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How State Borders Shape the Impact of Cigarette Taxes on Prices

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Abstract

The availability of lower-taxed goods in neighboring states incentivizes consumers to make cross-border purchases. Using transaction-level data from the NielsenIQ Consumer Panel, we analyze how proximity to a lower-tax state affects the pass-through of tax to cigarette prices. We analytically formulate tax pass-through to prices as the "true" pass-through rate attenuated by the "border effect". The "border effect" refers to the impact of cross-state purchasing behavior on the extent to which excise taxes are passed on to cigarette prices. We model the border effect as an exponential function that decreases with distance from the lower-tax state, reaching the highest value at the border itself and diminishing to zero at large distances. We estimate the parameters of the "border effect" function by employing an exponential regression model with location, time, and UPC fixed effects. The results of the robustness check, where we estimate a segmented regression using separate tax pass-through estimates for a range of distance intervals, support the linear pattern observed in the exponential model. We also extend the model to account for the tax differential between the home state and the nearest lower-tax state and perform a comparative analysis of the two model specifications. In addition to geographic variation, we also analyze how the pass-through of cigarette taxes varies across different demographic groups. High-income households face the highest tax pass-through and are largely unaffected by border proximity, while middle-income households are affected by the "border effect" only when the distance from the lower-tax state does not exceed 90 kilometers. Low-income households remain sensitive to "border effects" at greater distances, though their responsiveness declines beyond 200 kilometers. Moreover, consumers who are not engaged in paid employment exhibit significantly lower pass-through, suggesting greater scope for tax avoidance through flexible shopping behavior.

Keywords: excise taxation, cigarettes, tax pass-through rate, cross-state purchasing, tax avoidance, border effects

JEL Classification: D12, H26, H71, L66

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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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1 Introduction

In the United States, excise taxes on cigarettes serve as both a significant source of government revenue and a widely used public health policy tool. Raising cigarette prices through higher excise taxes effectively reduces smoking rates and thereby improves public health outcomes. However, the effectiveness of these tax measures can be considerably undermined by various forms of tax avoidance, such as cross-border purchases made in states with lower taxes, buying cigarettes from Indian reservations, smuggling, and making purchases over the Internet. These actions affect how much of the excise tax is reflected in cigarette prices. If the full tax amount is passed on to consumers, they face higher costs and may reduce their cigarette consumption. Conversely, if only a portion of the tax is passed on to consumers, the intended effects of the tax policy measure may not be fully realized.

In the United States, where we can track the variability of state excise taxes across states, geographic proximity to lower-tax jurisdictions creates opportunities for tax avoidance through cross-border purchases. Consumers living near state boundaries can partially offset the impact of local tax increases by buying cigarettes in neighboring states with lower tax rates. Moreover, due to profit motives, shops near borders may adjust their prices to mitigate the unfavorable tax difference to a certain extent. As a result, these "border effects" lead to spatial variation in the pass-through of taxes to prices, which tends to be systematically lower in areas close to the neighboring lower-tax states. This effect diminishes as the distance from the lower-tax state border increases.

This paper develops a novel analytical framework to model the "border effect"—the reduction in the pass-through of cigarette excise taxes to prices that arises from cross-border purchases. To quantify the magnitude of the border effect, we estimate an exponential growth model with UPC, location, and time-fixed effects. The border effect is specified as an exponentially declining function of distance to the nearest lower-tax border, with the strongest influence at the boundary and diminishing impact as distance increases. The analysis draws on comprehensive NielsenIQ Consumer Panel data from 2004 to 2019, which provide detailed information on household-level cigarette purchases over time and the geographic location of panelists.

As a robustness check, we also estimate a segmented regression using separate tax sensitivity estimates for a range of distance intervals. We verify that the segmented estimates are consistent with the pattern derived from the exponential model. Further, we refine the "border effect" specification by incorporating the difference between the home state's tax and the tax in the closest lower-tax state as an additional factor. We then compare the estimation results from both specifications.

Beyond geographic variation, we also examine how the pass-through of cigarette taxes 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 pass-through differ across population subgroups. The analysis reveals important heterogeneity across households. High-income households face the highest tax pass-through and are largely unaffected by border proximity, while middle-income households are affected by the "border effects" only when the distance from the lower-tax state does not exceed 90 kilometers. Low-income households remain sensitive to "border effects" at greater distances, though their responsiveness declines beyond 200 kilometers. Moreover, consumers who are not engaged in paid work exhibit significantly lower pass-through, suggesting greater scope for tax avoidance through flexible shopping behavior. Therefore, the welfare implications of cigarette taxation vary across demographic groups: high-income households experience a higher tax pass-through and thus bear a larger tax burden, while low-income and non-employed households face a lower effective tax burden due to reduced tax pass-through from cross-border cigarette purchases and other tax avoidance actions.

Our findings contribute to the literature in several important respects. First, we provide empirical evidence of spatial differences in how excise taxes are passed through to cigarette prices in the United States. Second, we quantify how these differences vary based on the distance to lower-tax state borders and differences in state tax rates. Third, we examine how tax pass-through varies across different demographic groups. Together, these results highlight the importance of considering spatial factors in the evaluation and design of excise tax policy, particularly in a tax system with heterogeneous tax regimes such as the US.

2 Previous Literature

High cigarette tax rates can lead to movement of tobacco products from low-tax states and neighboring countries into high-tax states. For policymakers, the degree to which excise tax increases are passed through to retail prices is an important issue for two main reasons: the taxes can aid in achieving public health goals by reducing cigarette consumption and in 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. These behaviors can weaken the intended impact of taxation by affecting how much of the tax is passed on to cigarette prices and how consumers respond to price changes resulting from the tax increases.

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 use historical data on state-level cigarette excise taxes in the United States, obtained from the Centers for Disease Control and Prevention (CDC). The data reports the excise tax per pack in US dollars and is available on a quarterly basis. Excise taxes are not uniform in the US and exhibit significant variability across states. This allows us to take into account both changes in excise taxes over time and 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 transaction-level data from NielsenIQ Consumer Panel containing information about the purchase histories of 40,000-60,000 households (numbers vary 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 2,847,908 individual cigarette purchase transactions recorded by 47,457 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. The data set includes 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 US (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 incorporation of spatial controls in empirical analyses. Figures 2 and 3 show the geographic distribution of household locations based on proximity to the borders of states with lower cigarette taxes. Specifically, they depict panelist ZIP codes located within 50 kilometers and more than 100 kilometers of such borders.

We measure the distance to the nearest lower-tax state using Census TIGER/Line shape files provided by 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 may not be a bordering state. 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 cigarette tax. Further, we match the tax rate in the corresponding lower tax state. Because we measure the distance to the lower tax state for each time period, we are able to correctly capture the state and time level heterogeneity in cigarette taxes and the cost of cross-border purchasing.

