values of the e-cigarette tax to the instruments; column (4) further adds the current period e-cigarette tax; on top of all these, column (4) further adds the two-period lagged price and the corresponding tax to the instrument list. According to the parameter estimates of the myopic model in Table 3.2, current price negatively relates to current e-cigarette consumption but income positively relates to that. The positive and statistically significant estimates for past consumption indicate that e-cigarette using is addictive. Except for restrictions of sales to minors get a negative coefficient, all policies get positive coefficient estimates (hold for all estimations in tables).

The forward-looking specifications suppose consumers take into account the amount that they would consume in the future for their current levels of e-cigarette consumption. Similar to past consumption, future consumption would be endogenous if incorporated directly into the model for current consumption because $C_{i,y,t}$ depends on $e_{i,y,t+1}$ through the optimizing behavior. The results of such a regression with OLS estimation indicates that consumers are forward-looking for e-cigarettes consumption (results not shown in table). In a similar fashion as the myopic model, column (6) shows that future price negatively influences current consumption, again suggesting that consumers are forward-looking. Columns (7) – (10) use different sets of instruments for future consumption. In column (7), future price and other explanatory variables in equation (4) work as the instruments for future consumption. On top of column (7), column (8) adds the one-period lead values of the e-cigarette tax to the instruments; column (9) further adds the current period e-cigarette tax; on top of all these, column (10) further adds the two-period lagged price and the corresponding tax to the instrument list. All of these specifications show that consumers are forward-looking as the coefficient estimates for the future consumption are all positive and statistically significant.

What separates a myopic addiction model from a rational addiction model is that the rational addiction model supposes that consumers are both addictive and forward-looking for e-cigarette consumption, while the myopic addiction model implies that consumers would not take the future amount of consumption into account at the current period consumption. Thus, if the data supports the myopic addiction model, the coefficient of the lagged consumption would be positive and statistically significant and the coefficient of the lead consumption or price would not be statistically significant. In contrast, the rational addiction model predicts the coefficient of the lead consumption would be positive and statistically significant. The OLS estimates in column (1) of Table 3.3 shows evidence of rational addiction.

To resolve the inconsistency problem as in Table 3.2, I use IVs for the endogenous lagged and lead consumptions in the 2SLS specifications. In Table 3.3, the instruments in column (2) consist of the one-period lag and lead of prices respectively for the corresponding consumption and other explanatory variables in the model. On top of column (2), column (3) adds the one-period lag and lead of taxes to the corresponding consumption. With these IVs included, column (4) further adds the current period tax as an IV; column (5) additionally adds the two-period lagged price and tax to the instrument list. All of these specifications are consistent with the hypothesis that consumers are rationally addicted to e-cigarettes as the coefficient estimates for the future and past consumptions are both positive and statistically significant. In these specifications, containing taxes as IVs is because consumers may have more information about taxes than prices. The inclusion of both taxes and prices as IVs allows for the possibility that consumers have information about the tax-exclusive price.

Based on corresponding columns in Table 3.3, Table 3.4 shows additional parameter estimates and elasticities of e-cigarette consumption in response to various price changes at the sample means of price and consumption. Consistent with the predictions of the rational model, the estimates of the discount factor β are positive and the two roots of equation (6) are positive. Unanticipated price change assumes that the price change is not anticipated until the corresponding period. In the 2SLS estimations, a 10-percent temporary increase in the current price of e-cigarettes would decrease current consumption by 6.9-8.8 percent if the price change is anticipated; in contrast, it would decrease current consumption by 6.1-8.5 percent if it is unanticipated (see rows for own price anticipated and unanticipated in Table 3.4). As to cross-price effects, a 10-percent unanticipated increase in current price leads to a 2.3-2.6 percent decrease in the previous period's consumption (see the row for future price unanticipated) and to a 1.2-1.8 percent decrease in the next period's consumption (see the row for past price unanticipated).

Moreover, the long-run response of a permanent price change of 10 percent leads to a 13.6-14.9 percent decrease in demand. A 10-percent price increase causes a 10.5-11.8 percent decrease in e-cigarette consumption in the short-run. The estimates of the long-run price elasticity are 1.2-1.4 times of those for the short-run. All these elasticity estimates provide evidence that e-cigarettes are addictive and rational: past and future price changes have statistically significant influences on current consumption. However, the estimates for the discount factor in these specifications correspond to negative interest rates ranging between -0.323 to -0.513. Additionally, the OLS estimation provides support for rational addiction though the coefficient estimates could be inconsistent. Column (1) in Table 3.4 indicates that the long-run price elasticity in the OLS model is -3.304 and the short-run elasticity is -1.007. The estimates for the discount factor is 1.072, corresponding to an interest rate of -0.040.

Therefore, OLS and 2SLS estimations all provide evidence that consumers are rationally addicted to e-cigarettes; however, these estimations do not provide reliable estimates for the discount factor. Follow BGM, Table 3.5 imposes the discount factor a *priori*, ranging from 0.70 to 0.95 (interest rates ranging from 5.3 percent to 42.9 percent). This means that I constrain the coefficient for future consumption to equal to the imposed discount factor multiplied by the estimated coefficient of past consumption. Model specifications in Table 3.5 are similar to those of columns (2) and (3) in Table 3.3 except for separating the year-week fixed-effects into year fixed-effects, month fixed-effects, and week fixed-effects. The unrestricted estimates for price coefficients, past-consumption coefficients, long-run price elasticities, and short-run elasticities are very close to those of Table 3.3 and Table 3.4. Therefore, the results of Table 5 are comparable to those of the two tables.

Estimates of Table 3.5 indicate that regardless of the restrictions of the discount factor, estimates of the long-run and short-run price elasticities are very similar to each other. Further comparing these estimates in Table 3.3, column (4) is my preferred specification, which reaches a long-run price elasticity of about -1.50 and the short-run price elasticity of -1.05, as taxes seem to be important predictors for consumptions. The main difference between the OLS and 2SLS estimates is that OLS reaches -3.30 for the long-run price elasticity estimate and -1.01 for the short-run estimate.

The results in Tables 3.3 and 5 do not pin down the discount factor with precision. This problem is similar to other studies of aggregate consumption, the consumption of specific goods, or the consumption of leisure over time. Some of these studies reach very high-interest rates while others obtain low or negative interest rates as mine (Bover, O., 1991; Epstein and Zin, 1991; Hansen and Singleton, 1983; Hotz et al., 1988; Mankiw et al., 1985). Overall, my model estimates are not sensitive to the choice of discount factors. The long-run and short-run price elasticity estimates reached from different sets of instruments are similar to each other.

3.5 Conclusions

I first investigate the addictive behaviors and forward-looking behaviors and find corresponding evidence for these behaviors. Then I test a rational addiction model inspired by BGM. Results provide evidence that e-cigarettes are rationally addictive rather than myopically addictive. With the rational addiction model, my estimates for the long-run price elasticity is about -1.50 and for the short-run price elasticity is -1.05. These results indicate that e-cigarettes are price elastic. Using the same data source and analysis methods, I have conducted similar regressions for the consumption of cigarettes as a comparison for e-cigarettes (not shown in tables, available upon request). Results indicate that e-cigarettes are generally less addictive than cigarettes because the estimate of addictiveness measurement, coefficient for past consumption, for e-cigarettes (0.26) is smaller than that for cigarettes (0.49).

Furthermore, the estimate of short-run price elasticity of cigarette consumption is -0.48 while the estimate for e-cigarettes is very close to one (-1.05). This comparison shows that raising taxes on e-cigarettes, if the taxes influence consumption by increasing price, may not generate as many revenues as cigarette taxes in the short-run; however, e-cigarette tax could be a more effective temporary tool for tobacco control of e-cigarettes as the demand of the product is elastic. For both products, the long-run tax effects would be stronger than the short-run effects. Additionally, potential assumption violations could affect the results. These assumptions include consumers' time-consistent preferences and complete information for decision-making. Relaxing these assumptions and using micro-panel data could be potential research directions in the future.

Table 3.1 Descriptive Analysis

Variables	N= 16,276	
Purchase Variables and Income	Mean	Std. Dev.
E-Cigarette Price ($/unit)	6.008	1.217
Number of E-Cigarette Purchase (units)	6,447.228	6,745.038
E-Cigarette Purchases by Per Thousand of Population (units)	1.204	0.781
Yearly Region Level Per Capita Personal Income ($)	49,424.880	8,516.305
Policy Variables		
E-Cigarette Taxes ($/ml)	0.126	0.611
Changes in Cigarette Excise Taxes ($/pack)	0.317	0.612
Retail Licensure on E-Cigarettes (Yes)	0.144	0.351
E-Cigarette Restrictions on Sales to Minors (Yes)	0.579	0.494
E-Cigarette SFA Laws (Yes)	0.081	0.273

Source: Author's calculations for data from the Nielsen Retail Scanner Data, the CDC STATE System, state government websites, and others. *Note*: Timespan is 2012 through 2017. Changes in cigarette taxes are compared to 2009; E-cigarette price, income, and all taxes are inflation-adjusted by CPI to the level of 2017 December.

Table 3.2 Estimates of E-Cigarette Myopic Addiction and Forward-Looking Behaviors

Dependent Variable: $C_{i,y,t}$					
Myopic Addiction					
Variables	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2FSLS	(5) 2SLS
$C_{i,y,t-1}$		0.285***	0.372***	0.484***	0.557***
		(0.044)	(0.038)	(0.032)	(0.027)
$P_{i,y,t}$	-1.044***	-0.941***	-0.839***	-0.708***	-0.621***
	(0.057)	(0.058)	(0.049)	(0.042)	(0.036)
$Y_{i,y}$	0.492***	0.359***	0.326***	0.283***	0.255***
	(0.127)	(0.095)	(0.085)	(0.074)	(0.067)
$P_{i,y,t-1}$	-0.278***				
	(0.056)				
R-Squared	0.964				
Centered R^2		0.582	0.663	0.748	0.793
Uncentered R^2		0.582	0.663	0.748	0.793
N	16,276	16,276	16,276	16,276	16,276
Forward-Looking					
Variables	OLS	2SLS	2SLS	2SLS	2SLS
$C_{i,y,t+1}$		0.347***	0.436***	0.518***	0.589***
		(0.039)	(0.033)	(0.029)	(0.025)
$P_{i,y,t}$	-0.978***	-0.880***	-0.778***	-0.685***	-0.604***
	(0.058)	(0.051)	(0.043)	(0.037)	(0.033)
$Y_{i,y}$	0.488***	0.309***	0.273***	0.240***	0.211***
	(0.127)	(0.088)	(0.078)	(0.070)	(0.064)
$P_{i,y,t+1}$	-0.360***				
	(0.057)				
R-Squared	0.964				
Centered R^2		0.643	0.717	0.773	0.813
Uncentered R^2		0.643	0.717	0.773	0.813
N	16,224	16,224	16,224	16,224	16,224

