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Incidence and Salience of Alcohol Taxes: Do Consumers Overreact?

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Abstract:

We use a unique, geocoded micro data set of retail prices to estimate the incidence of alcohol taxation. We estimate the pass-through of alcohol taxation employing both standard ordinary least squares (OLS) and a regression discontinuity design (RDD), using the abrupt change in excise tax occurring at state borders for identification. Our results show that sales and excise taxes on alcohol have different effects on final consumer price. Our estimates suggest that while 40 percent to 50 percent of sales taxes are passed on to consumers, excise taxes have a negative pass-through rate. Negative rates of pass-through on the excise portion of the alcohol tax are likely the result of consumers overreacting to the tax compared to how they would react to a general price increase, or that the alcohol tax is quite salient for consumers. This effect is particularly strong in areas near state borders when using the RDD estimation strategy.

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Alcohol consumption is linked to a variety of negative externalities including traffic fatalities, domestic violence, health expenditures, and crime (Biderman, de Mello, and Schneider 2010; Carpenter 2007; Chaloupka, Grossman, and Saffer 2002; Cutler 2002; Lovenheim and Slemrod 2010; Markowitz and Grossman 2000; Ruhm 1996). In principle, alcohol taxes, which generate over US$15 billion per year in revenue for federal, state, and local governments, work to mitigate the external effects of alcohol consumption, and reduce these negative externalities. In practice, however, the reduction in alcohol consumption that results from these taxes depends on the economic incidence and salience of them.

There is a wide range of alcohol tax incidence estimates, with some studies showing that alcohol taxes are undershifted onto consumers (i.e., the price passed onto consumers goes up by less than the amount of the tax) and others suggesting that prices increase by as much as four times the amount of the tax (Barzel 1976; Carbonnier 2013; Kenkel 2005; Young and Bielinska-Kwapisz 2002); see Dutkowsky and Sullivan (2014) for a review of this literature.[1] There is also a growing literature on tax salience (Chetty 2009; Chetty, Looney, and Kroft 2009; Finkelstein 2009; Hayashi, Nakamura, and Gamage 2013), but this work still remains sparse relative to the incidence literature.

We add to these literatures by estimating the incidence and salience of alcohol taxation using both standard ordinary least squares (OLS) and regression discontinuity design (RDD) estimation strategies. Both techniques rely on state-level variation in alcohol taxation but have different identifying assumptions. The RDD is particularly advantageous in this case, as it examines a narrow area around state borders where other factors correlated with alcohol prices are less likely to change than they are when considering an entire state. We are able to apply the RDD because of our unique geocoded data set of alcohol prices for retailers in the southeastern United States. We also examine how the difference in the salience of different alcohol taxes may potentially affect the interpretation of our results and incidence in general. Alcohol taxation is ideal in this regard, because it is subject to a tax that is included in the posted price (the excise portion, which should be more salient) and a tax that is added at the cash register (the sales tax, which should be less salient).

OLS estimates suggest that, depending on the product and specification, the combined (excise and sales tax) alcohol tax is only partially passed on to consumers at a rate of between 11 percent and 53 percent. Estimates separating the sales and excise tax show that between 40 percent and 45 percent of sales taxes are passed on to consumers, while excise taxes actually have negative pass-through rates of between 11 percent and 15 percent. The RDD estimates show an even sharper rate of negative pass-through to consumers, in many cases larger than 100 percent of the excise tax. We surmise that the negative incidence estimates are due to the salience of alcohol excise taxes. Previous research has shown that consumers are more attentive to excise taxes, which are included in the sticker price of the product, so they should be less easily passed on to consumers. These results imply that consumers ''overreact'' (or are extremely sensitive) to excise taxes on alcohol compared to the reduction in demand that occurs from a general price increase.

While both sets of results suggest negative pass-through of alcohol excise taxes, we are particularly confident in the RDD estimates as the assumption that no drastic changes at state borders (other than alcohol tax) holds up to additional testing. These results are robust to a variety of specifications including changing the bandwidth around borders, adding control variables, and the type of control function.

Empirical Models

We examine the incidence of alcohol taxation by gathering data on the excise tax inclusive price and state and local sales tax rates of nationally recognized products from retail outlets in the southeastern United States (all locations require product to be consumed off-site). We collect data on the price of two standard products—a six-pack of Bud Light beer and a six- pack of Miller Lite beer.[2] Throughout the article, we refer to the excise tax on alcohol as the tax placed on alcohol that is included in the posted price of a product and to the sales tax as the tax placed on alcohol at the sales counter; added together, they are the total tax on alcohol. Our strategy is to examine if and by how much the tax inclusive price of these products changes as the size of the excise and sales taxes changes across state, county, and municipal boundaries.

We chose the southeastern United States to study alcohol tax incidence primarily because of the variation in the excise tax on alcohol across states in this region. The area we study covers four states—Tennessee (TN), Georgia (GA), Alabama (AL), and Florida (FL). The excise tax per six-pack of beer is highest in TN at US$0.84. AL (US$0.59) and GA (US$0.57) have lower rates, and FL has the lowest excise tax of the four states at US$0.27. The sales tax on a six-pack of beer varies by the statutory rate and the posted price of product but is also notably different across states in our area of study. Average sales tax on a six-pack of beer in TN, AL, GA, and FL are US$0.57, US$0.55, US$0.42, and US$0.43, respectively.[3]

We implement two estimation strategies to explore the incidence of alcohol taxation: OLS and RDD. Each technique relies on different identifying assumptions. OLS estimation primarily relies on controlling for differences in observable factors that influence prices, while the RDD primarily relies on these factors being constant within an increasingly small geographic bandwidth around state borders. We believe that our use of individual store-level data for both estimation strategies avoids the problem of classic endogeneity, or reverse causality, as it is unlikely that individual retailers have an influence on alcohol tax policy. We also believe that our estimation strategies sufficiently control for relevant factors that explain alcohol prices, but it is possible there are still omitted factors that drive alcohol prices and tax differences.

