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Spatial Heterogeneity in Tax Sensitivity: Evidence from Cross-State Cigarette Purchases

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Abstract

Differences in excise taxes across states incentivize consumers to make cross-border purchases. In this study, we investigate the "border effect" phenomenon, which refers to the impact of cross-state purchasing behaviors on the excise tax sensitivity of consumption. We analytically formulate the "border effect" as a linear function that decreases with distance from the closest lower-tax state. We reasonably assume that the "border effect" reaches a maximum at the border with the lower-tax state and then linearly decreases with distance from the border, eventually reaching zero after a certain cutoff distance. We estimate the parameters of the "border effect" function employing a threshold regression model with location and time fixed effects. As a robustness check, we also run a segmented regression using separate tax sensitivity estimates for a range of distance intervals. We verify that the estimates from segmented regression align with the linear pattern derived from the threshold model. Further, we enhance the "border effect" function by incorporating a difference between the home state tax and the closest lower-tax state tax as an additional factor, and then compare the estimation results for the two specifications. Beyond geographic variation, we also examine how the tax sensitivity of cigarette consumption differs across demographic groups. Our analysis shows that tax sensitivity varies by income level: high-income consumers are the least responsive to excise tax increases, while low-income consumers are the most responsive, with middle-income consumers falling in between. All income groups are influenced by the "border effect", but for high-income consumers this effect is only present at distances up to 60 kilometers from the lower-tax state. Our analysis based on employment status indicates that both employed and non-employed consumers display a similar shape in the "border effect" function; however, non-employed consumers show significantly higher tax sensitivity than employed consumers.

Keywords: excise taxation, cigarettes, cross-state purchasing, tax avoidance, border effects
JEL Classification: D12, H26, H71, L66

1 Introduction

In the United States, cigarette excise taxes represent a significant source of government revenue and serve as a policy instrument with direct public health implications. Previous studies show

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†Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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that cigarette tax hikes reduce tobacco consumption, thereby contributing to the improvement of public health outcomes. However, the effectiveness of these tax measures can be considerably undermined by various forms of tax avoidance, including cross-border purchasing in the nearest lower-tax states or Indian reservations, smuggling, and Internet purchasing.

In the context of the United States, where we can track the variability of excise taxes across states, geographic proximity to the lower-tax states creates opportunities for tax arbitrage. Consumers residing near state borders may mitigate the impact of local tax hikes by purchasing cigarettes in neighboring states where the tax burden is lower. Moreover, because of profit motives, shops close to borders may adjust prices to smooth the unfavorable tax difference to a certain extent. Ignoring these "border effects" leads to a biased estimate of the tax elasticity of consumption.

Although several studies investigate cross-border purchasing from various perspectives, limited attention has been paid to analytically quantifying and modeling the spatial heterogeneity in tax responsiveness across consumers. Most existing studies focus on estimating cigarette demand elasticities or analyzing specific forms of tax avoidance behavior, such as smuggling or purchases in an Indian reservation. While informative, these approaches often fail to capture how the intensity of tax avoidance varies continuously with geographic location and tax differentials.

This paper suggests a novel analytical framework that explicitly models the "border effect"—the attenuation in tax sensitivity induced by spatial proximity to a lower-tax state. We formalize this effect as a linearly decreasing function of distance to the nearest lower-tax border, with a maximal influence at the boundary and a vanishing effect beyond a specified cutoff distance. Our approach leverages comprehensive NielsenIQ Consumer Panel Data covering the period from 2004 to 2019, allowing us to track household-level cigarette purchases over time and the panelist's geographic location.

To quantify the magnitude of the border effect, we estimate a threshold regression model with location and time fixed effects, identifying the critical distance beyond which the border effect is no longer present. As a robustness check, we also run a segmented regression using separate tax sensitivity estimates for a range of distance intervals. We verify that the segmented estimates align with the linear pattern derived from the threshold model. Further, we enhance the "border effect" function by adding a difference between the home-state tax and the closest lower-tax state tax as an additional factor, and compare the estimation results for the two specifications.

In addition to geographic variation, we also analyze how the tax sensitivity of cigarette consumption differs across demographic groups. By linking household-level purchase data with demographic characteristics from the NielsenIQ Consumer Panel, we assess whether the level and functional form of tax sensitivity differ among population subgroups. Our findings indicate that tax sensitivity decreases as income increases: high-income consumers are the least responsive to increases in excise taxes, low-income consumers are the most responsive, and middle-income consumers fall somewhere in between. This trend aligns with economic expectations. All income groups are influenced by the "border effect", but for high-income consumers this effect is only present at distances up to 60 kilometers from the lower-tax state. Furthermore, our analysis based on employment status reveals that both employed and non-employed consumers exhibit a similar pattern in the "border effect". However, non-employed consumers demonstrate significantly higher sensitivity to increases in excise taxes compared to employed consumers.

Our findings contribute to the literature in several ways. First, we provide empirical evidence showing that there is a spatial heterogeneity in the tax sensitivity of cigarette consumption within the United States. Second, we quantify how this sensitivity changes with distance and differences in state tax rates. Third, we examine how the tax sensitivity of cigarette consumption varies across different demographic groups. Together, these findings highlight the need to consider border effects when evaluating and designing excise tax policies in a tax system with heterogeneous tax regimes, such as the US.

2 Previous Literature

Previous literature suggests that excise tax hikes reduce tobacco consumption. The sensitivity of cigarette consumption to tax increases is an important question for policymakers for two main reasons: taxes can aid in achieving public health goals by reducing cigarette consumption and generating tax revenue. However, the effectiveness of these tax measures can be considerably undermined by tax avoidance strategies such as cross-border purchases made in nearby lower-tax states or on Indian reservations, smuggling, and Internet purchases.

A number of studies demonstrate that these tax avoidance actions result in imperfect tax pass-through to cigarette prices and may reduce the effectiveness of excise tax policy interventions. For example, Harding et al. (2012) find that excise taxes in the US are less than fully passed on to cigarette prices, primarily due to cross-border purchases. Using NielsenIQ scanner data from 2006–2007, which includes information on consumer locations, they show that opportunities for cross-border purchases lead to significant variations in the tax pass-through rate. Kim & Lee (2020), employing a similar estimation strategy to that used by Harding et al. (2012), find that cigarette taxes are shifted significantly less to consumer prices in cities with large minority (black and Hispanic) populations. They obtain their estimates using NielsenIQ scanner data on cigarette sales for the years 2009–2011 from 1,687 stores across the US. Xu et al. (2014) further show that the tax pass-through rate differs significantly by price minimizing strategy. Consumers who buy premium brands outside Indian reservations face a full tax burden with an additional premium, i.e., the pass-through rate is higher than 100%. In contrast, carton buyers likely to make purchases on Indian reservations pay only 30-83 cents for every 1$ tax increase. These insights point to considerable variation in consumer responses to tax changes depending on purchase behavior. Hanson & Sullivan (2009) analyze Wisconsin's $1 cigarette tax hike using micro-level data on cigarette prices from retail locations in Wisconsin and states that share its border. They conclude that consumers pay the entire amount of the tax as well as a premium of between 8–17 cents per pack of cigarettes. In addition, geo-coded data for locations near the borders of states with different tobacco taxation show that the premium amount is lower for stores located near a lower-tax state border.