Note: Model (2) includes a lagged price $P_{i,y,t-1}$ and policy variables as IVs for lagged consumption. In addition to the lagged price, model (3) adds a one-period lagged tax as IVs. On top of model (3), model (4) further adds the current tax as IVs; model (5) further adds a two-period lagged tax and price as IVs on top of the model (4). Models (6)-(10) are similar to models (2)-(5) for IVs, with a one-period lead price $P_{i,y,t+1}$ replace the one-period lagged price and a one-period lead tax replace the one-period lagged tax, and keeping the two-period lagged taxes and prices as IVs in the model (10). All regressions include region fixed-effects (FE), weekly dummies (year-week FE), yearly per capita income for each state, and policy variables. Variables for consumption, price, and income are in log form. Prices, taxes, and income are inflation-adjusted with CPI to the level of 2017 December. Robust standard errors are in the parentheses. *significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

Table 3.3 Estimates of E-Cigarette Rational Addiction: Dependent Variable = $C_{i,y,t}$

Variables	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
$C_{i,y,t-1}$	0.462***	0.130**	0.237***	0.259***	0.257***
	(0.013)	(0.057)	(0.046)	(0.042)	(0.041)
$C_{i,y,t+1}$	0.482***	0.267***	0.299***	0.371***	0.380***
	(0.013)	(0.055)	(0.046)	(0.041)	(0.040)
$P_{i,y,t}$	-0.184***	-0.819***	-0.656***	-0.549***	-0.542***
	(0.013)	(0.051)	(0.038)	(0.032)	(0.031)
$Y_{i,y}$	0.087***	0.295***	0.242***	0.206***	0.203***
	(0.044)	(0.082)	(0.067)	(0.058)	(0.058)
R-Squared	0.996				
Centered R^2		0.689	0.792	0.843	0.846
Uncentered R^2		0.689	0.792	0.843	0.846
N	16,224	16,224	16,224	16,224	16,224

Note: Model (2) includes a lagged price $P_{i,y,t-1}$, a lead price $P_{i,y,t+1}$, and policy variables as IVs for the lagged and the lead consumption. In addition to the lagged and lead prices, model (3) adds a one-period lagged tax and a lead tax as IVs. On top of model (3), model (4) further adds the current tax as IVs; model (5) further adds a two-period lagged taxes and prices as IVs on top of the model (4). All regressions include region fixed-effects (FE), weekly dummies (year-week FE), yearly per capita income for each state, and policy variables. Variables for consumption, price, and income are in log form. Prices, taxes, and income are inflation-adjusted with CPI to the level of 2017 December. Robust standard errors are in the parentheses. *significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

Table 3.4 Parameters and Elasticities Based on Model Results of Rational Addiction

Variables	(1) OLS	(2) 2SLS	(3) 2SLS	(4) 2SLS	(5) 2SLS
β	1.042***	2.052	1.261***	1.431***	1.477***
	(0.058)	(1.247)	(0.418)	(0.371)	(0.380)
Φ_1	0.725***	0.277***	0.324***	0.416***	0.426***
	(0.021)	(0.056)	(0.050)	(0.044)	(0.044)
Φ_2	1.438***	7.420**	3.889***	3.443***	3.465***
	(0.046)	(3.322)	(0.784)	(0.587)	(0.594)
Own Price:					
Anticipated	-0.559***	-0.883***	-0.776***	-0.700***	-0.694***
	(0.031)	(0.042)	(0.031)	(0.027)	(0.027)
Unanticipated	-0.277***	-0.850***	-0.711***	-0.615***	-0.608***
	(0.018)	(0.046)	(0.035)	(0.030)	(0.029)
Future Price:					
Unanticipated	-0.201***	-0.235***	-0.230***	-0.256***	-0.259***
	(0.013)	(0.043)	(0.033)	(0.025)	(0.025)
Past Price:					
Unanticipated	-0.193***	-0.115**	-0.183***	-0.179***	-0.176***
	(0.013)	(0.050)	(0.035)	(0.030)	(0.029)
LR-ε	-3.304***	-1.358***	-1.416***	-1.484***	-1.490***
	(0.196)	(0.035)	(0.039)	(0.044)	(0.044)
SR-ε	-1.007***	-1.175***	-1.052***	-1.053***	-1.060***
	(0.090)	(0.086)	(0.077)	(0.077)	(0.077)
Ratio of LR-ε to SR-ε	3.068	1.156	1.346	1.409	1.406

Notes: The standard errors for the parameters are approximate standard errors in parentheses. LR-ε represents long-run elasticity; SR-ε means short-run elasticity. Almost all the coefficients are statistically different from zero. *significant at the 0.1 level, ** significant at the 0.05 level, *** significant at the 0.01 level.

Table 3.5 Estimates of E-Cigarette Rational Addiction in Restricted Models

Dependent Variable = $\boldsymbol{C_{i,y,t}}$					
β	Model	$P_{i,y,t}$	$C_{i,y,t-1}$	LR-ε	SR-ε
0.70	(2)	-0.801	0.215	-1.261	-0.981
	(3)	-0.668	0.288	-1.307	-0.906
0.75	(2)	-0.800	0.209	-1.262	-0.989
	(3)	-0.667	0.280	-1.308	-0.917
0.80	(2)	-0.800	0.204	-1.263	-0.996
	(3)	-0.667	0.272	-1.308	-0.928
0.85	(2)	-0.799	0.199	-1.263	-1.003
	(3)	-0.666	0.265	-1.309	-0.938
0.90	(2)	-0.798	0.194	-1.264	-1.010
	(3)	-0.666	0.259	-1.310	-0.948
0.95	(2)	-0.798	0.189	-1.264	-1.017
	(3)	-0.666	0.252	-1.310	-0.957
Not Restricted	(2)	-0.801	0.119	-1.268	-1.113
	(3)	-0.667	0.218	-1.313	-1.007

Notes: Restricted models are similar to models (2) and (3) in Table 3 but with restrictions on β. Model (2) includes a lagged price $\mathrm{P}_{\mathrm{i,y,t-1}}$, a lead price $\mathrm{P}_{\mathrm{i,y,t+1}}$, and policies as IVs for the lagged and the lead consumption. On top of the model (2), model (3) adds a lagged tax and a lead tax as IVs. All regressions include region fixed-effects (FE), time FE (year, month, and week), and policy variables. If not restricted, β is greater than one in models (2) and (3).

APPENDICES

APPENDIX 1 TWO METHODS FOR CONVERTING E-CIGARETTE TAXES TO DOLLARS PER MILLILITER

Jurisdictions tax e-cigarettes mainly in two ways: ad valorem taxes, based on the wholesale or retail price, or specific excise taxes, according to the volume of the liquid contained. These taxes are levied on wholesalers or retailers. I call the ad valorem taxes price tax (P.Tax) and use the volumetric tax (V.Tax) to refer to specific excise taxes. By the end of 2017, Minnesota, the District of Columbia, California, and Montgomery County in Maryland tax e-cigarettes by percentages of the wholesale price; Pennsylvania taxes e-cigarettes by percentages of the retail price. In contrast, North Carolina, Louisiana, West Virginia, Kansas, and Cook County in Illinois tax e-cigarettes per fluid milliliter (ml) of the liquid. The city of Chicago in Illinois uses V.Tax not only via taxing per fluid ml of the liquid but also adds taxes per unit of e-cigarettes. To compare taxes in these regions, it is necessary to measure all taxes in the same unit. Thus, I convert P.Tax and the V.Tax in Chicago to the dollar amounts per ml. I reach very similar results when using the following two, completely different ways to convert the P.Tax.

(a) E-Cigarette Tax Conversion Based on Wholesale Price Calculations

The first method conducts the conversion by calculating the wholesale price. It uses retail prices in a region to compute wholesale prices based on guidelines of cigarette minimum price laws. According to the guidelines of Publication 509 from the Department of Taxation and Finance in New York State (2020), the retail price of cigarettes is at least 7% higher than the agent-to-retail-dealers minimum selling price. I assume the pricing mechanisms are the same for e-cigarettes, i.e. the price raising rates are the same from manufacturers, to wholesale dealers, to retail dealers, then to consumers. Thus, I have three steps. First, I divide the average retail price of e-cigarettes per ml for region i in week t by 1.07, giving the post-tax wholesale price. Second, dividing this price with $(1 + ad\ valorem\ rate_{it})$; I get the pre-tax wholesale price. Third, multiplying the pre-tax wholesale price with the tax rate for the current region-week observation, I get the e-cigarette tax per ml in this region-week combination.

Specifically, the formula is:

$$tax\ per\ ml_{it} = ad\ valorem\ rate_{it} * \frac{RetaiP_{it}}{1.07} / (1 + ad\ valorem\ rate_{it})$$

The formula for calculating the average retail price of e-cigarettes per ml is:

$$RetailP_{it} = Price\ per\ unit_{it} * Sales\ quantities\ in\ units_{it} / Sales\ quantities\ in\ mls_{it}$$

(b) E-Cigarette Tax Conversion Based on DC Taxes

The second method also has three steps for conversion. In the first step, it uses the District of Columbia's (DC's) tax to compute the dollar amounts for each percentage point of P.Tax, since the e-cigarette tax rate in DC matches 100% of the traditional cigarette excise tax at the state level. In the second step, I reach the total tax revenues for this region-week combination by multiplying the total percentage points of the ad valorem taxes by the value of each percentage point (PPV) from the first step and the total sales quantities in units for region i in week t. In the third step, dividing the tax revenues by the total sales quantities in ml gets the tax rate per ml. Since e-cigarette taxes in DC vary each year due to yearly changes in cigarette excise taxes, I reach different PPV each year. Generally, the value increases by about $0.002 each year. For example, values in 2015 and 2016 were $0.043 and $0.045 respectively. I adjust the PPV each year and use these values in my calculations to be accurate.