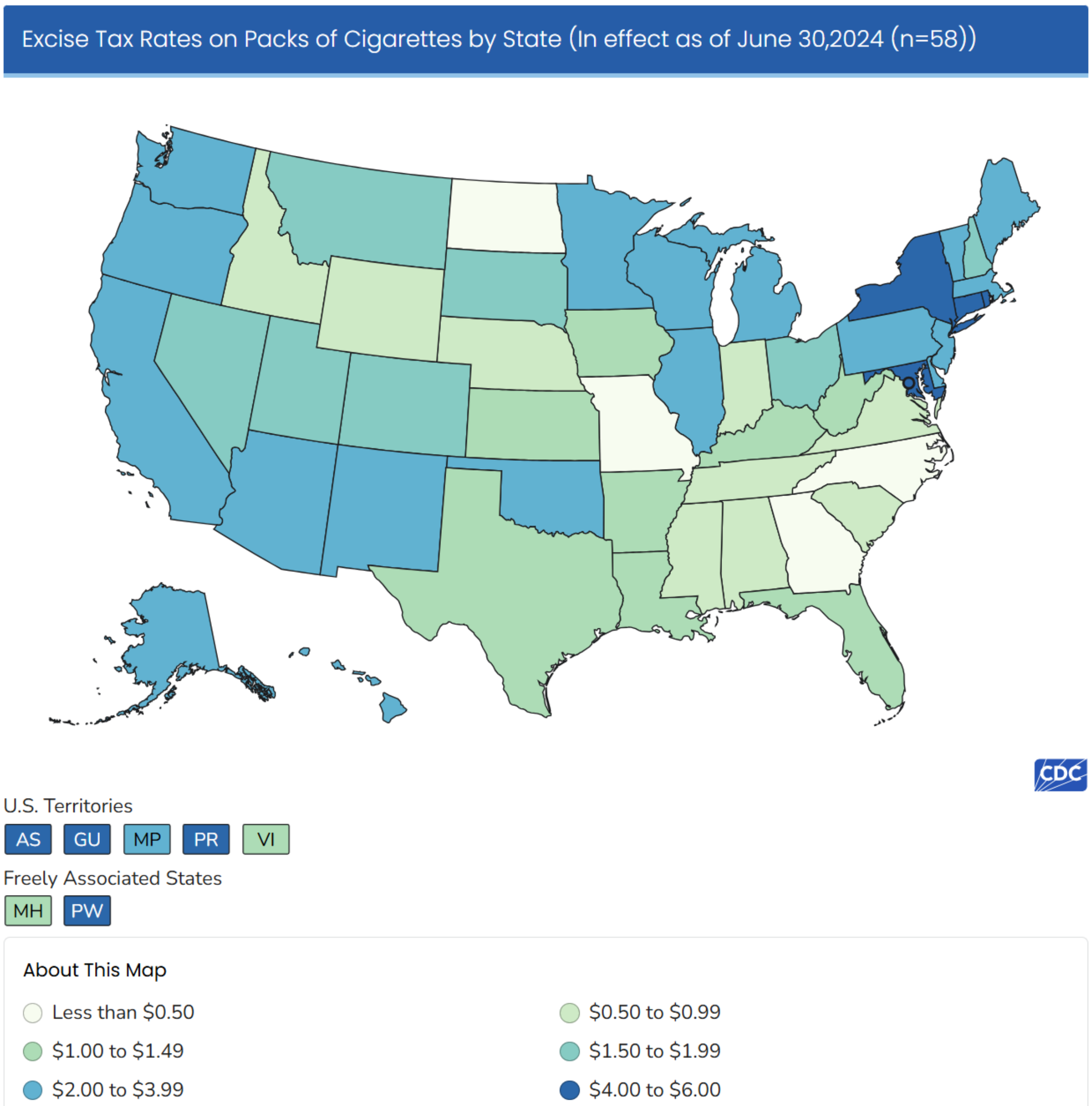


Figure 1: Excise Tax Rates on Packs of Cigarettes by State

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

As a target variable, we use the final price paid per cigarette pack adjusted for possible discounts and coupons. For cigarette multi-packs, we normalize the price paid to the number of units in a multi-pack. We adjust prices and taxes for inflation using the Consumer Price Index for tobacco and smoking products in the US City Average provided by the US Bureau of Labor Statistics and retrieved from the website of the Federal Reserve Bank of St. Louis (FRED). We use 2017 as a base year.

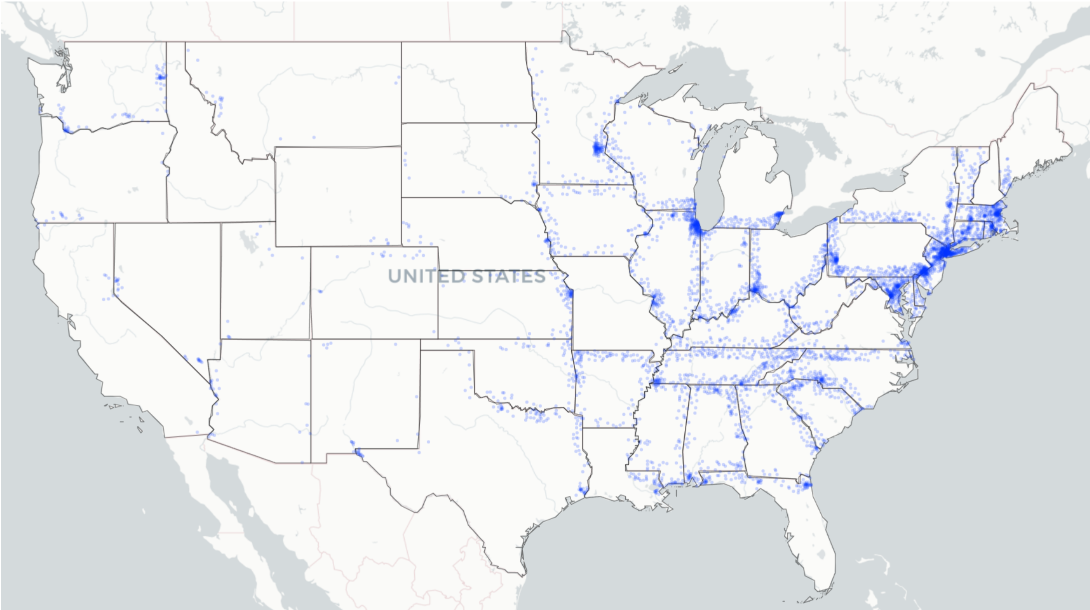


Figure 2: Distribution of Panelist ZIP Codes Located ≤ 50 km from a Lower-Tax State Border.