A related strand of literature examines how tax avoidance influences cigarette demand elasticities and the design of optimal excise tax policy. For example, Lovenheim (2008) develops and estimates a cigarette demand model that accounts for cross-border purchases using data from the Current Population Survey Tobacco Supplements (TUS-CPS) spanning from September 1992 to February 2002. He finds that demand elasticities concerning the home state price are indistinguishable from zero on average and vary significantly with the distance from which individuals live to a lower-price state border. When opportunities for tax avoidance are removed, the price elasticity becomes negative, although it remains inelastic. Using the same data source from TUS-CPS for February, June, and November 2003, Chiou & Muehlegger (2008) introduces a discrete choice model to examine tax avoidance and state border crossing in the cigarette market. The authors estimate a consumer's tradeoff between distance and price when choosing a location to maximize utility, which allows them to simulate tax avoidance under alternative cigarette excise tax amounts. Expanding on the welfare implications of tax avoidance, DeCicca et al. (2013) develop an extension of the standard formula for the optimal Pigouvian corrective tax to incorporate the possibility of cross-border purchases. To provide a key parameter to this formula, they estimate a structural endogenous switching regression model of border-crossing and cigarette prices using data from the 2003 and 2006–2007 cycles of the same data source, TUS-CPS. They conclude that, after considering tax avoidance in many states, the optimal tax is smaller than the standard Pigouvian tax. These three studies use the Current Population Survey Tobacco Supplements (TUS-CPS) dataset. The main advantage of this dataset is that consumers directly report the location of their most recent cigarette purchase. However, the authors acknowledge that the estimates could be potentially affected by several sources of reporting bias. First, an individual might not report cross-border purchasing if she perceives cross-border purchases as being quasi-illegal. Second, an individual may report their home state for internet cross-border purchases or the state in which an Indian reservation is located, rather than reporting that they purchased cigarettes on an Indian reservation. Thirdly, even though the last purchase can be considered a random draw from the distribution of each smoker's purchases, consumers might not respond to this question accurately but instead base their responses on their typical purchase location. The authors of these three studies performed a set of robustness checks to ensure the validity of the results obtained.

Alternative empirical strategies have also been employed to detect and quantify tax avoidance. Merriman (2010) used littered cigarette packs in Chicago, and treated cigarette packs without a local tax stamp as direct evidence of tax evasion. He concluded that large tax differentials with neighboring jurisdictions decrease the probability of a local stamp by almost 60 percent, and a one-mile increase in distance to the lower-tax state border increases the likelihood of a pack with a local stamp by about one percent. Using data on county-level sales tax remittances from cigarette retailers in Kansas (2001–2005), Nicholson et al. (2014) estimate the extent of smuggling activity and the revenue effects resulting from increases in cigarette excise tax rates. The authors find substantial sales tax revenue leakage near low-tax borders in response to rising cigarette excise tax rates, particularly affecting tobacco shops. This leakage diminishes as the distance from the border increases. The results indicate significantly negative taxable-sales elasticities—reflecting the responsiveness of a state's taxable cigarette sales to changes in the cigarette excise tax rate—at the border, highlighting meaningful cross-border substitution behavior. Gruber et al. (2003) estimate price elasticity of cigarette demand in Canada controlling for cigarette smuggling. They present two approaches to correcting the bias to estimate elasticities from smuggling. The first is to use legal sales data and exclude regions and years in which the smuggling problem was the worst. The second is to use micro-data on consumer cigarette expenditures and compare the elasticity estimates with the estimates derived from sales data after applying corrections for smuggling bias. However, Stehr (2005) later discusses in his study that this approach requires researchers to know the years and provinces in which smuggling occurred to verify that the difference in elasticities is due to smuggling and not to other differences between the datasets. Further, they also show that the sensitivity of smoking to price is much larger among lower-income demographic groups. Stehr (2005) investigates how increases in US state cigarette taxes lead to reduced consumption and increased tax avoidance through smuggling, cross-border purchases, and Internet purchases. The author compares cigarette sales data from the publication Tax Burden on Tobacco to cigarette consumption data from the Behavioral Risk Factor Surveillance System (BRFSS). Stehr (2005) reasonably assumes that if tax avoidance exists, then the elasticity of sales concerning price should be larger than that of consumption concerning price. He shows that after subtracting percent changes in consumption, residual percent changes in sales are associated with state cigarette tax changes, implying the existence of tax avoidance. Additionally, the author emphasizes that legal border crossings play a minor role compared to other avoidance methods.

This body of literature shows that opportunities for tax avoidance can significantly influence the effectiveness of excise taxation. Cross-border purchases, smuggling, and other tax-minimizing strategies lead to variations in how taxes are passed on to consumers and complicate the optimal design of a tax system. Therefore, a thorough analysis of cigarette tax policies must take into account tax avoidance behaviors in order to accurately assess both public health outcomes and fiscal efficiency.

3 Data

We obtain historical data on U.S. state-level cigarette excise taxes from the Centers for Disease Control and Prevention (CDC).