Specifically, the formula for this conversion is:

$$tax\ per\ ml_{it} = \ ad\ valorem\ rate_{it} * PPV_t * Sales\ quantities\ in\ units_{it} / Sales\ quantities\ in\ ml_{it}$$

(c) E-Cigarette Tax in the City of Chicago, Illinois

Chicago initially taxed e-cigarettes at $0.80 per unit plus $0.55 per ml. Cook County, to which Chicago belongs, implements an e-cigarette tax of $0.20 per ml, therefore making the total tax rate per ml $0.75 in Chicago later. For taxes in Chicago, I use the following formula:

$$tax\ per\ ml_{it} = 0.80 * Sales\ quantities\ in\ units_{it} + tax\_rate_{it} * \ Sales\ quantities\ in\ ml_{it}$$

APPENDIX 2 ECIGARETTE TAXES AND THEIR EFFECTS ON SALES OF E-CIGARETTES: INDIVIDUAL CASES

Table A2.a Regions in the US with E-Cigarette Taxes Effective by December 30, 2017

Location	Tax Rate	Effective Date	Tax in 2017 Dec
Price Tax (P.Tax)			
Minnesota	70% of the wholesale price	03/2010	
	95% of the wholesale price	07/2013	$5.358/ml
District of Columbia	67% of the wholesale price	10/2015	
	65% of the wholesale price	10/2016	
	60% of the wholesale price	10/2017	$5.825/ml
Pennsylvania	40% of the retail price	10/2016	$4.498/ml
California	27.30% of the wholesale price	04/2017	
	65.08% of the wholesale price	07/2017	$10.082/ml
Montgomery County, Maryland	30% of the wholesale price	08/2015	$2.454/ml
Specific Volumetric Tax (V.Tax)			
Chicago City, Illinois	$0.80/unit plus $0.55/ml	01/2016	$2.088/ml
Cook County, Illinois	$0.20 per fluid ml of the liquid	05/2016	$0.200/ml
North Carolina	$0.05 per fluid ml of the liquid	06/2015	$0.050/ml
Louisiana	$0.05 per fluid ml of the liquid	08/2015	$0.050/ml
West Virginia	$0.075 per fluid ml of the liquid	07/2016	$0.075/ml
Kansas	$0.05 per fluid ml of the liquid	07/2017	$0.050/ml

Note: Taxes for Puerto Rico, US Virgin Islands, and localities in Alaska are not included. Tax levels in December of 2017 for each region are inflation-adjusted with CPI to the level of 2017 December. These tax levels are converted from wholesale price calculations.

Figure A2.a Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (CA)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

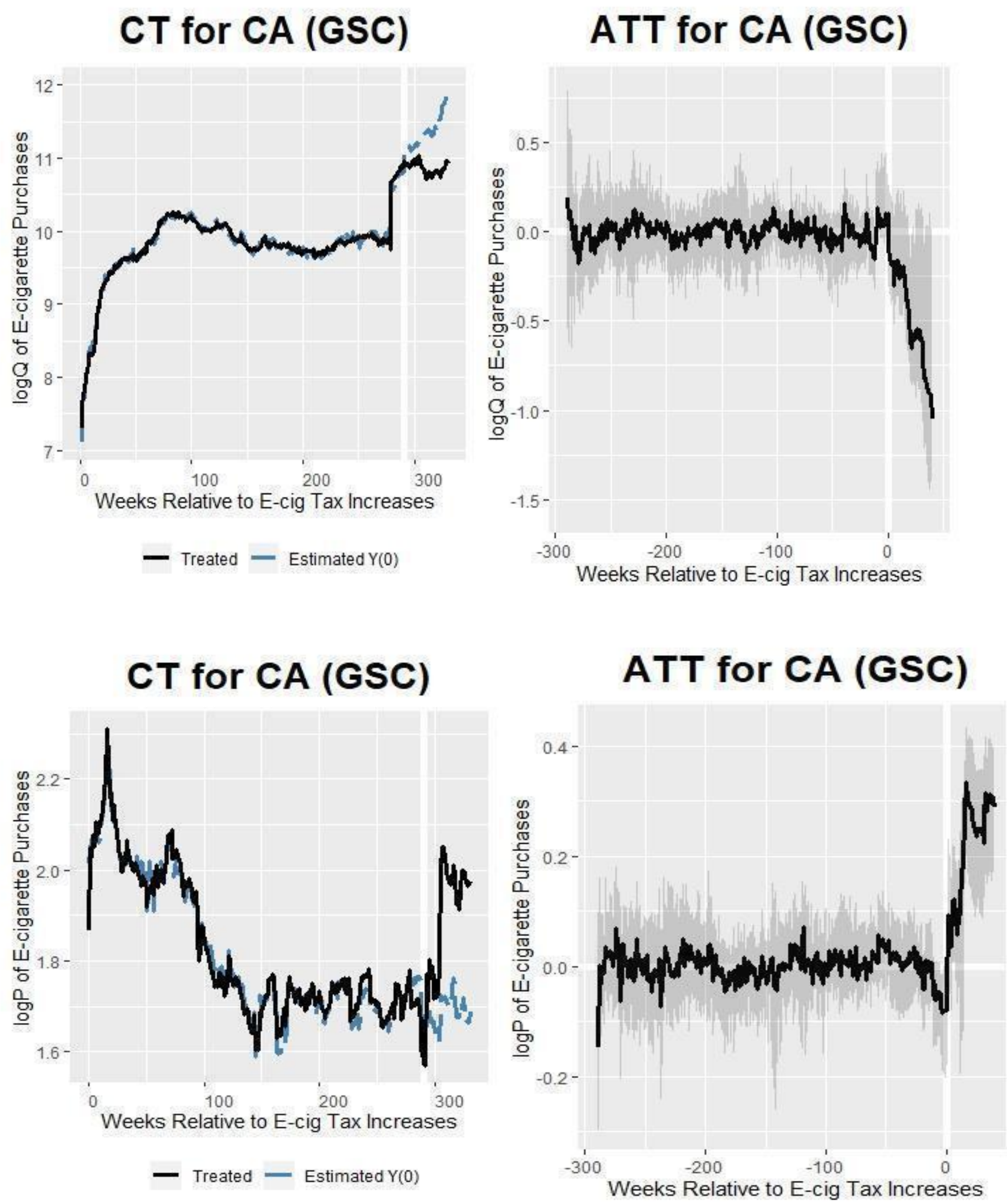


Figure A2.b Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (DC)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

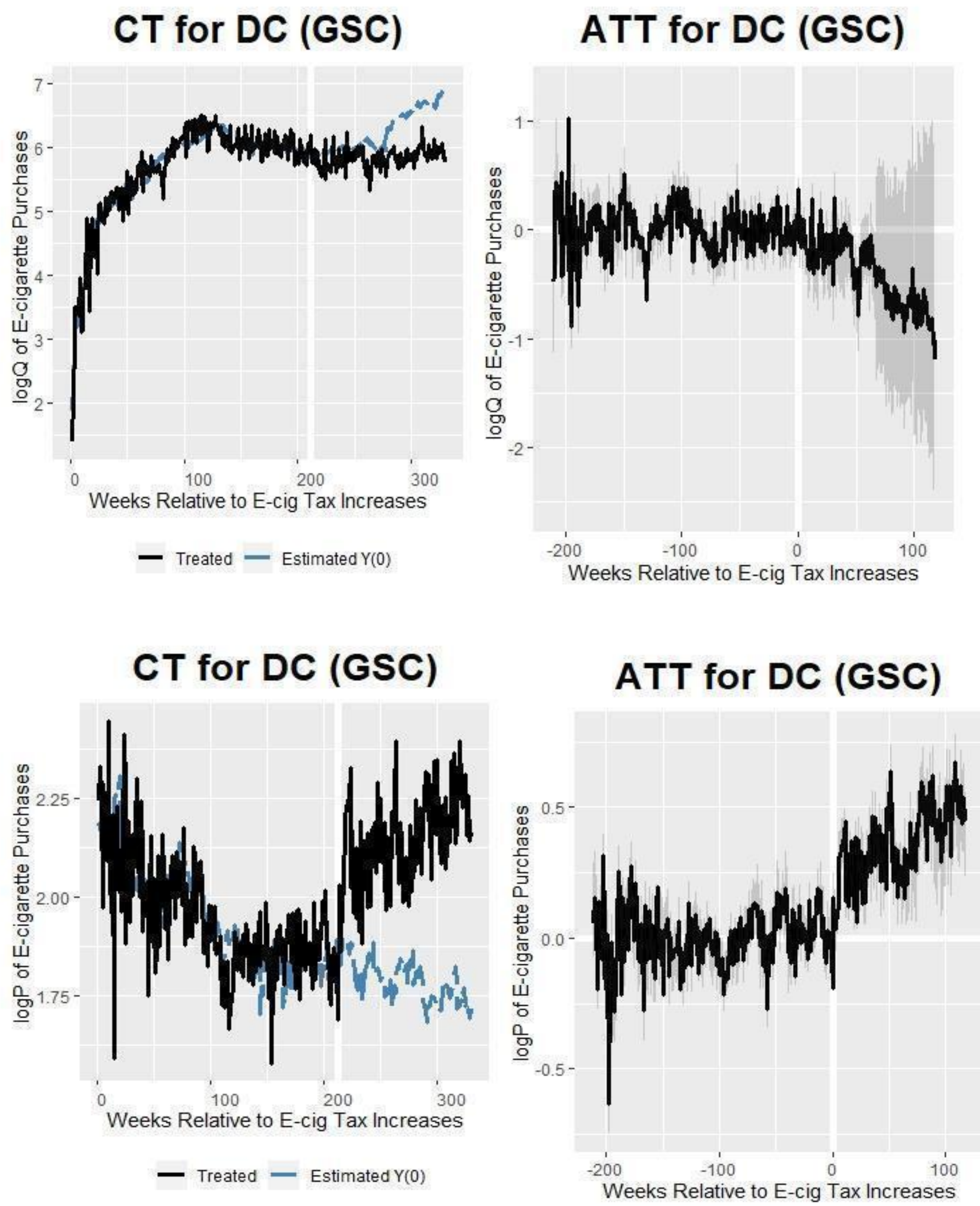


Figure A2.c Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (M1: Montgomery County, MD)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