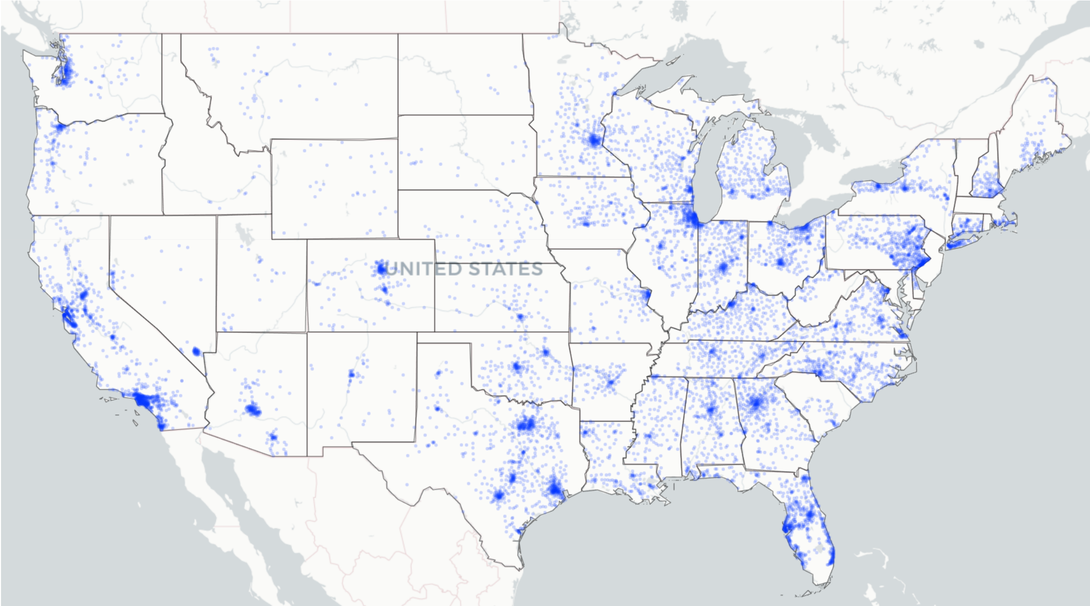


Figure 3: Distribution of Panelist ZIP Codes Located > 100 km from a Lower-Tax State Border.

Table 1 reports summary statistics for the key variables used in the analysis.

Table 1: Descriptive Statistics of Analysis Variables

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Final price per pack	6.4	2.1	1	5	7.4	35
Total packs purchased per trip	5.5	7.3	1	1	10	430
Distance to the lower tax state (km)	141	117	0.015	49	207	500
Tax value	1.8	1.1	0.065	0.94	2.4	5.6
Tax rate in the lower tax state	0.77	0.63	0.025	0.3	1	4.2
Tax difference	0.73	0.61	0.0046	0.24	1.2	4.1
Time span	2003 Q4 - 2019 Q4					
Number of ZIP codes	14,831					
Number of states	49					
Number of panelists	47,457					
Number of observations	2,847,908					
Number of UPC	6,418					

Finally, we define the rules used to construct demographic subgroups, with the distribution of variables across these characteristics reported in Table 2.

Table 2: Rules for Construction of Demographic Groups

Category	Panelists	N
Per capita income [1]		
High: Per capita income>40,000$	11,656	503,466
Middle: Per capita income 15.000$ - 40.000$	26,827	1,375,787
Low: Per capita income ≤ 15.000$	18,388	968,655
Household size		
1: 1 member	10,794	689,838
2: 2 members	21,436	1,251,405
3: 3 members	10,950	465,653
4: 4 members	8,130	263,690
5: 5 members	3,874	106,241
6 plus: ≥ 6 members	2,434	71,081
Head Employment [2]		
≤35 hours	6,899	316,162
35+ hours	29,551	1,410,850
Not employed	18,017	1,120,896

[1] We calculate 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 US City Average provided by the US Bureau of Labor Statistics and retrieved from the website of the Federal Reserve Bank of St. Louis (FRED). We use 2017 as a base year.

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

4 Model Specification

To assess the impact of excise taxes on cigarette prices, we estimate the following baseline econometric model using transaction-level data on cigarette purchases:

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

where $P_{u,i,s,t}$ denotes the price of a cigarette pack purchased for UPC u by consumer i in state s at time t; $\tau_{s,t}$ represents the cigarette tax in state s at time t; and γ_s, λ_t, and α_u denote state, time, and UPC fixed effects, respectively.

It is important to note that the use of UPC fixed-effects enables us to control for potential brand substitution effects following tax increases. In addition, state fixed effects account for unobserved interstate price differentials, while time fixed effects capture common trends in cigarette price dynamics over time.

We assume that the estimated pass-through of taxes to prices β is attenuated due to cross-border purchasing, wherein consumers purchase cigarettes from neighboring states with lower tax rates. We refer to this phenomenon as the "border effect". We analytically formulate tax pass-through β as a function of a consumer's proximity to the nearest lower-tax state, denoted by $Dist_i$:

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

where $\overline{\tau}$ reflects the "true" pass-through rate of cigarette taxes to prices, and $\tau(Dist_i)$ captures the "border effect" as a function of distance to the nearest lower-tax state. We assume that the "border effect" reaches a maximum at the border with the lower-tax state and then gradually declines with increasing distance from the border.

Consequently, the estimator of tax pass-through rate obtained from equation (1), which does not account for the "border effect", demonstrates a negative bias. The expected value of the tax pass-through rate can be expressed as:

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

where $\overline{\tau}$ represents the "true" tax pass-through 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 the pass-through of taxes to prices, we impose an exponential functional form on the $\tau(Dist_i)$ and estimate the following regression model:

$$P_{u,i,s,t} = \overline{\tau} \cdot \tau_{s,t} + \tau_{max} e^{-\phi \cdot Dist_i} \cdot \tau_{s,t} + \gamma_s + \lambda_t + \alpha_u + \epsilon_{u,i,s,t}, \tag{4}$$

where parameter ϕ controls the concavity of the distance function.

Figure 4 illustrates the shape of $e^{-\phi \cdot Dist_i}$ for a range of ϕ values.

be the primary buyers of cigarettes in a household.