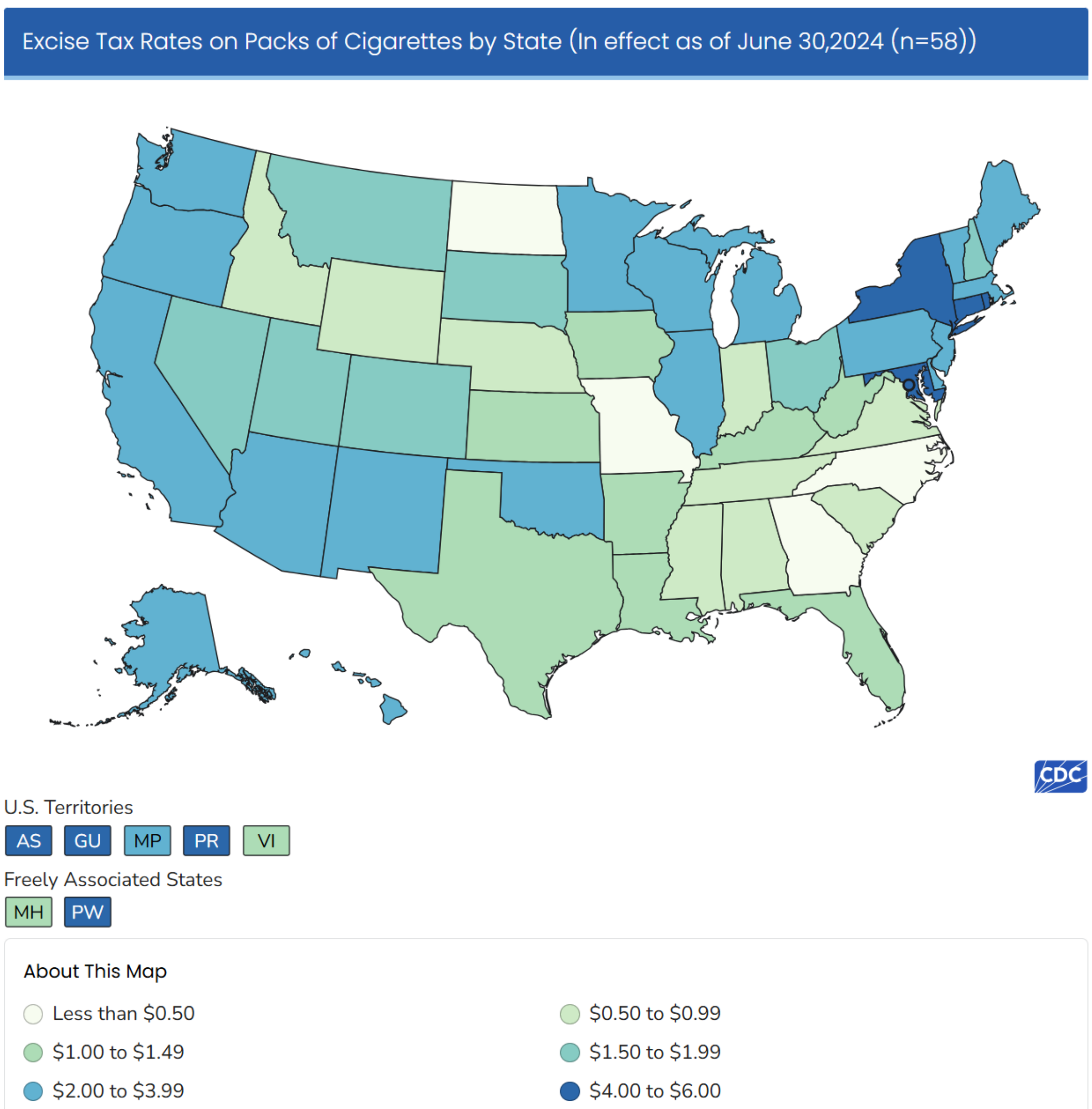


Figure 1: Excise Tax Rates on Packs of Cigarettes by State

Source: Centers for Disease Control and Prevention (CDC), 2024

Excise tax rate data is available quarterly. The main advantage of using US data is that excise taxes are not uniform in the US and exhibit significant variability across states. This allows us to take into account not only changes in excise taxes over time but also state-level heterogeneity. Figure 1 displays the variation in cigarette excise taxes across US states as of June 2024.

In this study, we employ NielsenIQ Consumer Panel Data containing information about the purchase history of 40,000-60,000 households (varies by year) who continually provide information to NielsenIQ about their demographic characteristics, products they buy, and the timing and location where they make purchases, in a longitudinal study. Consumer panelists use in-home scanners to record all purchases intended for personal, in-home use. Panelists are geographically dispersed and demographically balanced (James M. Kilts Center for Marketing, NielsenIQ datasets, n.d.). The dataset includes 2,861,278 individual cigarette purchase transactions recorded by 35,672 unique households between 2004 and 2019. We exclude observations from the COVID-19 period to avoid potential biases introduced by pandemic-related restrictions on mobility and retail access, which may bias the estimation of the "border effect" related to cross-border purchases. We transform the transactional data into a panel format by aggregating purchases to the household-quarter level, aligning the frequency with the CDC excise tax dataset. We only include households that have a minimum of two quarterly observations. The resulting panel data comprises 327,534 quarterly observations. The data set covers the demographic characteristics of the households, including income range, size, gender composition, presence and age of children, marital status, type of residence, race, and Hispanic origin.

Additionally, it includes geographic characteristics, such as the panelist's ZIP code and product characteristics, which contain UPC code, description, brand, multi-pack, and size. The geographies of the data cover the entire United States (James M. Kilts Center for Marketing, NielsenIQ datasets, n.d.).

A major strength of the NielsenIQ dataset is the inclusion of panelists' residential addresses, which permits the incorporation of spatial controls in the empirical analysis. Figures 2 and 3 show the geographic distribution of household locations based on proximity to lower-tax state borders. Specifically, they depict panelist ZIP codes located within 50 kilometers and more than 100 kilometers of such borders, respectively.

We measure the distance to the nearest lower-tax state using Census TIGER/Line shape files provided by the United States Census Bureau. We estimate the distance between consumers and lower-tax borders as the distance from the household's place of residence provided in the data to the border of the closest lower tax state. The lower tax state does not need to be a border state. We focus on identifying the distance to the nearest state with a lower tax rate, regardless of whether it shares a common border with the state of residence. We identify the coordinates of boundaries for each US state and calculate the distance from each consumer ZIP code to the state boundaries of every US state. We estimate the distance to the lower tax state for each time period and consumer ZIP code as the closest distance to the border of the state with the lower state cigarette tax. Further, we match the tax rate with the corresponding lower tax state. Since we measure the distance to the lower tax state for each time period, we are able to properly capture the state and time level heterogeneity in cigarette taxes and the cost of cross-border purchasing.

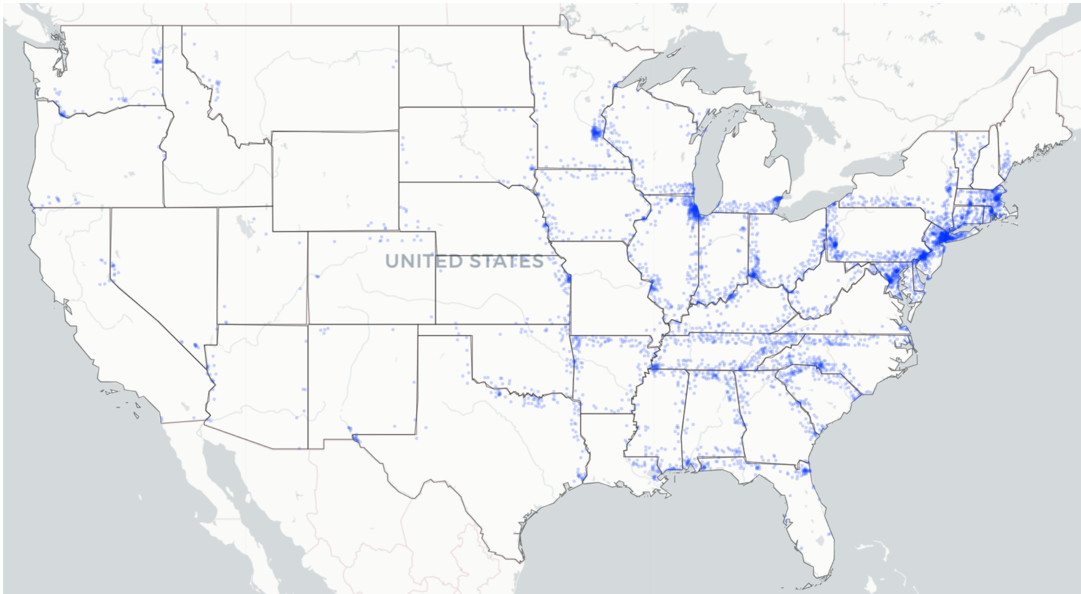


Figure 2: Distribution of Panelist ZIP Codes Located $\leq$ 50 km from a Lower-Tax State Border.

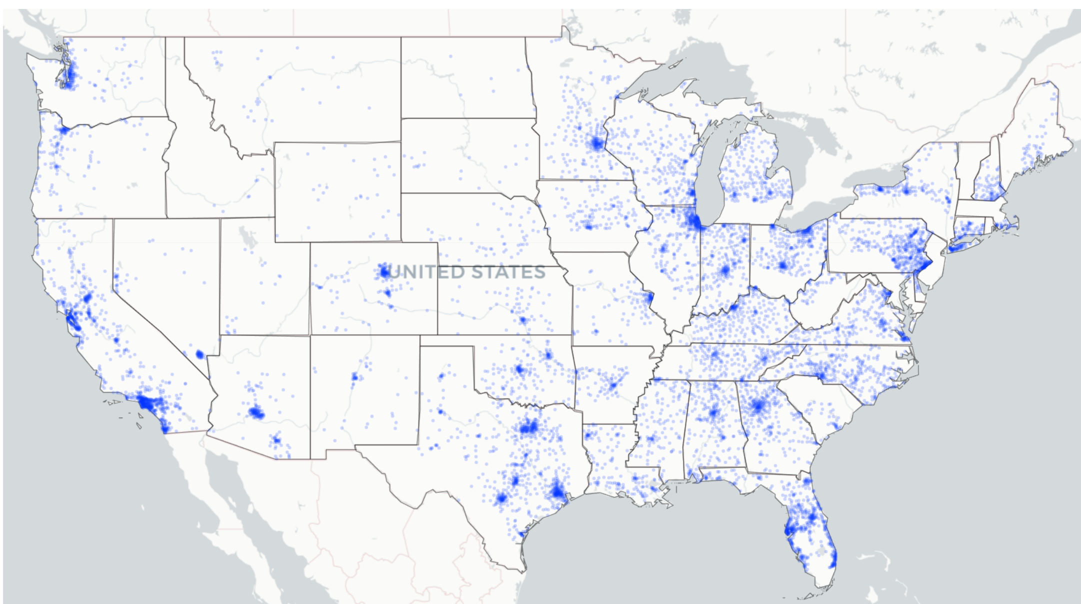


Figure 3: Distribution of Panelist ZIP Codes Located $>$ 100 km from a Lower-Tax State Border.