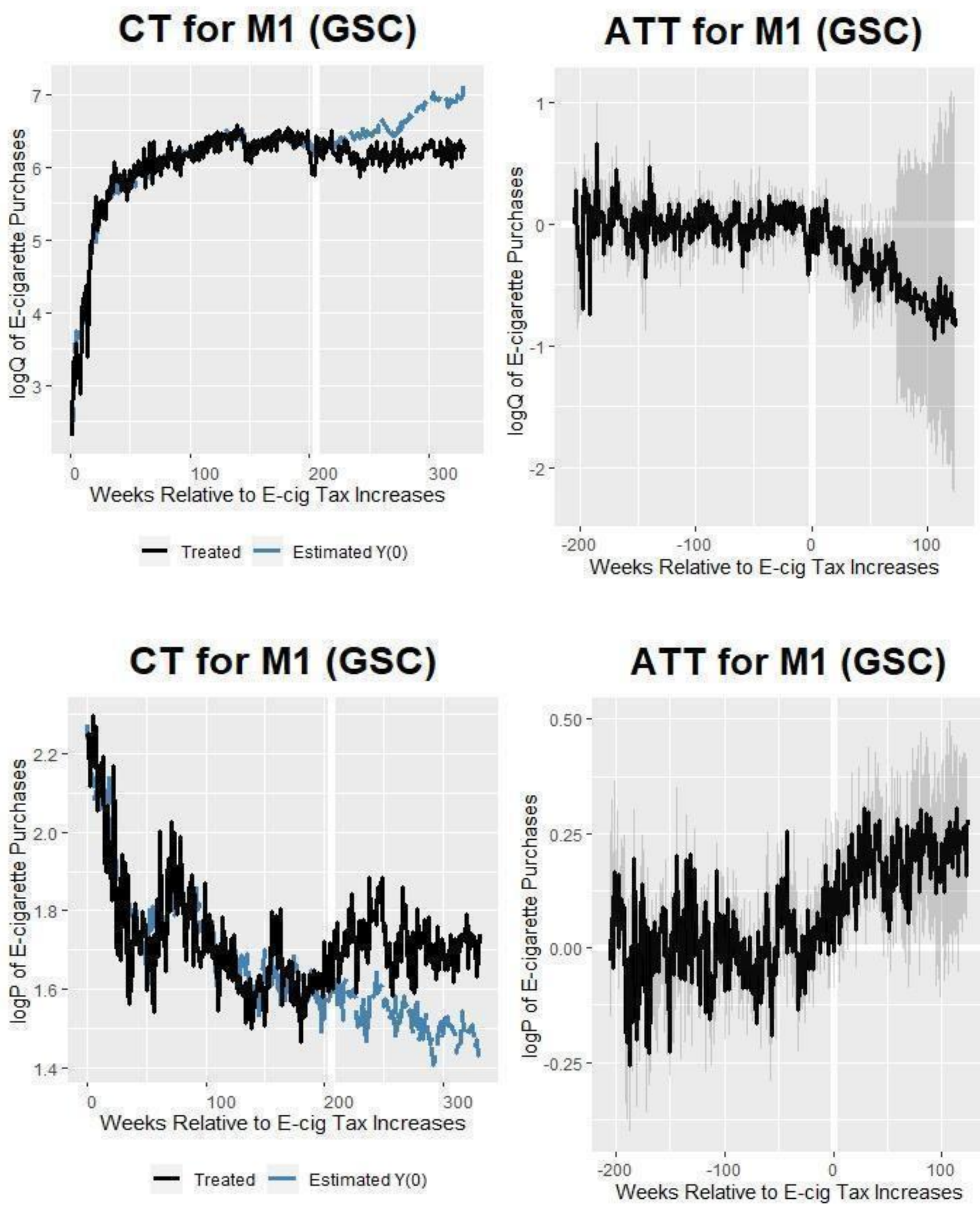


Figure A2.d Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (MN)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

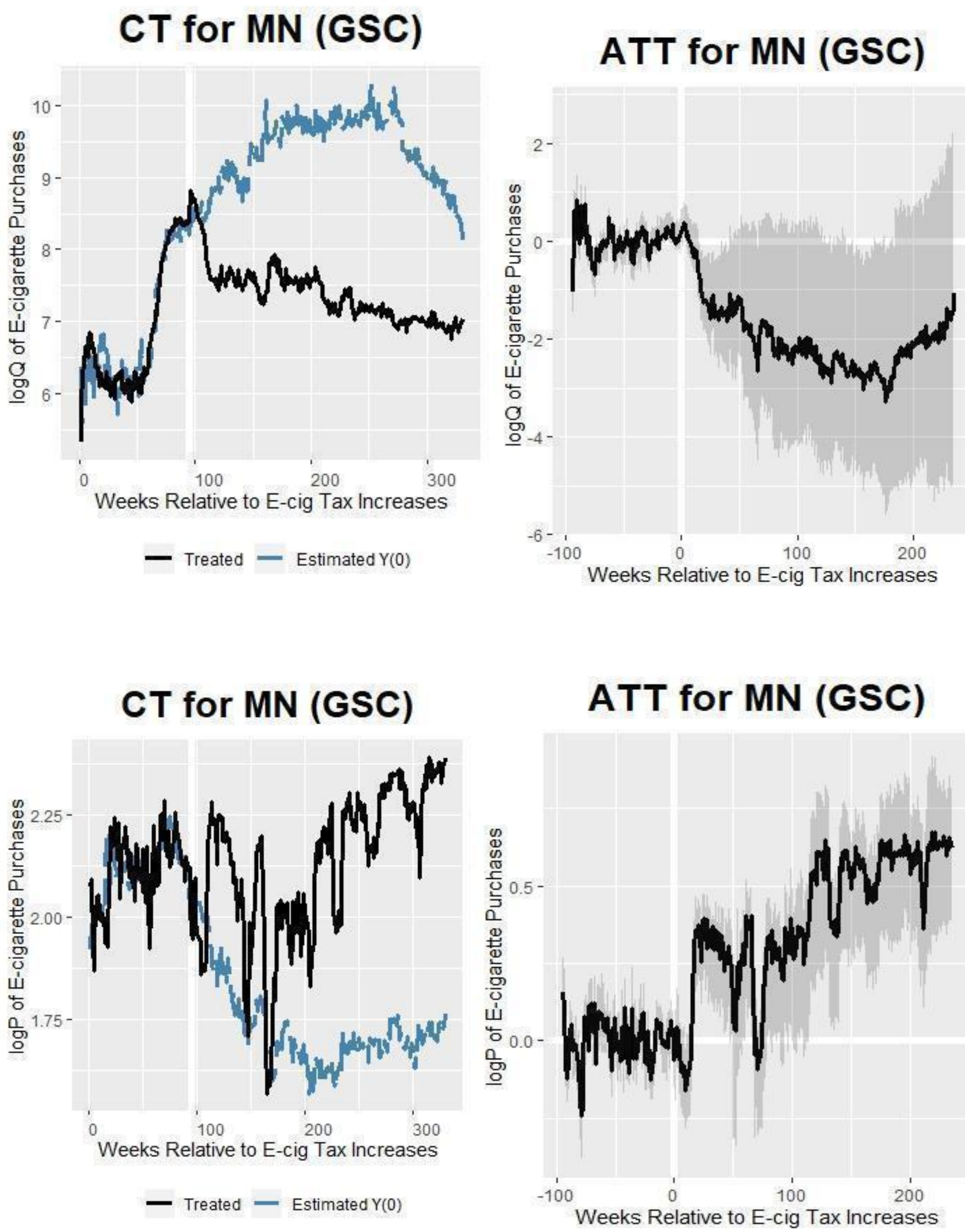


Figure A2.e Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (PA)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

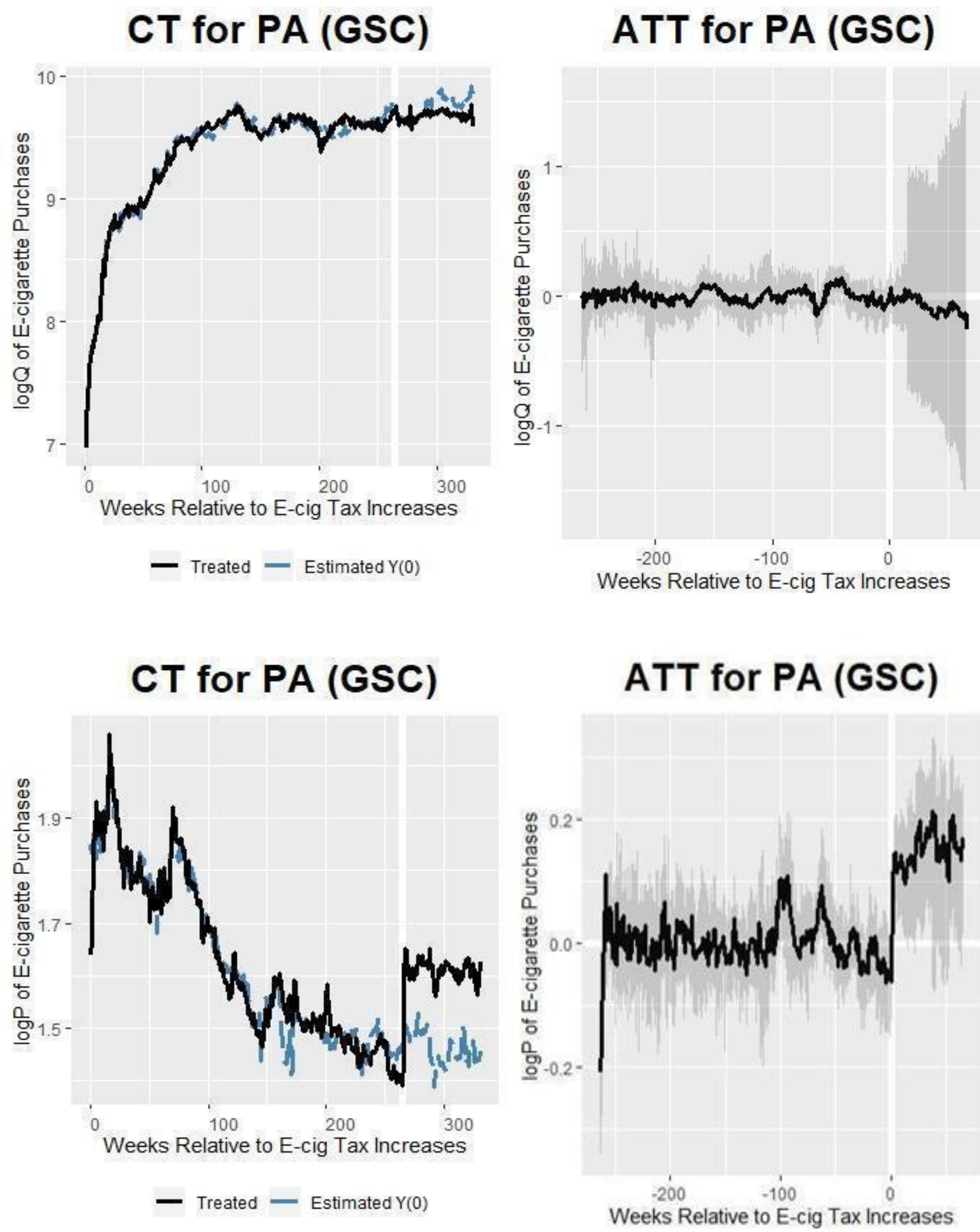


Figure A2.f Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (C1: Chicago City, IL)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