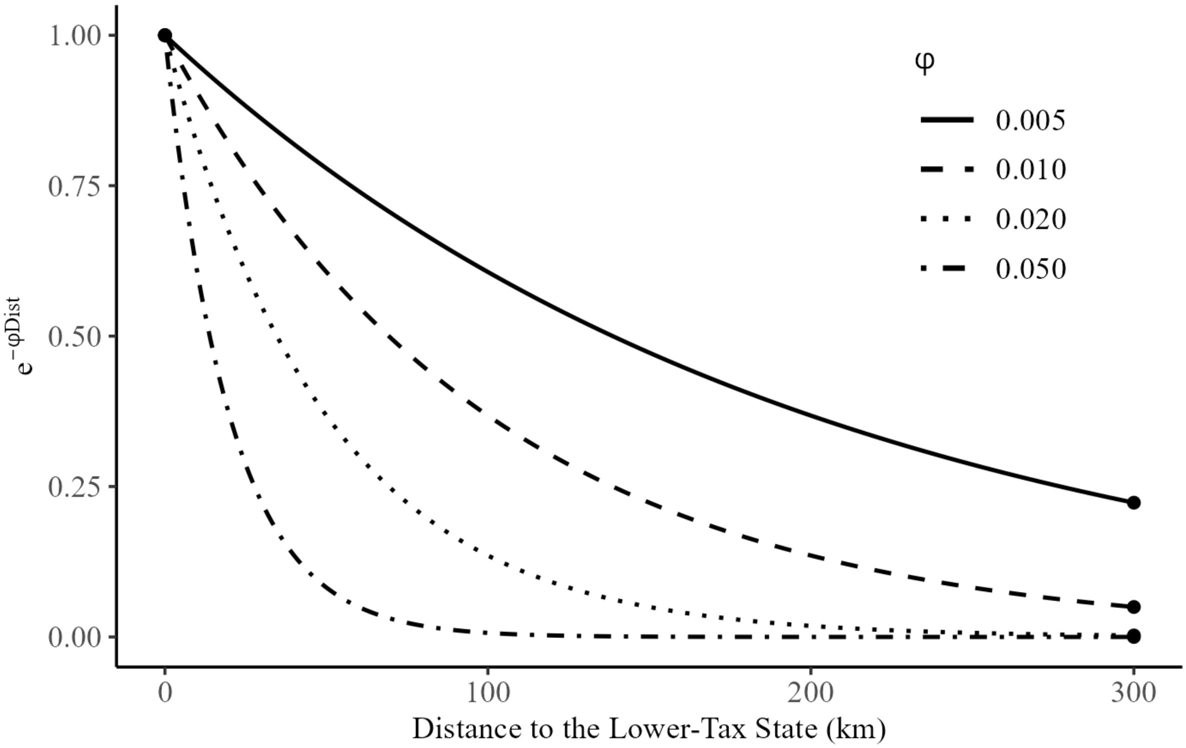


Figure 4: $e^{-\phi \cdot Dist_i}$ for a Range of ϕ Parameters

This specification allows the "border effect" to vary with proximity to the border, reaching its peak τ_{max} at the border and declining towards zero at large distances. Including this term enables us to recover both the unbiased tax pass-through $\overline{\tau}$ estimate and the magnitude of the border effect, thus providing a more accurate estimate of the tax pass-through in the presence of cross-border cigarette purchasing.

The tax pass-through Π, following equation (4), has the following analytical formulation:

$$\Pi = \overline{\tau} + \tau_{max} e^{-\phi \cdot Dist_i}, \tag{5}$$

where $\overline{\tau}$ term represents the "true" unbiased tax pass-through estimate and the term $\tau_{max} e^{-\phi \cdot Dist_i}$ represents the "border effect" function.

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

$$P_{u,i,s,t} = \overline{\tau} \cdot \tau_{s,t} + \tau_{max} e^{-\phi \cdot Dist_i} \cdot [\tau_{s,t} - \tau_{l,t}] + \gamma_s + \lambda_t + \alpha_u + \epsilon_{u,i,s,t}, \tag{6}$$

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" formulation is enhanced by the tax difference $[\tau_{s,t} - \tau_{l,t}]$, reaching its maximum at $\tau_{max} \cdot [\tau_{s,t} - \tau_{l,t}]$ at the border when $Dist_i = 0$. This formulation allows the strength of the "border effect" to vary both with spatial proximity and the magnitude of the inter-state tax differential.

The tax difference between the home state tax and the nearest lower tax state determines the slope of the distance function. Figure 5 illustrates the values for $\Delta\tau \cdot e^{-\phi \cdot Dist_i}$ for a range of different $\Delta\tau$ parameters with $\phi = 0.01$.

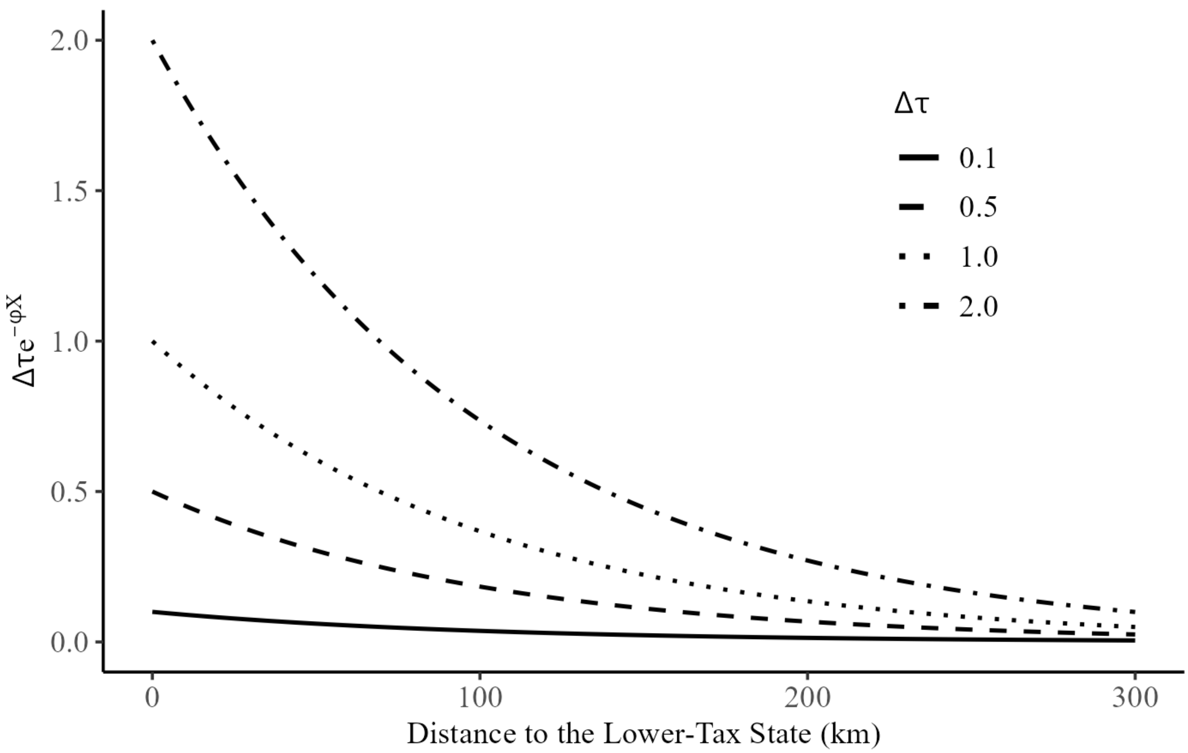


Figure 5: $\Delta\tau \cdot e^{-\phi \cdot Dist_i}$ for a Range of Different $\Delta\tau$ Parameters and $\phi = 0.01$

Note that equation (6) can be re-written in terms of relative tax difference $\Delta_{s,t} = \frac{[\tau_{s,t} - \tau_{l,t}]}{\tau_{s,t}}$, which allows us to recover tax pass-through rate estimate:

$$P_{u,i,s,t} = \overline{\tau} \cdot \tau_{s,t} + \tau_{max} e^{-\phi \cdot Dist_i} \cdot \Delta_{s,t} \tau_{s,t} + \gamma_s + \lambda_t + \alpha_u + \epsilon_{u,i,s,t}, \tag{7}$$

where $\Delta_{s,t}$ is defined as the tax difference between the home state and the lower-tax state relative to the home state tax rate. Consequently, the tax pass-through Π for the extended model can be expressed using the following equation:

$$\Pi = \overline{\tau} + \tau_{max} e^{-\phi \cdot Dist_i} \cdot \Delta_{s,t}, \tag{8}$$

in which the term $\overline{\tau}$ term represents "true" unbiased tax pass-through estimate and $\tau_{max} e^{-\phi \cdot Dist_i} \cdot \Delta_{s,t}$ term represents the "border effect" component.