Table 1 reports summary statistics for the key variables used in the analysis. Additionally, we outline the rules used to create demographic subgroups, with the distribution of variables across these characteristics shown in Table 2. It is important to note that demographic characteristics may change from year to year for the same household.

Table 1: Descriptive Statistics of Analysis Variables

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Total packs purchased	48	64	0.05	6	68	2,234
Price per pack [1]	6.3	2.6	0.011	4.9	7.2	99
Distance to the lower tax state (km)	144	118	0.015	50	210	500
Tax value [1]	1.8	1.1	0.065	0.91	2.4	5.6
Tax rate in the lower tax state	0.76	0.62	0.025	0.3	1	4.2
Tax difference	0.73	0.62	0	0.23	1.1	4.1
Smoking rate [2]	48	53	0.7	10	67	669
Time span	2003 Q4 - 2019 Q4					
Number of ZIP codes	13,431					
Number of states	49					
Number of panelists	35,672					
Number of observations	327,534					

Table 2: Rules for Construction of Demographic Groups

Category	Panelists	N
Per capita income [3]		
High: >40,000$	9,052	66,618
Middle: 15.000$ - 40.000$	21,315	157,598
Low: $\leq$ 15.000$	14,980	103,318
Household size		
1: 1 member	8,668	78,358
2: 2 members	17,085	138,461
3: 3 members	8,946	53,602
4: 4 members	6,375	33,769
5: 5 members	3,031	14,113
6 plus: $\geq$ 6 members	1,920	9,231
Head Employment [4]		
$\leq$35 hours	5,738	33,440
35+ hours	22,485	170,640
Not employed for pay	14,584	123,454

[1] The price per pack is adjusted for any applicable discounts and coupons. Cigarette prices and taxes are adjusted to inflation using the Consumer Price Index for tobacco and smoking products in the U.S. City Average provided by the U.S. Bureau of Labor Statistics and retrieved from the website of the Federal Reserve Bank of St. Louis (FRED). We used 2017 as the base year.

[2] The sample includes only those households in the NielsenIQ Homescan data sample that make at least one cigarette purchase. Smoking rate is calculated as the average number of cigarette packs consumed per household per quarter.

[3] We calculated per capita income by dividing annualized combined household income by household size. The income is adjusted to inflation using the Consumer Price Index for urban consumers in the U.S. City Average provided by the U.S. Bureau of Labor Statistics and retrieved from the website of the Federal Reserve Bank of St. Louis (FRED). We used 2017 as a base year.

[4] The sample includes only those households in the NielsenIQ Homescan data sample that make at least one

4 Model Specification

We utilize panel data on consumers, which include continuous quarterly records of cigarette consumption. This study examines the impact of cigarette tax increases on consumption behavior. The baseline econometric model is as follows:

$$Y_{i,t} = \beta \cdot \tau_{s,t} + \gamma_s + \lambda_t + \epsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ denotes the number of cigarette packs consumed by a consumer i in time t, $\tau_{s,t}$ is a cigarette tax in the state s at time t, and γ_s, λ_t are state and time-fixed effects respectively.

The estimated tax sensitivity β is attenuated due to cross-border purchasing behavior, wherein consumers acquire cigarettes from neighboring states with lower tax rates. We refer to this phenomenon as the "border effect". To formally capture this mechanism, we analytically formulate tax sensitivity β as a function of a consumer's proximity to the nearest lower-tax state, denoted by $Dist_i$. Specifically, we model:

$$\beta = \overline{\tau} + \tau(Dist_i), \tag{2}$$

where $\overline{\tau}$ reflects the true tax sensitivity of consumption, and $\tau(Dist_i)$ captures the magnitude of the border effect as a function of distance to the nearest lower-tax state. We reasonably assume that the "border effect" reaches a maximum at the border with the lower-tax state and then declines linearly with distance from the border of the lower-tax state, vanishing beyond a certain cutoff distance. Therefore, the function $\tau(Dist_i)$ is constructed such that $\tau(Dist_i) = 0$ for distances exceeding a threshold D_{cutoff} and attains its maximum value when $Dist_i = 0$.

Consequently, the estimator obtained from the regression that does not control for the "border effect" demonstrates a positive bias. In expectation, the observed coefficient can be expressed as:

$$\mathbb{E}[\beta] = \overline{\tau} + \mathbb{E}[\tau(Dist_i)], \tag{3}$$

where $\overline{\tau}$ represents the "true" tax sensitivity estimate, and $\mathbb{E}[\tau(Dist_i)]$ can be treated as the average bias introduced by cross-border tax evasion.

To parametrize the spatial heterogeneity in tax sensitivity, we impose a linear functional form on the $\tau(Dist_i)$ and estimate the following regression model:

$$Y_{i,t} = \overline{\tau} \cdot \tau_{s,t} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max} [1 - \frac{Dist_i}{D_{\text{cutoff}}}] \cdot \tau_{s,t} + \gamma_s + \lambda_t + \epsilon_{i,t}, \tag{4}$$

where $\mathbf{1}_{Dist_i \leq D_{\text{cutoff}}}$ is an indicator function which is equal to 1 if consumer i resides within D_{cutoff} kilometers of a lower-tax border and zero otherwise. This specification allows the "border effect" to vary linearly with proximity to the border, reaching its peak τ_{max} at the border and declining to zero at the cutoff threshold. Including this term enables us to recover both the unbiased tax sensitivity $\overline{\tau}$ and the magnitude of the "border effect", thus providing a more accurate estimation of the behavioral response to cigarette excise taxes in the presence of cross-border cigarette purchasing.

cigarette purchase. "Head Employment", "Head Age", and "Head Education" refer to male household head if a male household head is present. In the cases in which no male household head is present, these variables refer to the female household head. This is in line with the study by the National Institute of Drug Abuse (April 2021) that finds men tend to use tobacco products at higher rates than women, and therefore men are more likely to be the primary buyers of cigarettes in grocery stores in a two-headed household.

Further, we extend equation (4) by interacting the spatial effect with the difference in tax rates between the home state and the nearest lower-tax state. The extended regression is specified as follows:

$$Y_{i,t} = \overline{\tau} \cdot \tau_{s,t} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max}[1 - \frac{Dist_i}{D_{\text{cutoff}}}] \cdot [\tau_{s,t} - \tau_{l,t}] \cdot \tau_{s,t} + \gamma_s + \lambda_t + \epsilon_{i,t}, \tag{5}$$

where $\tau_{s,t}$ and $\tau_{l,t}$ denote the home state tax and the tax rate in the nearest lower tax state, respectively. In this case, the "border effect" is enhanced by the tax difference $[\tau_{s,t} - \tau_{l,t}]$, attaining its maximum at $\tau_{max} \cdot [\tau_{s,t} - \tau_{l,t}]$ when $Dist_i = 0$. This formulation allows the strength of the "border effect" to vary both with spatial proximity and the magnitude of the tax difference. This extension offers a more comprehensive understanding of the impact of cross-border cigarette purchasing on consumers' responses to cigarette taxation.