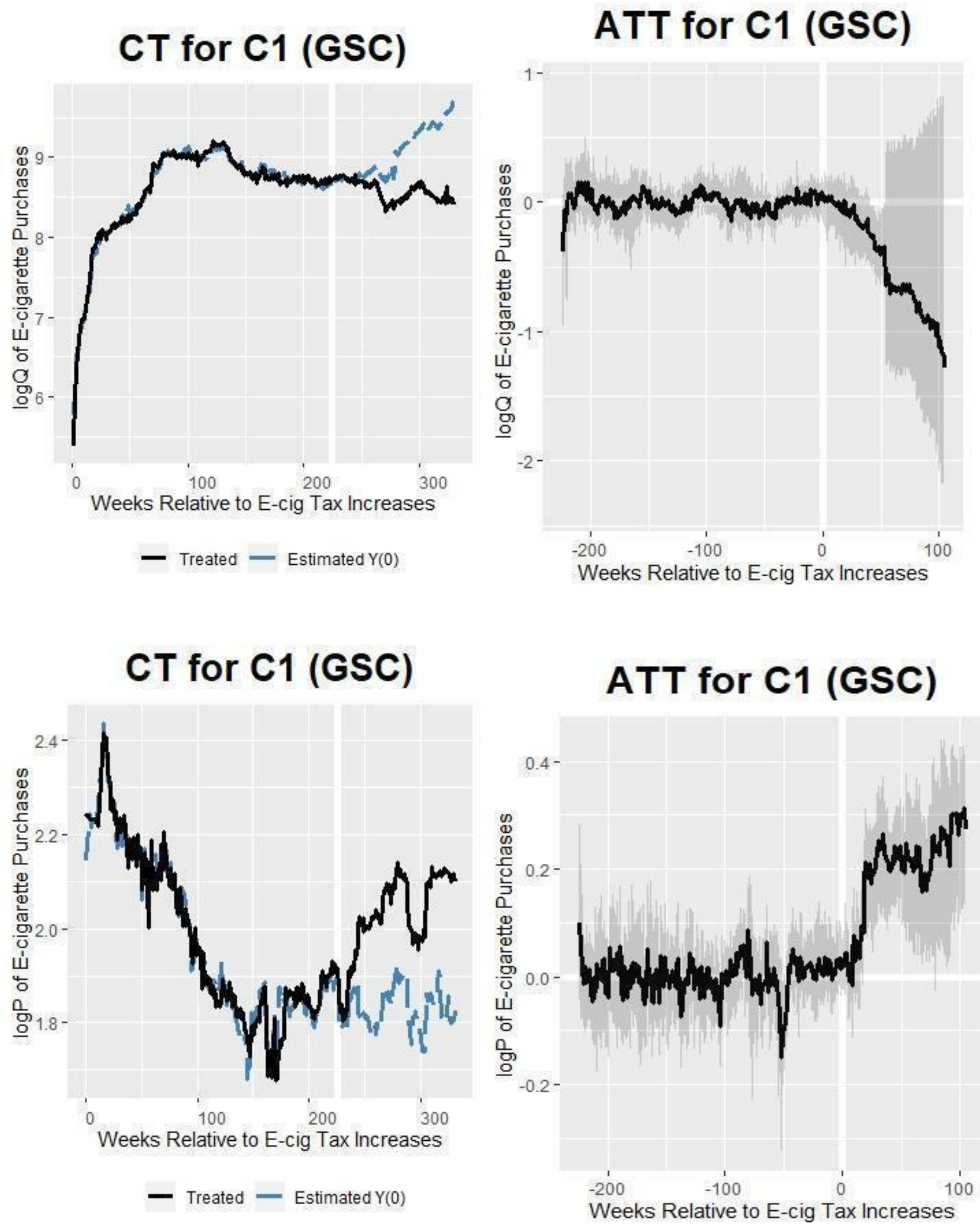


Figure A2.g Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (C2: Cook County, IL [Exclude Chicago City])

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

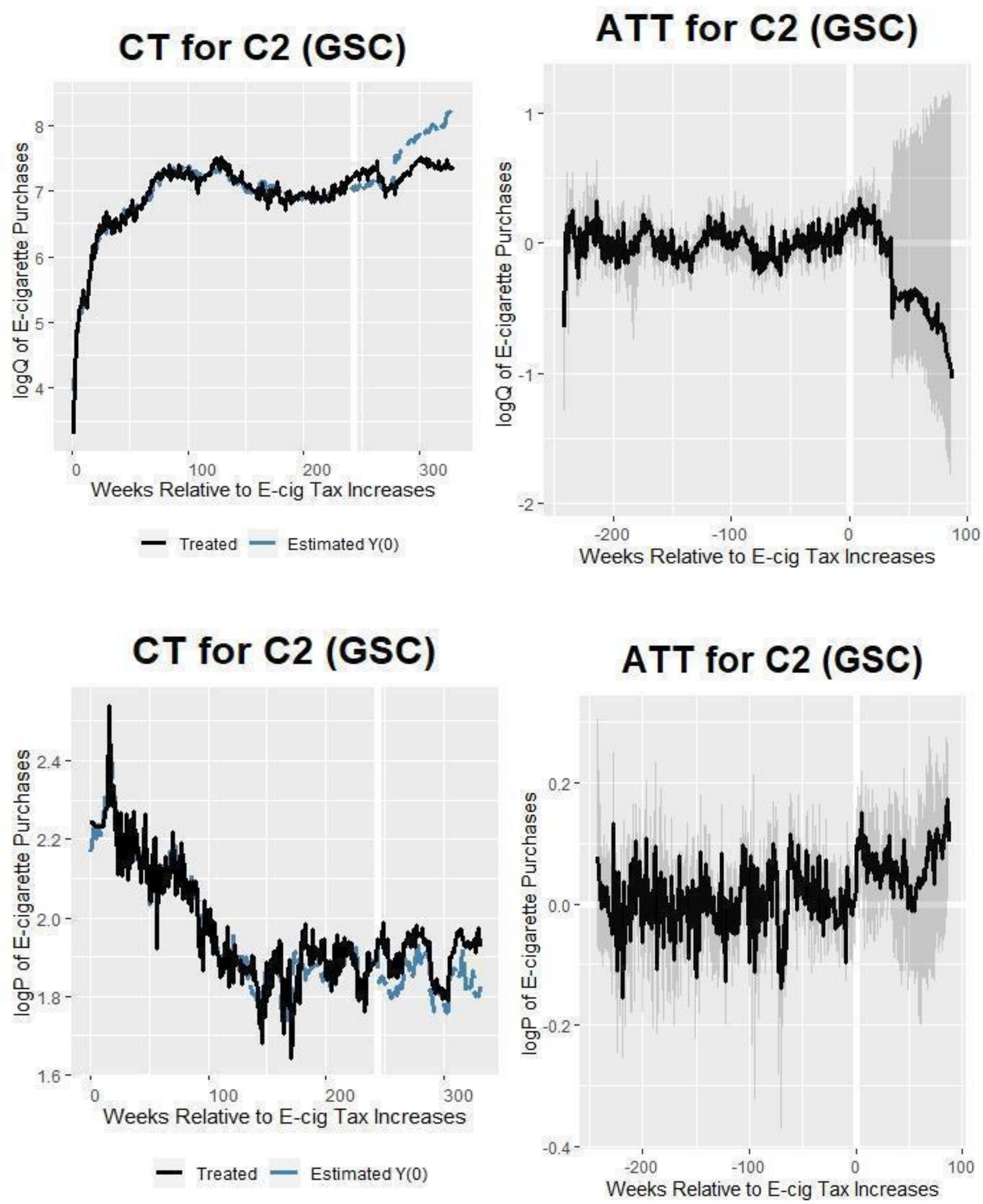


Figure A2.h Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (KS)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

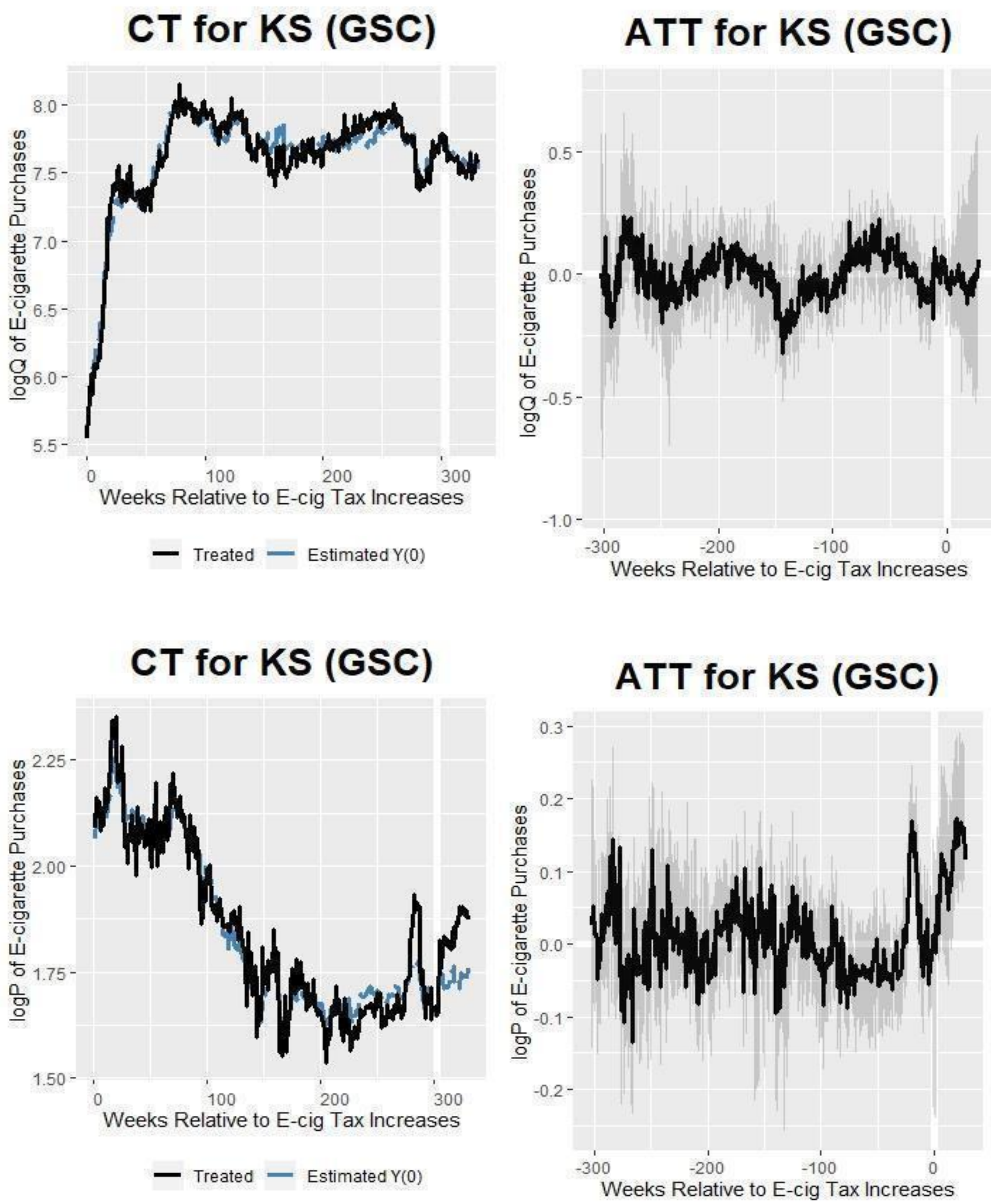


Figure A2.i Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (LA)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