5 Estimation Strategy and Results

We begin our empirical analysis by estimating the baseline equation (4). If ϕ were known, the equation (4) can be estimated by the ordinary least squares (OLS) method, and the estimates obtained will be consistent and asymptotically normal. In this problem setting, ϕ is unknown and needs to be estimated. We estimate the exponential growth model represented by equation (4) using the non-linear least squares (NLS) method, as the model is non-linear in parameter ϕ. Following the pioneering work of Becsey et al. (1968), we employ a direct grid search approach. Grid search is a brute-force optimization technique that systematically evaluates a range of possible parameter values and selects the one that minimizes the sum of squared errors, $S_n(\phi)$. Formally, the NLS estimator of ϕ is defined as:

$$\widehat{\phi} = \min_{\phi \in \Gamma} S_n(\phi), \tag{9}$$

where Γ is a bounded set for possible values of the parameter ϕ. For our purpose, we tried 200 possible values of ϕ for the grid ranging from 0.0005 to 0.1 in 0.0005 increments.

We selected this method due to its simplicity, robustness, and a large number of fixed effects. Our specification includes 6,418 UPC fixed effects, 49 state fixed effects, and 65 time fixed effects. Estimating a non-linear model with such high dimensionality would be computationally intensive. Because the fixed-effect estimates themselves are not focus of interest, we reduce the dimensionality of the problem by applying the Frisch–Waugh–Lovell (FWL) theorem. Using this theorem, we regress the residualized target variable on the residualized components of the predictors of interest. The residuals are obtained from models in which both the target and the predictors are regressed on the complete set of fixed effects. In our setting, the target variable is the price of a cigarette pack, while the key predictors are the state cigarette tax and the border effect variable.

The residualized version of each variable is obtained in two steps. In the first stage, we regress the variables of interest (including state and time fixed effects) on UPC fixed effects and compute the residuals. This step is equivalent to subtracting UPC-specific averages from each variable. In the second stage, we regress these first-stage residuals on the residualized state and time fixed effects to obtain the second-stage residuals, which are then used in the final reduced-form regression. In this problem setting, the residualized versions of the target variable and the tax rate are computed only once, and only the residualized version of the "border effect" variable is recalculated at each iteration of the grid search. This approach significantly simplifies computational complexity.

Under the assumption that the model falls into the category of moderately non-linear models with normally distributed errors, we can construct an approximate confidence interval for the parameter ϕ following the methodology proposed by Beale (1960). In this framework, confidence regions for non-linear estimators are derived using the likelihood ratio criterion. Specifically, a given parameter ϕ is included in the $1-\alpha$ confidence region if the corresponding residual sum of squares, $S_n(\phi)$, lies within the margin defined by the following equation:

$$S_n(\phi) = S_n(\widehat{\phi}) \cdot [1 + \frac{p}{n-p} F_{1-\alpha}(p, n-p)], \tag{10}$$

where p is number of parametes, $F_{1-\alpha}(p, n-p)$ is an appropriate quantile of F-distribution with $(p, n-p)$ degrees of freedom. It is important to note that when the number of observations n is large, the scaled $p \cdot F$-distribution converges to a χ^2_p distribution.

Given the large sample size, and following equation (10), the F-type statistic for the non-linear parameter ϕ has an asymptotic χ^2_1 distribution:

$$F_n(\phi) = n \cdot \frac{S_n(\phi) - S_n(\widehat{\phi})}{S_n(\widehat{\phi})}, \tag{11}$$

Thus $1-\alpha$ asymptotic confidence interval for ϕ can be defied as the set of ϕ for which $F_n(\phi)$ is smaller than critical value $c_{1-\alpha}$ of χ^2_1 distribution:

$$C_\phi = \{\phi : F_n(\phi) \leq c_{1-\alpha}\}, \tag{12}$$

This approach is particularly convenient for parameters obtained using the grid-search method, because confidence intervals can be directly obtained from the computation results of the least-square minimization. For example, the same approach was used by Hansen (2017) to construct confidence intervals for the threshold parameter in the regression kink model using the grid search method.

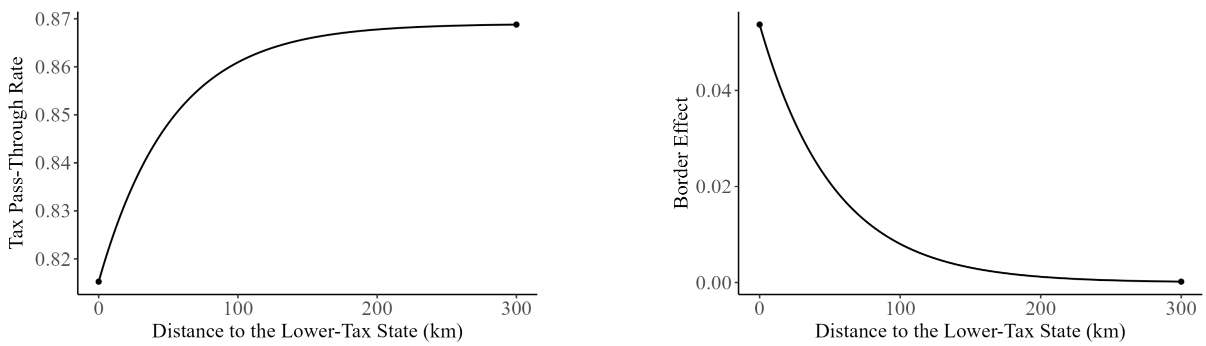
Confidence intervals for the regression coefficients $\overline{\tau}$ and τ_{max} are obtained by computing confidence intervals for each $\phi \in C_\phi$ and taking their union.

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 Pass-Through Estimates

Variable	Estimate	95% CI	
ϕ	0.019	[0.0165,	0.0215]
τ_{max}	-0.0537	[-0.0581,	-0.0495]
$\overline{\tau}$	0.8690	[0.8630,	0.8754]

Figure 6 illustrates how the estimated pass-through rate and border effect vary with distance to the nearest lower-tax state.



(a) Tax Pass-Through

(b) Border Effect

Figure 6: Baseline Model: Exponential Growth Model.

The results confirm the presence of spatial heterogeneity in the pass-through of state cigarette taxes to prices. The model allows us to recover both the "true" behavioral tax pass-through estimate $\overline{\tau}$ and the magnitude of the "border effect" bias τ_{max}.

The analysis proceeded with estimation of the enhanced equation (6). We follow the same estimation procedure as described for the baseline equation (4). For this purpose, we tried 191 possible values of ϕ for the grid ranging from 0.001 to 0.02 in 0.0001 increments. Table 4 demonstrates estimation results of the equation (6) together with heteroskedasticity-robust asymptotic 95%-level confidence regions.

Table 4: Extended Model: Border Effect and Tax Pass-Through Estimates

Variable	Estimate	95% CI	
ϕ	0.0076	[0.0072,	0.0079]
τ_{max}	-0.3036	[-0.3105,	-0.2964]
$\overline{\tau}$	0.9573	[0.9516,	0.9634]

The two-dimensional Figure 7 illustrates the evolution of the pass-through rate across distance to the nearest lower tax state, as well as the relative difference between the home-state tax and the lower tax state.