5 Estimation Strategy and Results

We begin our analysis by estimating the baseline equation (4). This equation represents a continuous threshold regression model, where the threshold variable is the distance to the nearest lower-tax state $Dist_i$. The "border effect" variable decreases linearly with distance and eventually reaches zero at a certain cutoff distance, D_{cutoff}. Beyond this cutoff, the variable remains set to zero. As a result, the regression function is continuous, with no discontinuous jumps at the threshold point; however, there is a discontinuity in the slope at the threshold.

If D_{cutoff} were known, equation (4) can be estimated by the ordinary least squares method, and the estimates obtained will be consistent and asymptotically normal. In our problem setting, D_{cutoff} is unknown and needs to be estimated. Using the results of Hansen (2017) and Chan (1998), this model can be estimated by the method of conditional least squares (CLS). The regression parameters $(\overline{\tau}, \tau_{max}, \gamma_s, \lambda_t)$ are estimated by minimizing the sum of squared errors function $S_n(D_{\text{cutoff}})$ for a range of possible values of D_{cutoff}. CLS estimator of $\widehat{D}_{\text{cutoff}}$ is the value that minimizes $S_n(D_{\text{cutoff}})$:

$$\widehat{D}_{\text{cutoff}} = \min_{D_{\text{cutoff}} \in \Gamma} S_n(D_{\text{cutoff}}), \tag{6}$$

where Γ is a bounded set for possible values of the threshold parameter D_{cutoff}. Given a large number of unique distance values in the dataset, we approximated Γ by a grid of size N. More specifically, $\Gamma_N = \left\{D_{cutoff,(1)}, ..., D_{cutoff,(N)}\right\}$, which requires N functions evaluations. For our purpose, we tested 250 possible values of D_{cutoff}, spanning a grid ranging from 50 to 300 kilometers in 1-kilometer increments.

Chan (1998) shows that under suitable regularity conditions, the CLS estimator of the parameters, including the threshold parameter, is $n^{-\frac{1}{2}}$ consistent and asymptotically normally distributed. We construct approximate confidence intervals for the threshold parameter estimates following the methodology outlined by Hansen (2017). The proposed approach is based on inverting the F-type test statistic for the threshold parameter D_{cutoff}:

$$F_n(D_{\text{cutoff}}) = n \cdot \frac{S_n(D_{\text{cutoff}}) - S_n(\widehat{D}_{\text{cutoff}})}{S_n(\widehat{D}_{\text{cutoff}})}, \tag{7}$$

Assuming normally distributed errors and given asymptotic normality of the threshold regression estimates, this test statistic has an asymptotic χ^2_1 distribution. Specifically, the $1 - \alpha\%$ confidence interval for the threshold is given by the set $\widehat{\Gamma}$ consisting of those values for which the null hypothesis is not rejected at significance level $1 - \alpha$:

$$\widehat{\Gamma} = \{D_{\text{cutoff}} : \quad F_n(D_{\text{cutoff}}) \leq c_{1-\alpha}\}\,, \tag{8}$$

where $c_{1-\alpha}$ represents critical value for the F-type test statistic distribution.

Following Hansen (2017), confidence intervals for regression parameters $(\overline{\tau}, \tau_{\max}, \gamma_s, \lambda_t)$ are obtained by computing confidence intervals for each $D_{\text{cutoff}} \in \widehat{\Gamma}$ and taking their union.

This approach is particularly convenient for parameters obtained using the grid-search method, since confidence intervals can be directly obtained from the computation results of the least-square minimization.

We follow Hansen (2017) and calculate heteroskedasticity-robust asymptotic 95%-level confidence intervals for our threshold parameter D_{cutoff}. A graphical method to find the region $\widehat{\Gamma}$ is to plot the test statistic $F_n(D_{\text{cutoff}})$ against D_{cutoff} values and draw a flat line at 95%-level critical value $c_{1-\alpha}$. Figure 4 illustrates confidence interval construction for the threshold parameter in the baseline model.

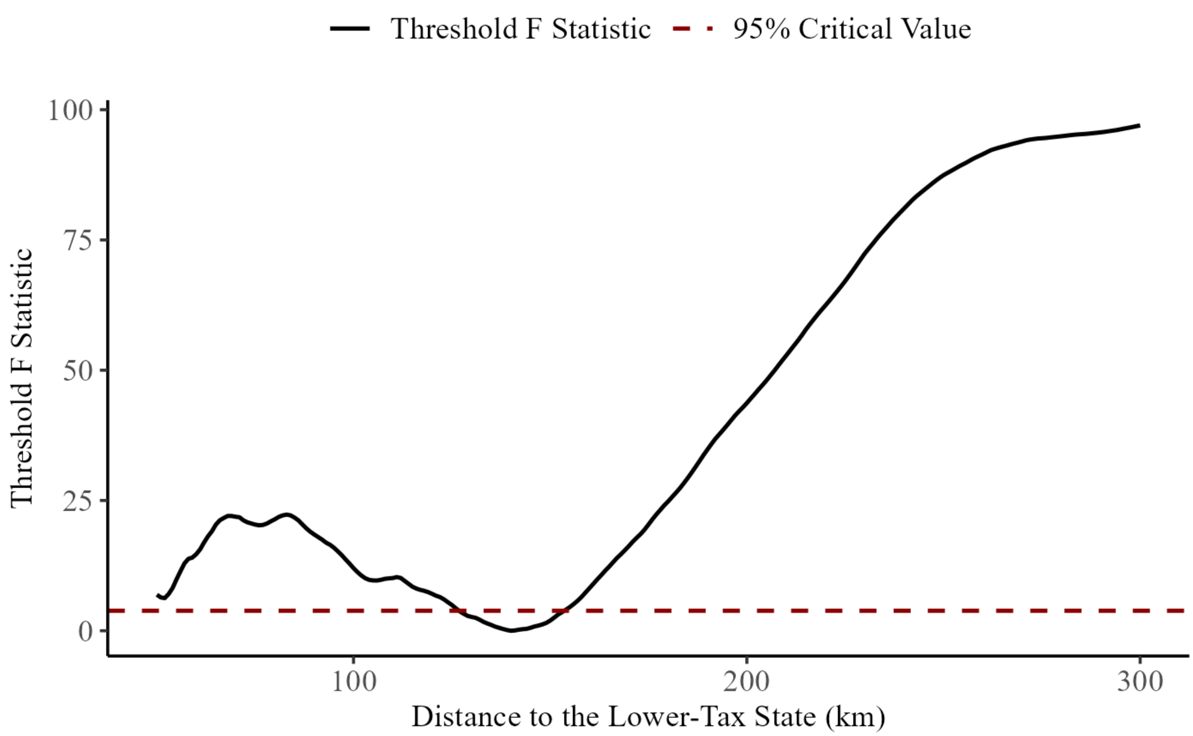


Figure 4: Baseline Model: Confidence Interval Construction for Threshold Parameter

Table 3 demonstrates estimation results of the equation (4), along with heteroskedasticity-robust asymptotic 95%-level confidence regions.

Table 3: Baseline Model: Border Effect and Tax Sensitivity Estimates

Variable	Estimate	95% CI
D_{cutoff}	140	[127, 153]
τ_{max}	2.9272	[2.4944, 3.3505]
$\overline{\tau}$	-5.2329	[-5.8556, -4.5990]

The results confirm the presence of spatial heterogeneity in the tax sensitivity. Specifically, consumers residing within 140 kilometers of the nearest lower-tax state are subject to the "border effect" and exhibit attenuated sensitivity to local cigarette excise tax increases. Our model allows us to recover both the true behavioral tax sensitivity $\overline{\tau}$ and the magnitude of the "border effect" bias τ_{max}.