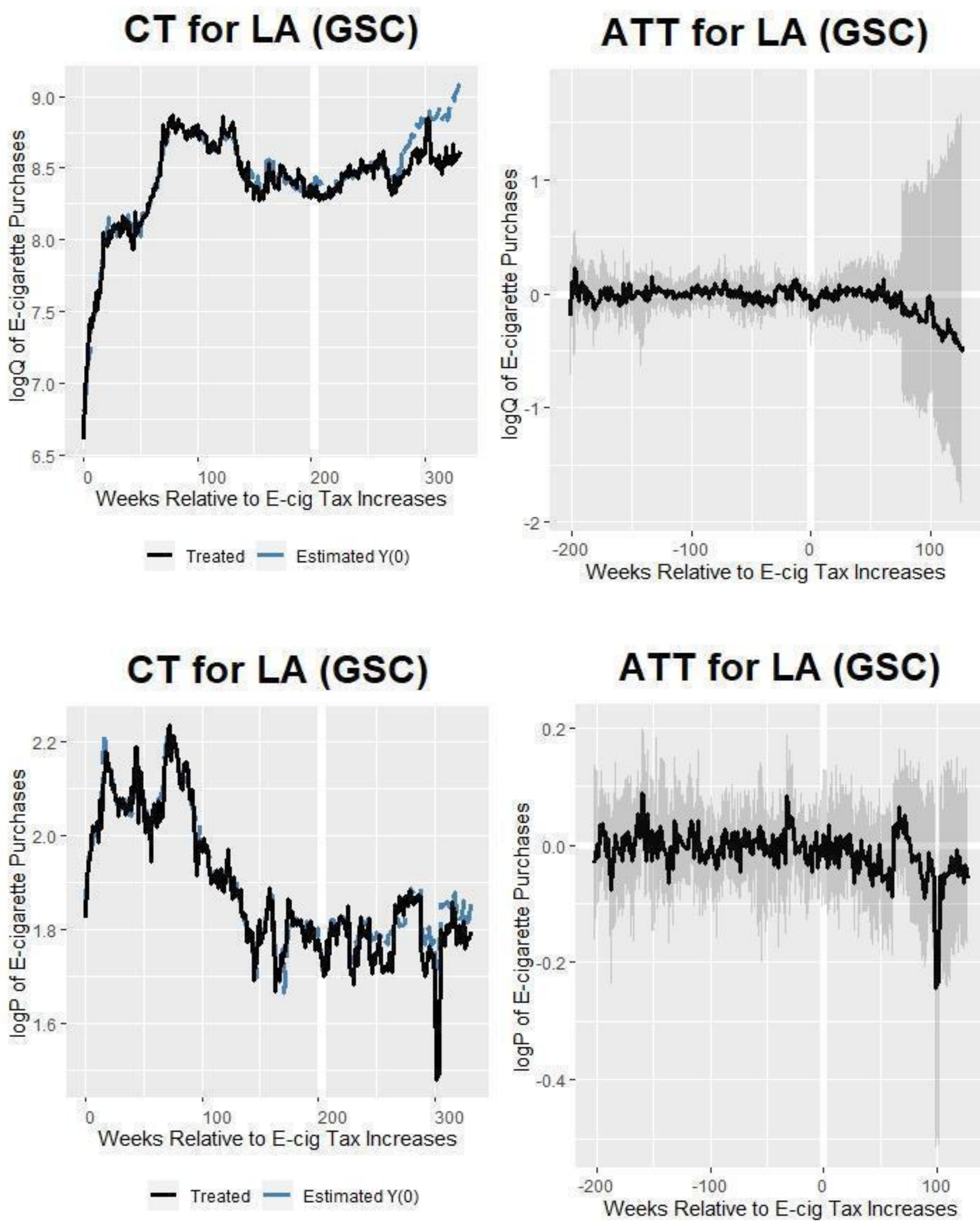


Figure A2.j Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (NC)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).

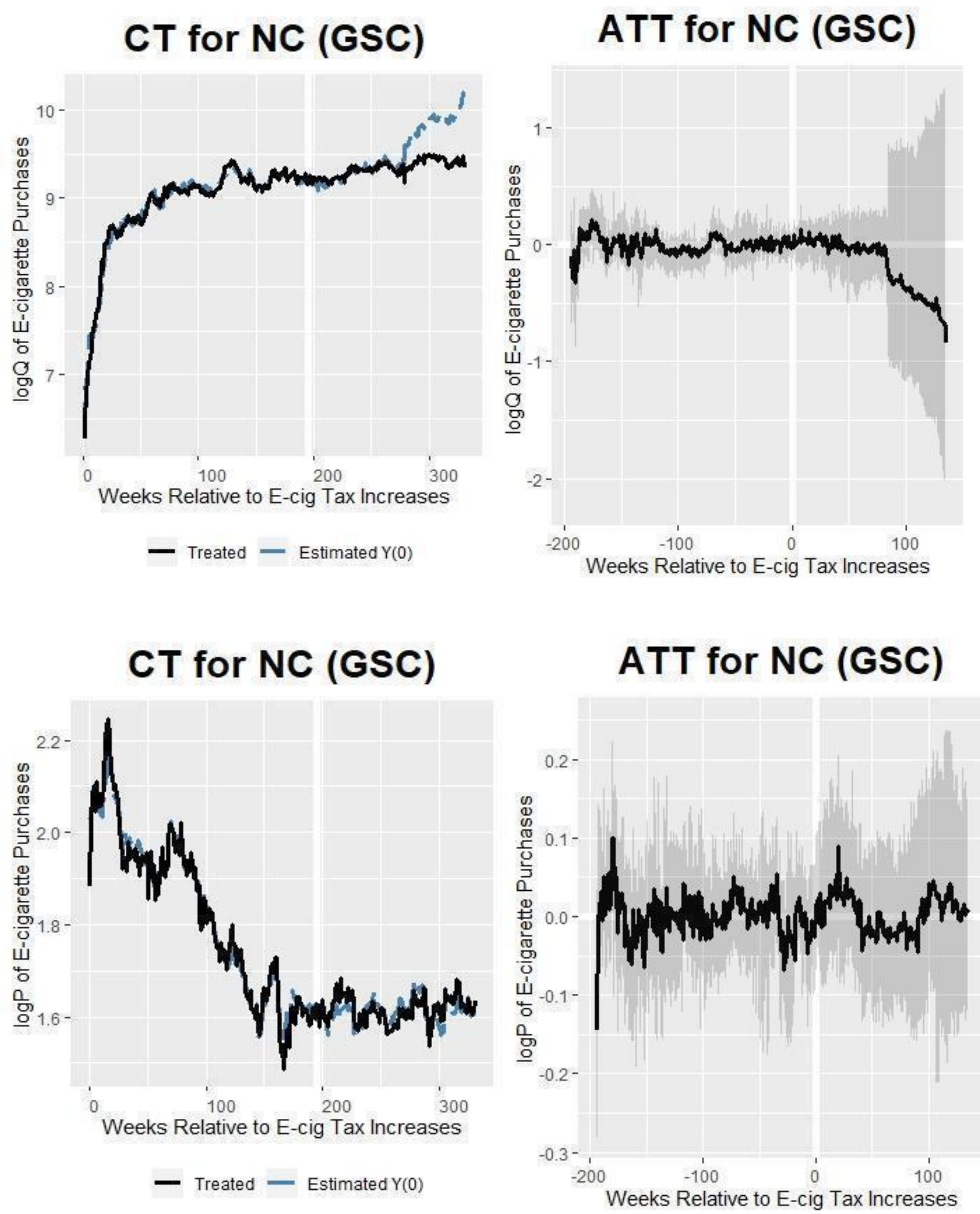
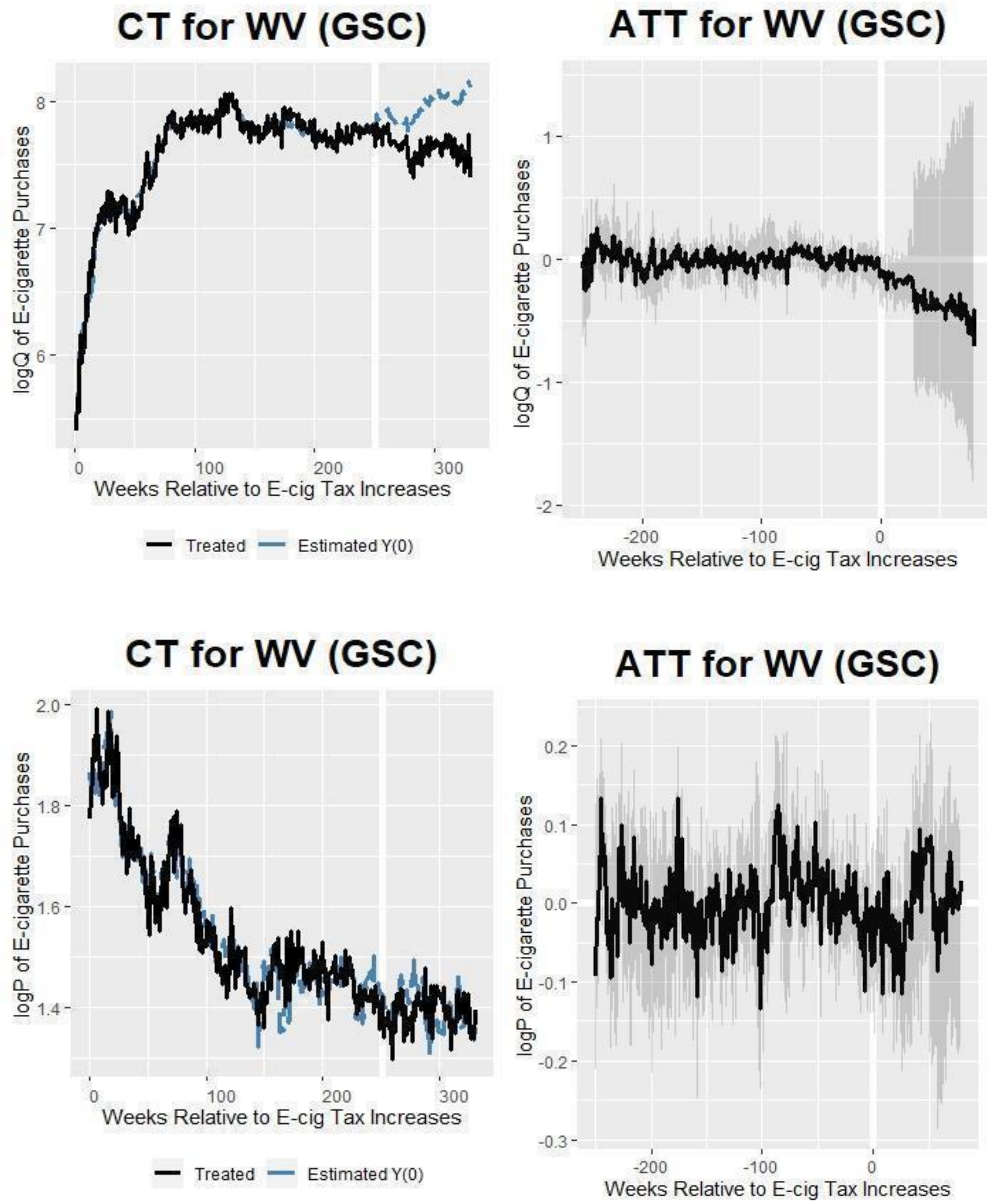


Figure A2.k Effects of EET on Sales Quantities and Prices of E-Cigarettes: Individual Cases (WV)

Note: CT means treated counterfactuals. ATT represents the average treatment effect on the treated unit. The top panel shows figures of LogQ(unit). The bottom panel shows figures of LogP(unit).