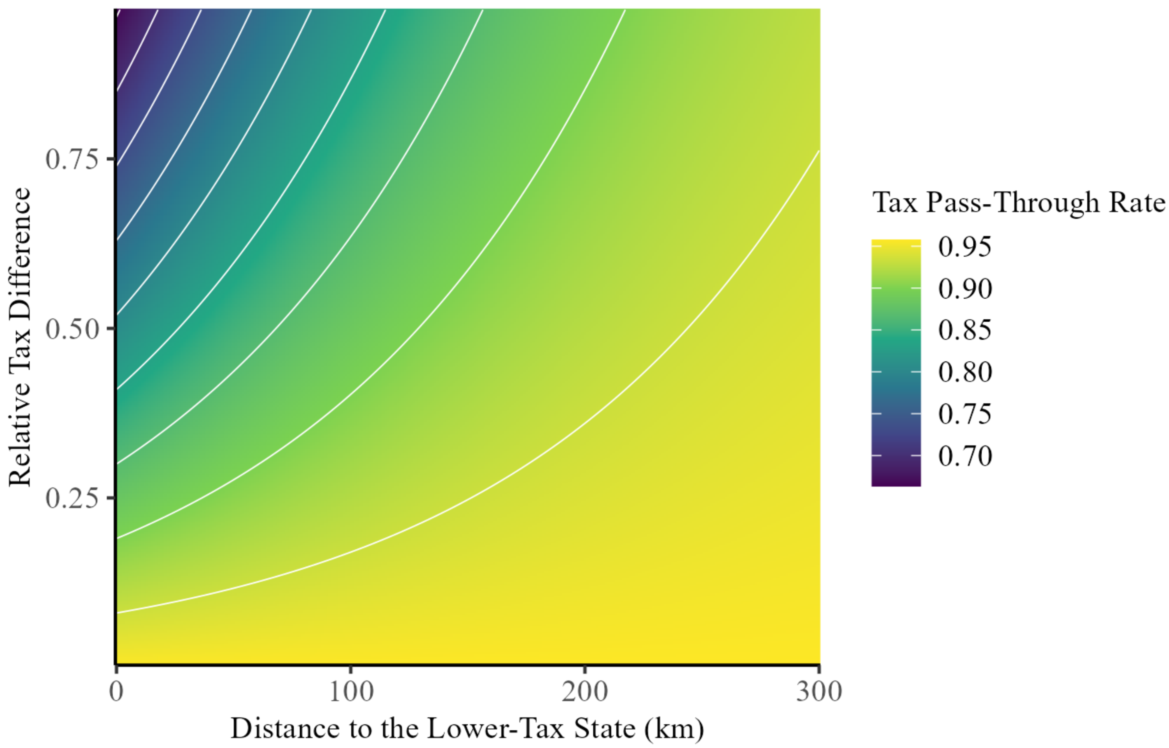


Figure 7: Extended Model: Exponential Growth Model.

The results suggest that incorporating tax differentials into the model substantially increases the variation of the estimated tax pass-through, with values ranging from 0.67 to 0.96. In contrast, the baseline model produces a significantly narrower range of estimates, between 0.81 and 0.87. This greater variation observed in the extended model underscores the importance of including inter-state tax differentials into the model equation.

6 Robustness Check

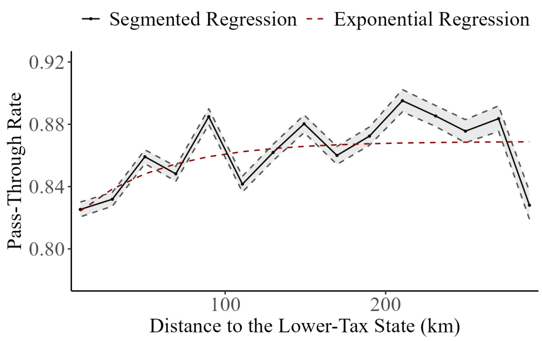
To assess the robustness of the results obtained, we perform additional analysis of the models. Specifically, to validate the model assumptions, we examine how the pass-through of state excise taxes to cigarette prices varies with distance to the nearest lower-tax state without imposing the parametric structure specified in equations (4) and (6). We then compare these findings with the non-linear regression estimates reported in Section 5.

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

$$P_{u,i,s,t} = \sum_{g=1}^{G} \tilde{\tau}_g \cdot \mathbf{1}_{\left(Dist_i \geq D_{(g-1)}\right) \& \left(Dist_i < D_{(g)}\right)} \cdot \tau_{s,t} + \gamma_s + \lambda_t + \alpha_u + \epsilon_{u,i,s,t}, \tag{13}$$

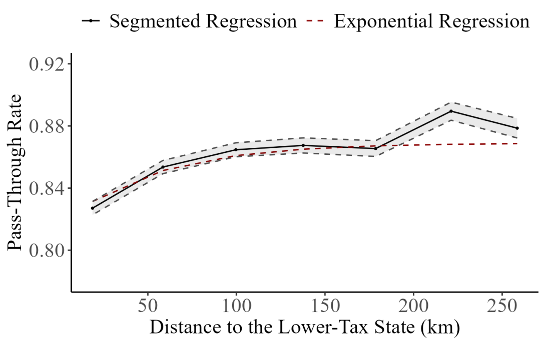
where $D_{(g-1)}$ and $D_{(g)}$ define cutoff values for the distance interval g, $D_{(0)}$ and $D_{(G)}$ correspond to the minimum and maximum values of the distance variable in the dataset.

The figures below display G estimates of tax pass-through $\tilde{\tau}_g$ along with 95%-level confidence bands from the equation (13). We plot the tax pass-through estimates from the segmented regression against each midpoint of the distance interval. The red-dotted line overlays the fitted tax pass-through function $\Pi = \overline{\tau} + \tau_{max} e^{-\widehat{\phi} \cdot Dist_i}$ from the exponential model (4). We observe that small interval sizes may produce volatile estimates, and too-large intervals may absorb meaningful variation.



(a) 20-km interval size

(b) 30-km interval size



(c) 40-km interval size

(d) 50-km interval size

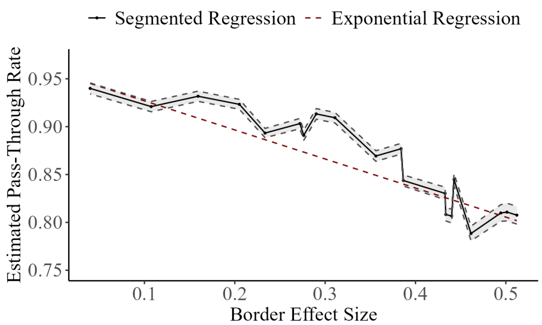
Figure 8: Segmented regression estimates of tax pass-through $\tilde{\tau}_g$ along with 95%-level confidence bands from the baseline model for 20, 30, 40, and 50-kilometer interval sizes. The red-dotted line overlays the fitted tax pass-through function $\Pi = \overline{\tau} + \tau_{\max} e^{-\widehat{\phi} \cdot \mathrm{Dist}_i}$ from the exponential model.