We further proceed with our analysis by estimating the enhanced equation (5). We follow the same estimation procedure as described for the baseline equation (4). Figure 5 illustrates confidence interval construction for the threshold parameter in the extended model.

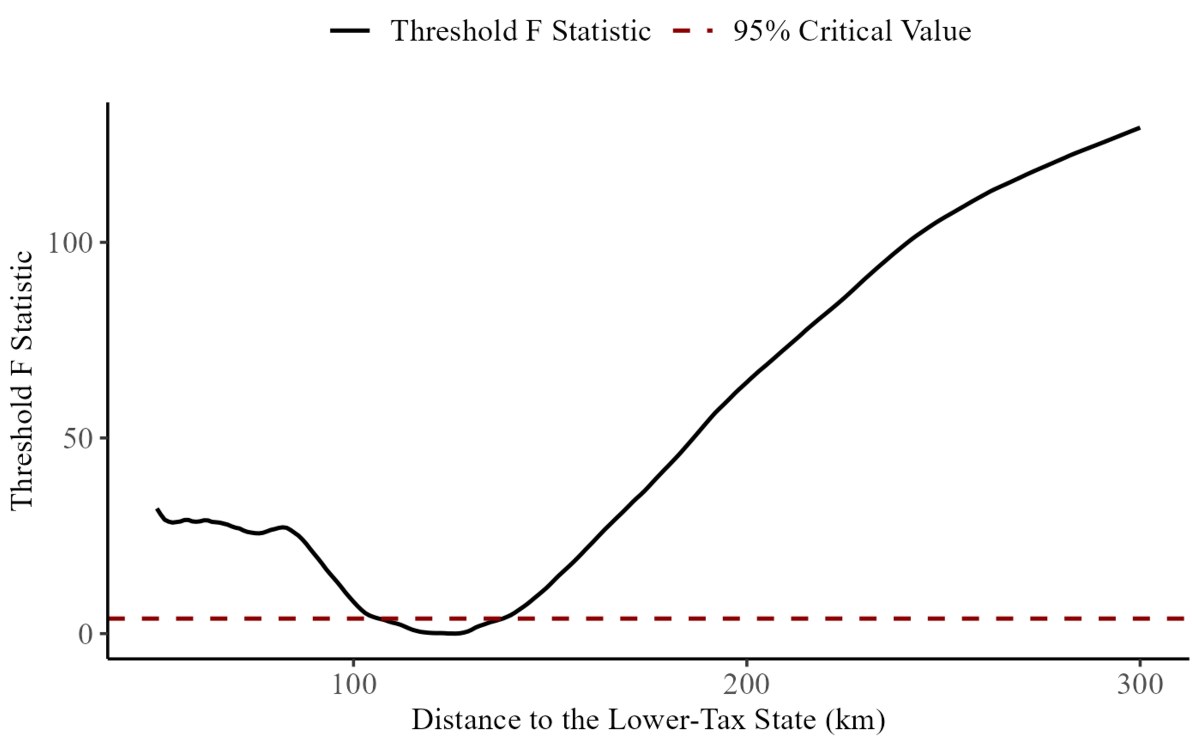


Figure 5: Extended Model: Confidence Interval Construction for Threshold Parameter

Table 4 demonstrates estimation results for the extended model, along with heteroskedasticity-robust asymptotic 95%-level confidence regions.

Table 4: Extended Model: Border Effect and Tax Sensitivity Estimates

Variable	Estimate	95% CI	
D_{cutoff}	126	[107,	137]
τ_{max}	1.7686	[1.5733,	1.9593]
$\overline{\tau}$	−5.6186	[−6.2403,	−4.9202]

The estimated threshold decreases slightly to 126 km, while the border effect parameter τ_{max} remains statistically significant. The enhanced model considers both geographic proximity and tax differentials to model the "border effect".

Our findings suggest that cross-border purchasing opportunities and differences in state taxes contribute to spatial heterogeneity in consumer sensitivity to cigarette taxes. This variation is an important factor to consider when developing an effective tobacco tax policy. Our model offers a more detailed understanding of how consumers respond to cigarette taxation in a system with heterogeneous tax regimes.

6 Robustness Analysis

To assess the robustness of our findings, we proceed with the robustness analysis of our models. Specifically, to confirm our assumptions, we examine how the responsiveness to cigarette excise taxes evolves with distance to the nearest lower-tax state without imposing a linear parametric structure as in equations (4) and (5) and then compare our results with the threshold regression estimates from Section 5.

We begin by estimating a segmented regression model corresponding to the baseline equation (4) in which the tax sensitivity is allowed to vary across equally sized discrete distance intervals. The specification is as follows:

$$Y_{i,t} = \sum_{g=1}^{G} \tilde{\tau}_g \cdot \mathbf{1}_{\left(Dist_i \geq D_{(g-1)}\right) \& \left(Dist_i < D_{(g)}\right)} \cdot \tau_{s,t} + \tilde{\gamma}_s + \tilde{\lambda}_t + \tilde{\epsilon}_{i,t}, \tag{9}$$

where $D_{(g-1)}$ and $D_{(g)}$ define cutoff values for the distance interval g, $D_{(0)}$ and $D_{(G)}$ correspond to the minimum and maximum values of the distance variable in the dataset.

Figures 6 display G estimates of tax sensitivity $\tilde{\tau}_g$ along with 95%-level confidence bands from equation (9). We plot the tax sensitivity estimates from the segmented regression against each midpoint of the distance interval. The red-dotted line overlays the fitted tax sensitivity function $\overline{\tau} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max}[1 - \frac{Dist_i}{D_{\text{cutoff}}}]$ from the threshold model (4). We observe that small interval sizes may produce volatile estimates, and too large intervals may absorb meaningful variation.

We proceed by estimating a segmented regression model corresponding to the extended equation (5). In this case, the tax sensitivity estimate varies across two dimensions: (1) distance to the nearest lower-tax state and (2) the difference in tax rates between the home state and the nearest lower-tax state. In order to evaluate a combined impact of these two factors on tax sensitivity, we estimated the segmented regression, in which the combined "border effect" defined as $\mathbf{1}_{Dist_i \leq \widehat{D}_{\text{cutoff}}}[1 - \frac{Dist_i}{\widehat{D}_{\text{cutoff}}}] \cdot [\tau_{s,t} - \tau_{l,t}]$ is allowed to vary across equally sized discrete intervals.

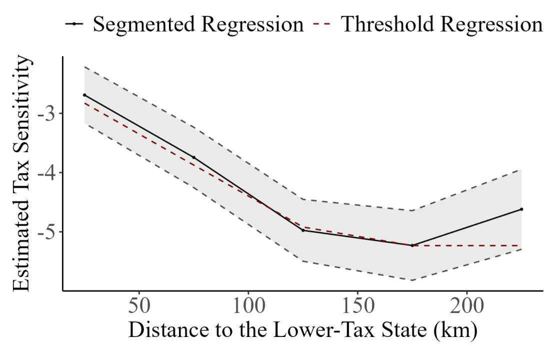
$$
\begin{aligned}
Y_{i,t} =& \bar{\tau}_{max,0} \cdot \mathbf{1}_{\text{BorderEffect}_i=0} \cdot \tau_{s,t} + \\
& \sum_{g=1}^{G} \bar{\tau}_{max,g} \cdot \mathbf{1}_{\left(\text{BorderEffect}_i > B_{(g-1)}\right) \& \left(\text{BorderEffect}_i \leq B_{(g)}\right)} \cdot \tau_{s,t} + \bar{\gamma}_s + \bar{\lambda}_t + \bar{\epsilon}_{i,t},
\end{aligned} \tag{10}
$$

where BorderEffect_i is defined as $\mathbf{1}_{Dist_i \leq \widehat{D}_{\text{cutoff}}}[1 - \frac{Dist_i}{\widehat{D}_{\text{cutoff}}}] \cdot [\tau_{s,t} - \tau_{l,t}]$ using estimate $\widehat{D}_{\text{cutoff}}$ from the threshold regression, $B_{(g-1)}$ and $B_{(g)}$ define cutoff values for the BorderEffect_i interval g, and $B_{(0)}$ and $B_{(G)}$ correspond to the minimum and maximum values of the "border effect" variable in the dataset.