REFERENCES

Abadie, A., A. Diamond, and J. Hainmueller. 2015. "Comparative Politics and the Synthetic Control Method." American Journal of Political Science 59:495-510.

---. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." Journal of the American Statistical Association 105:493-505.

Abcede, A. (2017) "E-Cig Sales to Hit $27 Billion by 2022: Study." In., CSP Daily News.

Abouk, R., and S. Adams. 2017. "Bans on Electronic Cigarette Sales to Minors and Smoking among High School Students." Journal of Health Economics 54:17-24.

Abouk, R., S. Adams, B. Feng, J.C. Maclean, and M.F. Pesko. 2019. "The Effect of E-Cigarette Taxes on Pre-Pregnancy and Prenatal Smoking, and Birth Outcomes." National Bureau of Economic Research.

Adioetomo, S.M., and T. Djutaharta. 2005. "Cigarette Consumption, Taxation, and Household Income: Indonesia Case Study."

Allcott, Hunt, and Charlie Rafkin. 2020. "Optimal Regulation of E-cigarettes: Theory and Evidence." NBER Working Paper, (27000).

Amato, M.S., and R.G. Boyle. 2016. "Evaluating an Excise Tax on Electronic Cigarette Consumption: Early Results." Tobacco Regulatory Science 2:123-132.

Amato, M.S., R.G. Boyle, and B. Brock. 2015. "Higher Price, Fewer Packs: Evaluating a Tobacco Tax Increase with Cigarette Sales Data." American Journal of Public Health 105:e5-e8.

American Lung Association. 2020a. "State Legislated Actions on Tobacco Issues (SLATI)."

American Lung Association. 2020b."State of Tobacco Control 2019."

Bai, J. 2009. "Panel Data Models with Interactive Fixed Effects." Econometrica 77:1229-1279.

Baltagi, B. H., and Griffin, J. M. 1995. "A Dynamic Demand Model for Liquor: the Case for Pooling." *The Review of Economics and Statistics*, 545-554.

---. 2001. "The Econometrics of Rational Addiction: The Case of Cigarettes." *Journal of Business & Economic Statistics*, 19(4), 449-454.

---. 2002. "Rational Addiction to Alcohol: Panel Data Analysis of Liquor Consumption." *Health Economics, 11*(6), 485-491.

Becker, G. S., Grossman, M., and Murphy, K. M. 1994. "An Empirical Analysis of Cigarette Addiction." *The American Economic Review*, 84(3), 396-418.

Becker, G. S., and Murphy, K. M. 1988. "A Theory of Rational Addiction." *Journal of Political Economy, 96*(4), 675-700.

Bover, O. 1991. "Relaxing Intertemporal Separability: A Rational Habits Model of Labor Supply Estimated from Panel Data." *Journal of Labor Economics*, 9(1), 85-100.

Calvert, R. L. 1985. "The Value Of Biased Information: A Rational Choice Model of Political Advice." *The Journal of Politics*, 47(2), 530-555.

Cameron, S. 1999. "Rational Addiction and The Demand for Cinema." *Applied Economics Letters*, 6(9), 617-620.

Cammenga, J. 2019 "How High Are Vapor Excise Taxes in Your State?" In. Tax Foundation.

Campaign for Tobacco-Free Kids. 2020a. "State Cigarette Excise Tax Rates & Rankings." https://www.tobaccofreekids.org/assets/factsheets/0097.pdf."

Campaign for Tobacco-Free Kids. 2020b. "State Excise Tax Rates for Non-Cigarette Tobacco Products."

Cawley, J. H. 2000. "Rational Addiction, The Consumption of Calories, and Body Weight."

Centers for Disease Control and Prevention. 2019a. "Best Practices for Comprehensive Tobacco Control Programs—2014." In., pp. https://www.cdc.gov/tobacco/stateandcommunity/best_practices/index.htm.

---. 2019b. "State Tobacco Activities Tracking and Evaluation (STATE) System." In., pp. https://www.cdc.gov/statesystem/index.html.

Centers for Disease Control and Prevention. 2020a. "E-cigarette Unit Sales, by Product and Flavor Type — United States, 2014–2020." *Morbidity and Mortality Weekly Report* 69(37):1313-1318.

---. 2020b. "State Tobacco Activities Tracking and Evaluation (STATE) System."

Chaloupka, F. (1991). "Rational Addictive Behavior and Cigarette Smoking." *Journal of Political Economy*, *99*(4), 722-742.

Cotti, C., Courtemanche, C., Maclean, C., Nesson, E., Pesko, M., and Tefft, N. 2020. The Effects of E-Cigarette Taxes on E-Cigarette Prices and Tobacco Product Sales: Evidence from Retail Panel Data. NBER Working Paper, (w26724).

Cotti, C., Nesson, E., and Tefft, N. 2018. "The Relationship between Cigarettes and Electronic cigarettes: Evidence from Household Panel Data. Journal of Health Economics, 61, 205-219.

Counotte, D.S., S. Spijker, L.H. Van de Burgwal, F. Hogenboom, A.N. Schoffelmeer, T.J. De Vries, A.B. Smit, and T. Pattij. 2009. "Long-lasting Cognitive Deficits Resulting from Adolescent Nicotine Exposure in Rats." Neuropsychopharmacology 34:299.

Craver, R. 2013. "Analyst Projection: E-cigs Will Overtake Traditional Tobacco Revenue at Reynolds in 2021." Winston-Salem Journal.

Dave, D., B. Feng, and M.F. Pesko. 2019a. "The Effects of E-Cigarette Minimum Legal Sale Age Laws on Youth Substance Use." Health Economics 28:419-436.

Dave, D., D. Dench, M. Grossman, D.S. Kenkel, and H. Saffer. 2019b. "Does E-cigarette Advertising Encourage Adult Smokers to Quit?" Journal of Health Economics:102227.

DeCicca, P., D. Kenkel, and F. Liu. 2013. "Who Pays Cigarette Taxes? The Impact of Consumer Price Search." Review of Economics and Statistics 95:516-529.

Deng, X. 2020. Estimating The Effects of E-Cigarette Taxes: A Generalized Synthetic Control Approach. Working Paper.

Dwyer, J.B., S.C. McQuown, and F.M. Leslie. 2009. "The Dynamic Effects of Nicotine on the Developing Brain." Pharmacology & Therapeutics 122:125-139.

Einav, L., E. Leibtag, and A. Nevo. 2010. "Recording Discrepancies in Nielsen Homescan Data: Are They Present and Do They Matter?" Quantitative Marketing and Economics 8:207-239.

Epstein, L. G., & Zin, S. E. 1991. "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis." *Journal of Political Economy*, 99(2), 263-286.

Euromonitor International. 2017. "Cigarettes in the US." In.

Evans, W.N., J.S. Ringel, and D. Stech. 1999. "Tobacco Taxes and Public Policy to Discourage Smoking." Tax Policy and the Economy 13:1-55.

FDA (U.S. Food & Drug Administration). 2020. "Tobacco 21." https://www.fda.gov/tobacco-products/retail-sales-tobacco-products/tobacco-21.

FDA (U.S. Food & Drug Administration). 2016. "Deeming Tobacco Products To Be Subject to the Federal Food, Drug, and Cosmetic Act, as Amended by the Family Smoking Prevention and Tobacco Control Act; Restrictions on the Sale and Distribution of Tobacco Products and Required Warning Statements for Tobacco Products."

Farsalinos, K.E., and R. Polosa. 2014. "Safety Evaluation and Risk Assessment of Electronic Cigarettes as Tobacco Cigarette Substitutes: A Systematic Review." Therapeutic Advances in Drug Safety 5:67-86.

Fiore, M.C., R.T. Croyle, S.J. Curry, C.M. Cutler, R.M. Davis, C. Gordon, C. Healton, H.K. Koh, C.T. Orleans, and D. Richling. 2004. "Preventing 3 Million Premature Deaths and Helping 5 Million Smokers Quit: A National Action Plan for Tobacco Cessation." American Journal of Public Health 94:205-210.

Fraser, D., M. Weier, H. Keane, and C. Gartner. 2015. "Vapers' Perspectives on Electronic Cigarette Regulation in Australia." International Journal of Drug Policy 26:589-594.

Friedman, A.S. 2015. "How Does Electronic Cigarette Access Affect Adolescent Smoking?" Journal of Health Economics 44:300-308.

Gartner, C., and W. Hall. 2015. "A Licence to Vape: Is It Time to Trial of A Nicotine Licensing Scheme to Allow Australian Adults Controlled Access to Electronic Cigarettes Devices and Refill Solutions Containing Nicotine?" International Journal of Drug Policy 26:548-553.

Gordon, B. R., & Sun, B. 2015. "A Dynamic Model of Rational Addiction: Evaluating Cigarette Taxes." *Marketing Science, 34*(3), 452-470.

GovTrack. 2020. "H.R. 4742: Protecting American Lungs Act of 2019." https://www.govtrack.us/congress/bills/116/hr4742/summary.

Grossman, M., & Chaloupka, F. J. 1998. "The Demand for Cocaine by Young Adults: A Rational Addiction Approach." *Journal of Health Economics*, 17(4), 427-474.

Grossman, M., Chaloupka, F. J., & Sirtalan, I. 1998. "An Empirical Analysis of Alcohol Addiction: Results from the Monitoring the Future Panels." *Economic Inquiry, 36*(1), 39-48.

Hanson, A., and R. Sullivan. 2009. "The Incidence of Tobacco Taxation: Evidence from Geographic Micro-Level Data." National Tax Journal:677-698.

Hansen, L. P., & Singleton, K. J. 1983. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns." *Journal of Political Economy*, *91*(2), 249-265.

Hotz, V. J., Kydland, F. E., & Sedlacek, G. L. (1988). "Intertemporal Preferences and Labor Supply." *Econometrica: Journal of the Econometric Society*, 335-360.

Huang, J., J. Tauras, and F.J. Chaloupka. 2014. "The Impact of Price and Tobacco Control Policies on The Demand for Electronic Nicotine Delivery Systems." Tobacco Control 23:iii41-iii47.

IARC. 2011. "Effectiveness of Tax and Price Policies for Tobacco Control, Handbooks of Cancer Prevention." Tobacco Control 14.