We next estimate a segmented regression model corresponding to the extended equation (6). In this case, the tax pass-through 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 the combined impact of these two factors on pass-through rate, we estimate the segmented regression, in which the combined "border effect" defined as $e^{-\widehat{\phi} \cdot Dist_i} \cdot [\tau_{s,t} - \tau_{l,t}]$ is allowed to vary across equally sized discrete intervals.

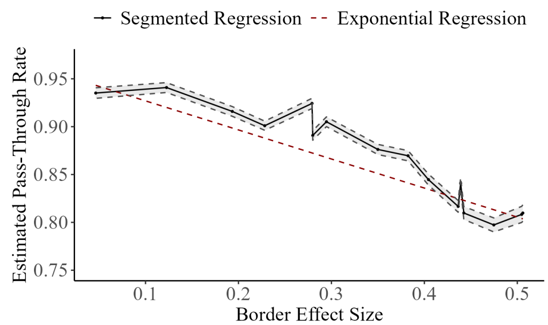
$$
\begin{aligned}
P_{u,i,s,t} =& \bar{\tau}_{max,0} \cdot \mathbf{1}_{\text{BorderEffect}_i=0} \cdot \tau_{s,t} + \\
& \sum_{g=1}^{G} \bar{\tau}_{max,g} \cdot \mathbf{1}_{\left(\text{BorderEffect}_i > B_{(g-1)}\right) \& \left(\text{BorderEffect}_i \leq B_{(g)}\right)} \cdot \tau_{s,t} + \gamma_s + \lambda_t + \alpha_u + \epsilon_{u,i,s,t},
\end{aligned} \tag{14}
$$

where BorderEffect_i is defined as $e^{-\widehat{\phi}\cdot Dist_i} \cdot [\tau_{s,t} - \tau_{l,t}]$ using estimate $\widehat{\phi}$ from the exponential 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.

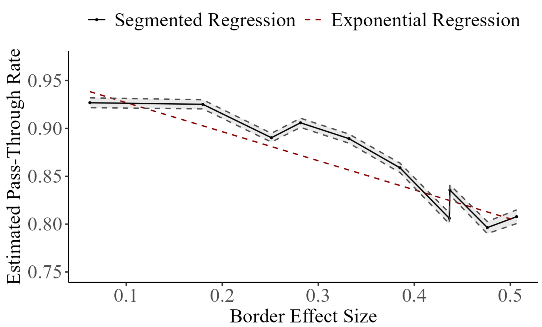
The figures below display G estimates of tax pass-through $\overline{\tau}_{max,g}$ along with 95%-level confidence bands from the equation (14) for $G = 6$, $G = 10$, $G = 16$, and $G = 20$. We plot the tax pass-through estimates from the segmented regression against mean values of $e^{-\widehat{\phi}\cdot Dist_i} \cdot \Delta_{s,t}$ at each "border effect" interval. The red-dotted line overlays the fitted tax pass-through function $\Pi = \overline{\tau} + \tau_{max} e^{-\widehat{\phi}\cdot Dist_i} \cdot \Delta_{s,t}$ from the exponential model (7).



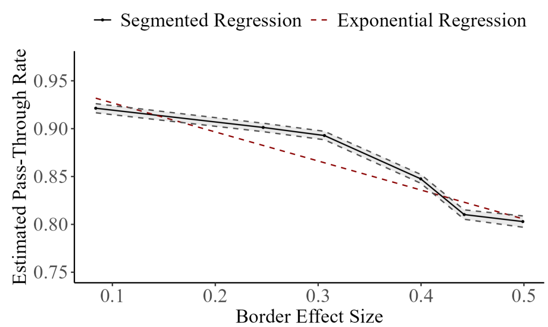
(a) Number of intervals used is 20



(b) Number of intervals used is 16



(c) Number of intervals used is 10



(d) Number of intervals used is 6

Figure 9: Segmented regression estimates of the tax pass-through estimate $\overline{\tau}_{\max,g}$ along with 95% confidence bands from the extended model for $G = 6$, $G = 10$, $G = 16$, and $G = 20$. The red-dotted line overlays the fitted tax pass-through function $\Pi = \overline{\tau} + \tau_{\max} e^{-\widehat{\phi}\cdot Dist_i} \cdot \Delta_{s,t}$ from the exponential model.

The results provide strong evidence of a negative relationship between tax pass-through rates and the extent of the composite "border effect", which depends on both the distance to the nearest lower-tax state and the differences in tax rates between the home state and the nearest lower-tax state.

Furthermore, the robustness analysis supports our parametric specifications: the tax pass-through observed in the segmented regressions is consistent with the tax pass-through predicted by the exponential models.

7 Demographic Heterogeneity

In this section, we analyze how tax pass-through rates differ among various demographic subgroups. We concentrate on two important aspects of demographic heterogeneity: annual per capita income and employment status. Both of these factors are closely linked to consumers' financial situation and, therefore, are likely to shape their behavioral responses to taxation.

7.1 Income Groups

We begin by analyzing pass-through rates across households with different levels of annual per capita income. Per capita income is computed by dividing the combined annualized household income by household size. All 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	11,656	503,466
Middle: \$15,000 – \$40,000	26,827	1,375,787
Low: $\leq$ \$15,000	18,388	968,655

For each income group, we estimate the extended model defined in equation (6). For each observation in the dataset, we calculate the predicted pass-through rate. Figure 10 shows the average predicted pass-through rate along the distance to the nearest lower-tax state.

The results indicate that high-income households exhibit the highest tax pass-through rates and are largely unaffected by cross-border shopping opportunities. Middle-income consumers display sensitivity to the "border effect" only when they reside within 90 kilometers of a lower-tax state border. Beyond this distance, higher travel costs discourage cross-border shopping. In contrast, low-income consumers remain highly responsive to the "border effect", even at distances greater than 90 kilometers. However, beyond 200 kilometers, low-income consumers demonstrate higher tax pass-through compared to middle-income consumers.