(a) 20-km interval size

(b) 30-km interval size

(c) 40-km interval size



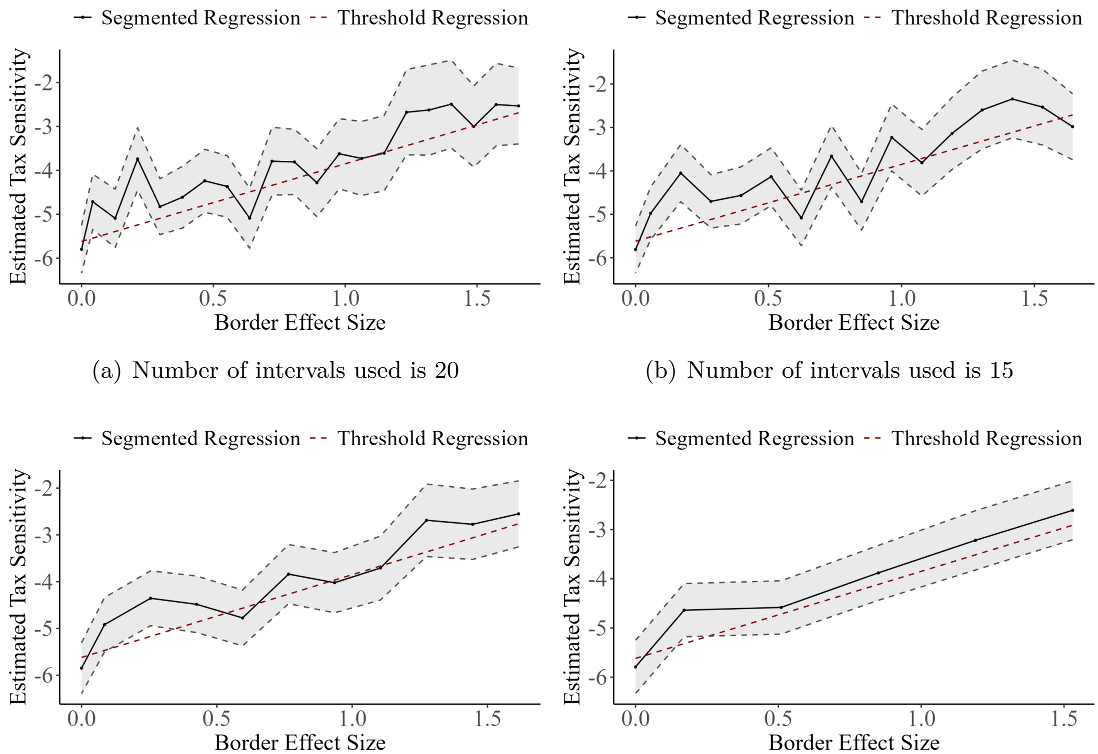
(d) 50-km interval size

Figure 6: Segmented regression estimates of tax sensitivity $\tilde{\tau}_g$ along with 95%-level confidence bands from the baseline model for 20, 30, 40 and 50-kilometer interval sizes. Red-dotted line overlays the fitted tax sensitivity function $\overline{\tau} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max}[1 - \frac{Dist_i}{D_{\text{cutoff}}}]$ from the threshold model.

Figures 7 display G estimates of tax sensitivity $\bar{\tau}_{max,g}$ along with 95%-level confidence bands from equation (10) for $G = 5$, $G = 10$, $G = 15$, and $G = 20$. We plot the tax sensitivity estimates from the segmented regression against each midpoint of the "border effect" interval. The red-dotted line overlays the fitted tax sensitivity function $\overline{\tau} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max}[1 - \frac{Dist_i}{D_{\text{cutoff}}}] \cdot [\tau_{s,t} - \tau_{l,t}]$ from the threshold model (5).

The results provide strong evidence of a positive and increasing relationship between tax sensitivity and the size of the composite "border effect" that is jointly dependent on both distance to the nearest lower tax state and tax differentials.

We can conclude that the robustness analysis results validate our parametric specification: the observed tax sensitivities from the segmented regressions follow the analytical tax sensitivity imposed in the threshold models.



(a) Number of intervals used is 20

(b) Number of intervals used is 15

(c) Number of intervals used is 10

(d) Number of intervals used is 5

Figure 7: Segmented regression estimates of the tax sensitivity estimate $\bar{\tau}_{max,g}$ along with 95%-level confidence bands from the extended model for $G = 5$, $G = 10$, $G = 15$, and $G = 20$. The red-dotted line overlays the fitted tax sensitivity function $\overline{\tau} + \mathbf{1}_{Dist_i \leq D_{\text{cutoff}}} \tau_{max}[1 - \frac{Dist_i}{D_{\text{cutoff}}}] \cdot [\tau_{s,t} - \tau_{l,t}]$ from the threshold model.

7 Demographic Heterogeneity

In this section, we analyze demographic heterogeneity in tax sensitivities across demographic groups. We focus on two key dimensions: annual per capita income and employment status. Both dimensions are directly related to the financial situation of consumers and, therefore, likely to shape their behavioral responses to taxation.

7.1 Income Groups

We begin by analyzing tax sensitivities across households with different levels of annual per capita income. Per capita income is calculated by dividing the combined annual household income by the household size. Income values are adjusted for inflation, using 2017 as the base year. Households are classified into three income groups, as shown in Table 5.

Table 5: Distribution of Households by Income Group

Category	Panelists	N
Per capita income[1]		
High: >40,000$	$9,052$	$66,618$
Middle: 15.000$ - 40.000$	$21,315$	$157,598$
Low: $\leq$ 15.000$	$14,980$	$103,318$

For each income group, we estimate the extended model defined in equation (5). For each observation in the dataset, we calculate the predicted tax sensitivity of cigarette consumption. Figure 8 shows the average predicted tax sensitivity along the distance to the nearest lower-tax state.

The results indicate that tax sensitivity decreases with income levels. High-income consumers show the lowest sensitivity to excise tax increases, while low-income consumers exhibit the highest sensitivity. The tax sensitivity of middle-income consumers falls in between these two groups, which aligns with economic expectations.

All income groups are influenced by the "border effect". However, for high-income consumers, this effect is present only for distances up to 60 kilometers from the lower-tax state. For middle- and low-income consumers, the shape of the "border effect" functions is similar; however, low-income consumers demonstrate significantly higher sensitivity to excise tax increases compared to middle-income consumers.