Jones, A.M. 1989. "A Double-Hurdle Model of Cigarette Consumption." Journal of Applied Econometrics 4:23-39.

Katz, M.L., and H.S. Rosen. 1985. "Tax Analysis in an Oligopoly Model." Public Finance Quarterly 13:3-20.

Keeler, T.E., T.-w. Hu, P.G. Barnett, W.G. Manning, and H.-Y. Sung. 1996. "Do Cigarette Producers Price-Discriminate by State? An Empirical Analysis of Local Cigarette Pricing and Taxation." Journal of Health Economics 15:499-512.

Kwon, H. E., So, H., Han, S. P., & Oh, W. (2016). "Excessive Dependence on Mobile Social Apps: A Rational Addiction Perspective." *Information Systems Research*, 27(4), 919-939.

Lee, J.-M. 2007. "The Synergistic Effect of Cigarette Taxes on the Consumption of Cigarettes, Alcohol and Betel Nuts." BMC Public Health 7:121.

Lusk, J.L., and K. Brooks. 2011. "Who Participates in Household Scanning Panels?" American Journal of Agricultural Economics 93:226-240.

Mankiw, N. G., Rotemberg, J. J., & Summers, L. H. (1985). "Intertemporal Substitution in Macroeconomics." *The Quarterly Journal of Economics*, 100(1), 225-251.

Marr, C., and C. Huang. 2014. "Higher Tobacco Taxes Can Improve Health and Raise Revenue." Center on Budget and Policy Priorities (March 19, 2014), available at< http://www. cbpp. org/research/higher-tobacco-taxes-can-improve-health-and-raise-revenue>(last visited April 12, 2016).

Mobilia, P. 1993. "Gambling as A Rational Addiction." *Journal of Gambling Studies*, 9(2), 121-151.

Nesson, E. 2017. "Heterogeneity in Smokers' Responses to Tobacco Control Policies." Health Economics 26:206-225.

New York State Department of Taxation and Finance. 2020. " Cigarette and Tobacco Products Tax Publications and Tax Bulletins: PUB-509." https://www.tax.ny.gov/pubs_and_bulls/publications/cig_tob_prod_pubs.htm.

Ohsfeldt, R.L., R.G. Boyle, and E. Capilouto. 1997. "Effects of Tobacco Excise Taxes on The Use of Smokeless Tobacco Products in The USA." Health Economics 6:525-531.

Olekalns, N., & Bardsley, P. 1996. "Rational Addiction to Caffeine: An Analysis of Coffee Consumption." *Journal of Political Economy, 104*(5), 1100-1104.

Opazo Breton, M., J. Britton, Y. Huang, and I. Bogdanovica. 2018. "Comparison Between Online and Offline Price of Tobacco Products Using Novel Datasets." International Journal of Environmental Research and Public Health 15:2282.

Pesko, M.F., and C. Warman. 2017. "The Effect of Prices on Youth Cigarette and E-Cigarette Use: Economic Substitutes or Complements." Social Science Research Network.

Pesko, M.F., D.S. Kenkel, H. Wang, and J.M. Hughes. 2016. "The Effect of Potential Electronic Nicotine Delivery System Regulations on Nicotine Product Selection." Addiction 111:734-744.

Pesko, M.F., J. Huang, L.D. Johnston, and F.J. Chaloupka. 2018. "E-Cigarette Price Sensitivity among Middle-and High-School Students: Evidence from Monitoring the Future." Addiction 113:896-906.

Public Health Law Center. 2020. "U.S. E-Cigarette Regulations - 50 State Review (2020)" https://publichealthlawcenter.org/resources/us-e-cigarette-regulations-50-state-review."

Richards, T. J., Patterson, P. M., & Tegene, A. 2007. "Obesity and Nutrient Consumption: A Rational Addiction?." *Contemporary Economic Policy*, 25(3), 309-324.

Robertson, L., Hoek, J., Blank, M. L., Richards, R., Ling, P., & Popova, L. 2019. "Dual Use of Electronic Nicotine Delivery Systems (ENDS) and Smoked Tobacco: A Qualitative Analysis." Tobacco Control, 28(1), 13-19.

Rojas, C., and E.Y. Wang. 2017. "Do Taxes for Soda and Sugary Drinks Work? Scanner Data Evidence from Berkeley and Washington."

Ryder, H. E., & Heal, G. M. 1973. "Optimal Growth with Intertemporally Dependent Preferences." *The Review of Economic Studies*, 40(1), 1-31.

Saffer, H., D. Dench, M. Grossman, and D. Dave. 2020. "E-Cigarettes and Adult Smoking: Evidence from Minnesota." Journal of Risk and Uncertainty:1-22.

Sharma, A., B. Vandenberg, and B. Hollingsworth. 2014. "Minimum Pricing of Alcohol versus Volumetric Taxation: Which Policy Will Reduce Heavy Consumption without Adversely Affecting Light and Moderate Consumers?" PLoS One 9:e80936.

Slawecki, C.J., A.K. Thorsell, A. El Khoury, A.A. Mathé, and C.L. Ehlers. 2005. "Increased CRF-like and NPY-like Immunoreactivity in Adult Rats Exposed to Nicotine During Adolescence: Relation to Anxiety-like and Depressive-like Behavior." Neuropeptides 39:369-377.

Stern, N. 1987. "The Effects of Taxation, Price Control and Government Contracts in Oligopoly and Monopolistic Competition." Journal of Public Economics 32:133-158.

Sung, H. Y., Hu, T. W., & Keeler, T. E. 1994. "Cigarette Taxation and Demand: An Empirical Model." *Contemporary Economic Policy*, *12*(3), 91-100.

Tauras, J.A. 2006. "Smoke-free Air Laws, Cigarette Prices, and Adult Cigarette Demand." Economic Inquiry 44:333-342.

Tiberii, Jeff. 2019. " How Did Big Tobacco Influence a Plan to Increase NC’s Taxes on Vaping Products?" https://www.wunc.org/post/how-did-big-tobacco-influence-plan-increase-nc-s-taxes-vaping-products.

U.S. Department of Health and Human Services. 2016. "E-Cigarette Use Among Youth and Young Adults: A Report of the Surgeon General. Atlanta, GA: U.S. Department of Health and Human Services, CDC; 2016."

U.S. Food & Drug Administration. 2020a. "FDA Finalizes Enforcement Policy on Unauthorized Flavored Cartridge-Based E-Cigarettes that Appeal to Children, Including Fruit and Mint." https://www.fda.gov/news-events/press-announcements/fda-finalizes-enforcement-policy-unauthorized-flavored-cartridge-based-e-cigarettes-appeal-children.

U.S. Food & Drug Administration. 2020b. " Tobacco 21." https://www.fda.gov/tobacco-products/retail-sales-tobacco-products/tobacco-21.

Wasserman, J., W.G. Manning, J.P. Newhouse, and J.D. Winkler. 1991. "The Effects of Excise Taxes and Regulations on Cigarette Smoking." Journal of Health Economics 10:43-64.

Weyl, E.G., and M. Fabinger. 2013. "Pass-Through As an Economic Tool: Principles of Incidence Under Imperfect Competition." Journal of Political Economy 121:528-583.

World Health Organization. 2010. "The Political Economy of Tobacco Taxation."Technical Manual on Tobacco Tax Administration: Chapter IV.

Xu, Y. 2017. "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models." Political Analysis 25:57-76.

Zheng, Y., C. Zhen, D. Dench, and J.M. Nonnemaker. 2017. "US Demand for Tobacco Products in a System Framework." Health Economics 26:1067-1086.

VITA

Xueting Deng

EDUCATION

University of Kentucky, Lexington, KY, USA
M.S., Economics 2017
Graduate Certificate, Applied Statistics 2017
M.S., Agricultural Economics 2014
Northwest A&F University, China
B.S., Plant Protection 2009

RESEARCH AND TEACHING INTERESTS

Research: Health Economics, Consumer Economics, Behavioral Economics, Food & Health Policy
Teaching: Intermediate Microeconomics, Econometrics

RESEARCH EXPERIENCE

University of Kentucky, Lexington, KY
Graduate Researcher 2017 – 2020

Research Analyst 2011 – 2017

LEADERSHIP EXPERIENCE

University of Kentucky, Lexington, KY
Graduate and Family Housing Office 2010 – 2020
Facility Manager

Department of Agricultural Economics 2017 – 2018
Teaching Assistant

PUBLICATIONS & WORKING PAPERS

Deng, Xueting, Butler, J.S. (2018). Expenditures on Wine in General and Local Wine in Particular: Market and Econometric Analysis. *Journal of Agribusiness*, 36, 2.
Woods, Timothy, **Deng, Xueting**, Nogueira, Lia, and Yang, Shang-Ho. (2015). Local Wine Expenditure Determinants in the Northern Appalachian States. *Journal of Food Distribution Research*, 46, 2.
Deng, Xueting, Zheng, Yuqing, Butler, J.S. What Impacts Core Economics Journals in Charging Submission Fees and Paying Referee Fees. In progress.
Deng, Xueting. Effects of Managerial Engagement on Carbon Emissions and Disclosures of Firms. In progress.
Deng, Xueting, Zheng, Yuqing. Examining the Effects of E-Cigarette Taxes and Regulations on the Demand for Tobacco Products. Under review.
Deng, Xueting. An Empirical Analysis of Electronic Cigarettes Addiction. In Progress.
Deng, Xueting. Estimating the Effects of Taxes on the Sales and Price of E-Cigarettes with a Generalized Synthetic Control Approach. In progress.

SCHOLASTIC & PROFESSIONAL HONORS

- Certificate in Global Commerce and Strategy from the World Trade Center Kentucky Office 2017
- Certificate in Innovation and Entrepreneurship from the Von Allmen Center for Entrepreneurship 2016

- Global Health Case Competition Awarded Second Place at the University of Kentucky 2020
- Research Activity Award ($1,800) in FY 2018-19 by the University of Kentucky 2018
- Research and Travel Grant by the CAFE Research Office, University of Kentucky 2018
- Student Travel Grant for the 43rd Eastern Economic Association Annual Conference in New York City 2017
- Scholarship for Academic Performance from the Department of Agricultural Economics 2016
- Student Travel Grant for the 40th Eastern Economic Association Annual Conference in Boston 2014
- Student Travel Grant for the 46th SAEA Annual Meeting in Dallas 2014

ACADEMIC SERVICES

- Abstract Reviewer for Agricultural & Applied Economics Association (AAEA) Annual Meeting, 2020
- Student Evaluator for Faculty Candidate Interviews at the Department of Agricultural Economics, UK
- Session Chair of Southern Agricultural Economics Association (SAEA) Annual Meeting, 2018
- Session Chair of Eastern Economic Association (EEA) Annual Conference, 2017
- Quiz Bowl Voluntary Moderator and Computer Operator in the AAEA Annual Meeting, 2014