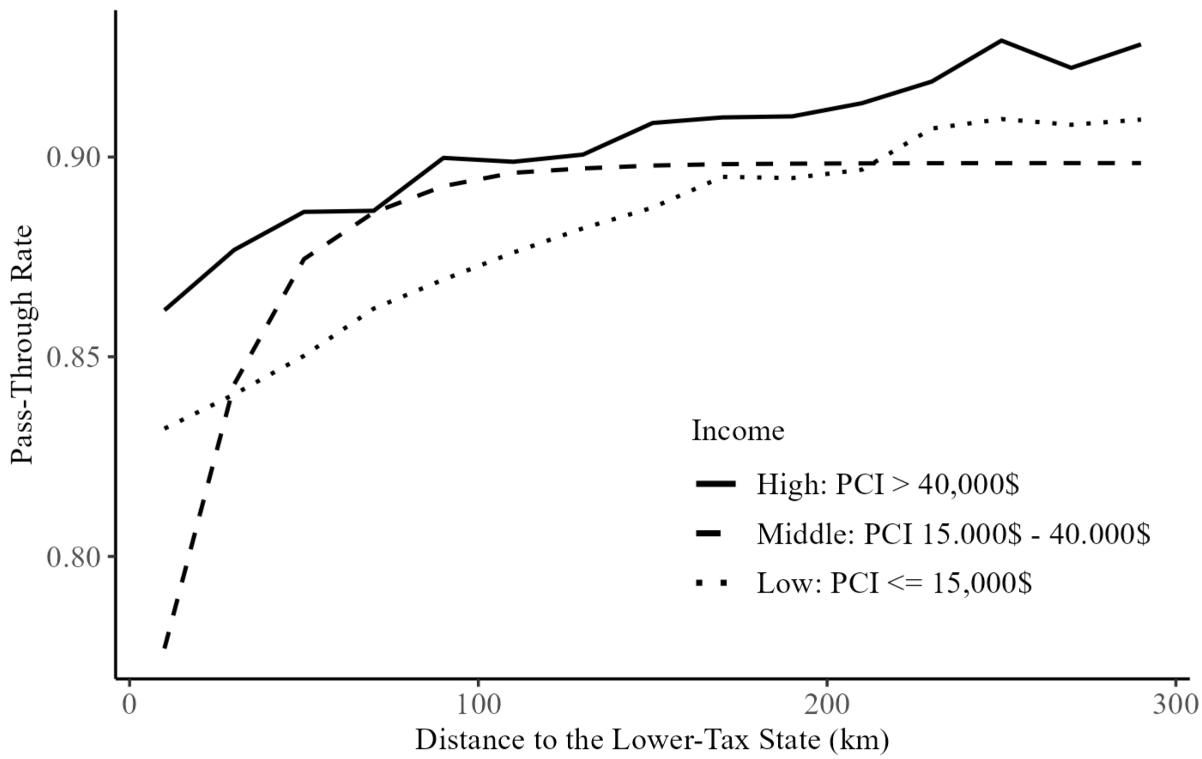


Figure 10: Predicted Tax Pass-Through by Income Group.

7.2 Employment Status

Next, we examine demographic heterogeneity by employment status. We divide households 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 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	36,450	1,727,012
Not employed for pay	18,017	1,120,896

As before, we estimate the extended model defined in equation (6) for each demographic sub-group. For every observation in the dataset, we calculate the predicted pass-through rate. Figure 11 displays the predicted pass-through rates based on employment status along the distance to the nearest lower-tax state.

Figure 11: Predicted Tax Pass-Through by Employment Status.

The findings show that households in which the head is not employed for pay demonstrate significantly lower pass-through rates compared to households with an employed head. This suggests that non-employed consumers are more likely to avoid taxes, possibly due to greater flexibility in shopping behavior or stronger incentives to engage in cross-border purchases.

8 Conclusion

This study provides empirical evidence of spatial heterogeneity in the pass-through of cigarette taxes to prices driven by cross-border purchasing behavior. Using detailed NielsenIQ Consumer Panel data from 2004 to 2019, we develop and estimate an exponential growth model with UPC, location, and time-fixed effects to assess the "border effect"—a systematic attenuation in tax pass-through among consumers residing near lower-tax states. Our results show that this effect is a declining function of distance to the nearest lower-tax border, with the strongest influence at the boundary and diminishing impact as distance increases. Additionally, we find that the border effect's strength increases with the magnitude of the tax difference between a consumer's home state and the nearest lower-tax state. Our robustness analysis validates the parametric assumptions of our model and supports the conclusion that spatial variation in tax pass-through rate is statistically and economically meaningful.

In addition to geographic variation, we investigate differences in cigarette tax pass-through across demographic groups. High-income households face the highest tax pass-through and are largely unaffected by border proximity, while middle-income households are affected by the "border effect" only when the distance from the lower-tax state does not exceed 90 kilometers. Low-income households remain sensitive to "border effects" at greater distances, though their responsiveness declines beyond 200 kilometers. Moreover, consumers not employed for pay exhibit significantly lower pass-through, suggesting greater scope for tax avoidance through flexible shopping behavior. Therefore, the welfare implications of cigarette taxation differ across demographic groups. High-income households experience a higher tax pass-through, meaning they bear a larger tax burden. In contrast, low-income and non-employed households face a lower effective tax burden because they benefit from reduced tax pass-through resulting from cross-border cigarette purchasing and other tax avoidance actions.

These findings have important implications for the design of tobacco tax policy. We show that cigarette excise taxes, while effective on average, may operate unevenly across geographies and demographic groups. These results emphasize the need to incorporate spatial considerations into the evaluation and design of excise tax policy, particularly in a tax system with heterogeneous tax regimes such as the US. Future research could build on these results by exploring interstate cross-border purchases in Mexico and investigating the additional impact of the variability in sales taxes.

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Abstrakt

Dostupnost zboží s nižší daní v sousedních státech motivuje spotřebitele k přeshraničním nákupům. Na základě transakčních dat z panelu NielsenIQ Consumer Panel analyzujeme, jak blízkost k sousednímu státu s nižší daní ovlivňuje přenesení daně do cen cigaret. Analyticky formulujeme přenesení daně do cen jako „skutečnou“ míru přenesení daně, která je oslabena tzv. „hraničním efektem“. „Hraniční efekt“ označuje dopad přeshraničního nákupního chování na míru, do jaké se spotřební daně promítají do cen cigaret. Tento efekt modelujeme jako exponenciální funkci, která klesá se vzdáleností od státu s nižší daní, dosahuje nejvyšší hodnoty přímo na hranici a s rostoucí vzdáleností se blíží nule. Parametry funkce „hraničního efektu“ odhadujeme pomocí exponenciálního regresního modelu s fixními efekty pro lokaci, čas a produkt (UPC). Výsledky testu robustnosti, ve kterém provádíme segmentovanou regresi s oddělenými odhady přenesení daně pro jednotlivá pásma vzdálenosti, podporují lineární vzorec pozorovaný v exponenciálním modelu. Model dále rozšiřujeme o rozdíl mezi daní v domovském státě a daní v nejbližším státě s nižší daní a provádíme srovnávací analýzu obou specifikací. Kromě geografických rozdílů také zkoumáme, jak se přenesení spotřební daně na ceny cigaret liší mezi různými demografickými skupinami. Domácnosti s vysokými příjmy čelí nejvyššímu přenesení daně a blízkost hranice na ně má jen minimální vliv, zatímco domácnosti se středními příjmy jsou ovlivněny „hraničním efektem“ pouze tehdy, pokud vzdálenost od státu s nižší daní nepřesahuje 90 kilometrů. Domácnosti s nízkými příjmy zůstávají citlivé na „hraniční efekt“ i na větší vzdálenosti, i když jejich reakce po překročení 200 kilometrů slábne. Navíc spotřebitelé, kteří nejsou zaměstnáni, vykazují výrazně nižší míru přenesení daně, což naznačuje větší možnosti daňové optimalizace díky flexibilnějším nákupním zvyklostem.

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