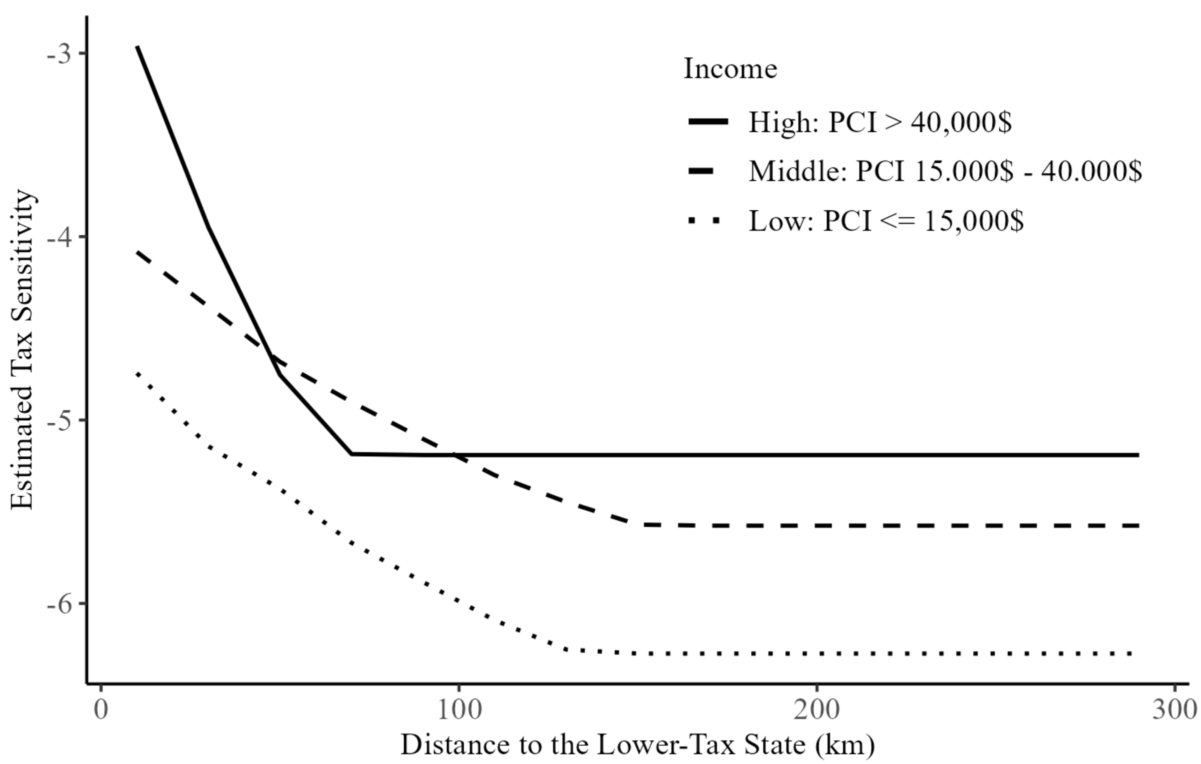


Figure 8: Predicted Tax Sensitivity by Income Group.

7.2 Employment Status

Next, we examine demographic heterogeneity by employment status. Households are divided into two categories based on the employment status of the male household head: "Employed" and "Not Employed for Pay". If there is no male head in the household, we will consider the female head of the household. The distribution of households across these categories is summarized in Table 6.

Table 6: Distribution of Households by Employment Status

Category	Panelists	N
Head Employment[2]		
Employed	25,813	204,080
Not employed for pay	14,584	123,454

As before, we estimate the extended model outlined in equation (5) for each demographic subgroup. For every observation in the dataset, we calculate the predicted tax sensitivity of cigarette consumption. Figure 9 illustrates the predicted tax sensitivities by employment status along the distance to the nearest lower-tax state.

Figure 9: Predicted Tax Sensitivity by Employment Status.

For both employed and non-employed consumers, the shape of the "border effect" function is similar. However, non-employed consumers demonstrate significantly higher sensitivity to excise tax increases compared to employed consumers.

8 Conclusion

This study provides empirical evidence of spatial variation in consumer responses to cigarette excise taxes, which is influenced by cross-border purchasing behavior. We developed and estimated a threshold regression model to capture the "border effect", which represents a systematic decrease in tax sensitivity among consumers living near states with lower taxes. Our results indicate that this effect diminishes with distance and disappears beyond a critical threshold estimated to be approximately 126–140 kilometers, depending on the model specification. Furthermore, we found that the strength of the border effect increases with the size of the tax differential between a consumer's home state and the nearest lower-tax state. Our robustness analysis confirms the validity of the parametric assumptions underlying our main model and supports the conclusion that spatial variation in tax sensitivity is both statistically and economically significant.

Additionally, our analysis reveals that this heterogeneity extends across different demographic sub-groups. Tax sensitivity decreases with income levels. High-income consumers exhibit the lowest sensitivity to excise tax increases, while low-income consumers show the highest sensitivity. The tax sensitivity of middle-income consumers falls between these two groups, which aligns with economic expectations. All income groups are influenced by the "border effect", but for high-income consumers, this effect is only present at distances up to 60 kilometers from the lower-tax state. While the shape of the "border effect" functions for middle- and low-income consumers is similar, low-income consumers demonstrate significantly higher sensitivity to excise tax increases compared to middle-income consumers. Moreover, our analysis based on employment status indicates that both employed and non-employed consumers display a similar shape in the "border effect" function; however, non-employed consumers show significantly higher sensitivity to excise tax increases than employed consumers.

These findings have important implications for the design of tobacco tax policy within heterogeneous tax regimes such as the United States. Future research could build on these results by exploring interstate cross-border purchasing with Mexico and investigating the additional impact of variability in sales tax.

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Abstrakt

Rozdíly ve spotřebních daních mezi jednotlivými státy motivují spotřebitele k přeshraničním nákupům. V této studii zkoumáme fenomén „hraničního efektu“, který označuje dopad přeshraničního nákupního chování na citlivost spotřeby vůči spotřební dani. Analyticky formulujeme „hraniční efekt“ jako lineární funkci, která klesá se vzdáleností od nejbližšího státu s nižší daní. Předpokládáme, že „hraniční efekt“ dosahuje maxima přímo na hranici se státem s nižší daní a poté lineárně klesá se vzdáleností od hranice, až po určité prahové vzdálenosti dosáhne nuly. Parametry funkce „hraničního efektu“ odhadujeme pomocí prahového regresního modelu s fixními efekty pro lokaci a čas. Jako test robustnosti dále provádíme segmentovanou regresi, která využívá samostatné odhady daňové citlivosti pro různá intervalová pásma vzdálenosti. Ověřujeme, že odhady ze segmentované regrese odpovídají lineárnímu vzoru odvozenému z prahového modelu. Dále rozšiřujeme funkci „hraničního efektu“ o rozdíl mezi daní ve státě bydliště a daní v nejbližším státě s nižší daní jako o dodatečný faktor a porovnáváme výsledky odhadů pro obě specifikace. Nad rámec geografických rozdílů zkoumáme také, jak se daňová citlivost spotřeby cigaret liší mezi demografickými skupinami. Naše analýza ukazuje, že daňová citlivost se liší podle úrovně příjmu: spotřebitelé s vysokými příjmy reagují na zvýšení spotřební daně nejméně, zatímco spotřebitelé s nízkými příjmy reagují nejvíce, přičemž spotřebitelé se středními příjmy se nacházejí mezi těmito extrémy. Všechny příjmové skupiny jsou ovlivněny „hraničním efektem“, avšak u spotřebitelů s vysokými příjmy se tento efekt projevuje pouze do vzdálenosti přibližně 60 kilometrů od státu s nižší daní. Analýza podle zaměstnaneckého statusu ukazuje, že jak zaměstnaní, tak nezaměstnaní spotřebitelé vykazují podobný tvar funkce „hraničního efektu“; nezaměstnaní však vykazují výrazně vyšší daňovou citlivost než zaměstnaní.

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