OLS

Using OLS, we identify the incidence of alcohol taxation by controlling for other factors that are relevant to alcohol prices. We focus on demand side variables, as it seems reasonable to consider supply side factors are fixed across units of observation within the small geographic area of our study and given that we examine prices of national brands of beer. We are able to control for factors unique to retail outlets as well as factors that are unique to the census tract where the store is located. The store-specific factors we consider are distance to the nearest state border (where alcohol taxation differs), the type of retail store (a dummy variable for being a liquor specialty store and a dummy variable for being a grocery store), and whether the store is a national retail chain (a dummy variable equal to one if it is). The census tract level characteristics we consider are the percentage of white residents, median income, unemployment rate, number of residents over the age of eighteen, the percentage of residents with a bachelor's degree or higher, and being part of a major metropolitan area (a dummy variable equal to one if the county is part of a metropolitan area in our region of study: Atlanta, Miami, Orlando, Tampa, Jacksonville, Nashville, Memphis, or Birmingham). We also control for the number of large colleges and universities (with an enrollment of at least 10,000 students) in the county where the store is located.

We examine the incidence of alcohol taxation in two ways, first by combining all relevant excise and sales taxes, and then, following Chetty, Looney, and Kroft (2009), by estimating separate coefficients for the excise and sales tax portions of the alcohol tax. As Chetty, Looney, and Kroft (2009) describe, separating the excise and sales tax components of the total tax allows us to examine how the salience of the tax may affect incidence. Chetty, Looney, and Kroft (2009) suggest that the salience of a tax influences how the economic incidence of a tax is shared between consumers and producers, implying that the statutory incidence of a tax can influence the economic incidence of the tax. They find that consumers are more responsive to excise taxes (which are included in posted prices) than to sales taxes (which are applied at the register). Their results imply that the incidence of a tax on consumers is inversely related to the degree of attention (salience) to the tax. Because the excise portion of the alcohol tax is reflected in posted prices, we expect that consumers may pay more attention to it, and thus it is less likely to be passed on to consumers in comparison to the sales tax portion of the alcohol tax.

The OLS estimating equations are

$$P_{it} = \propto + \beta_1(\text{Total Tax})_i + \mathbf{X}_i'\lambda + \mathbf{Z}_t'\delta + \varepsilon \qquad (1)$$

and

$$P_{it} = \propto + \beta_1(\text{Excise Tax})_i + \beta_2(\text{Sales Tax})_i + \mathbf{X}_i'\lambda + \mathbf{Z}_t'\delta + \varepsilon, \qquad (2)$$

where P is the after sales and excise tax inclusive price of a six-pack of beer in individual store i and t references the census tract the store operates in. The matrix **X** represents all store-level characteristics, and the matrix Z represents all census tract level characteristics. All prices and tax amounts are measured in dollars, so that the coefficients can be interpreted as the dollar change in retail price for a US$1 change in tax.

In equation (1), we are interested in the size of the β_1 coefficient. If β_1 equals one, alcohol taxes are completely passed through to consumers; if β_1 is less than one, then consumers do not bear the full burden of the tax, and the coefficient size represents the share of tax paid by consumers. It is also possible that β_1 is greater than one, implying that alcohol taxes are ''overshifted'' to consumers, or that β_1 is less than zero, implying that alcohol taxes are ''overshifted'' to producers.

In equation (2), we test whether $\beta_1 = \beta_2$ (i.e., if the incidence of excise and sales taxes is the same). It is less common in previous work to separately identify the incidence of excise and sales taxes. In regard to the alcohol literature, only Chetty, Looney, and Kroft (2009) and Carbonnier (2013) have analyzed how differences between ad valorem and excise (per unit) taxes differentially impact this market. Carbonnier (2013) finds that the change in prices due to excise taxes was significantly larger than that due to value-added taxes in the French market for alcohol. Chetty, Looney, and Kroft (2009) find that alcohol excise taxes negatively affect beer consumption, but sales taxes have no economic or statistically significant effect on beer consumption.

The primary identifying assumptions in equations (1) and (2) are that there are no omitted variables that are correlated with both price and alcohol taxation and that retail prices do not influence alcohol tax policies. We believe these assumptions are reasonable at the retail store level after controlling for the store characteristics and the census tract level demand-side variables we specify. We perform several robustness checks after our main results to account for other alcohol regulations in our area of study.

Regression Discontinuity Design

State alcohol taxes change abruptly at borders, but other factors driving consumer demand are unlikely to follow the abrupt pattern that alcohol taxes do, making the RDD a potentially attractive method for estimating tax incidence. We use the abrupt change in alcohol tax policy along the AL–GA–TN border and the AL–GA–FL border as an alternative to our OLS estimation strategy to estimate incidence. The idea behind the RDD is to test for a discontinuous change in alcohol prices at the state border where alcohol taxes change abruptly but to limit the bandwidth around this area to supress the influence of unobservable variables on price. The primary assumption behind the RDD is that unobservable factors should be similar on either side of the border for retailers within a small bandwidth of the border. Although we cannot test what happens to unobservable factors at state borders, we do examine the continuity of observable factors at state borders in the RDD robustness section, as suggested in Lee and Lemieux (2010).

We create a dummy variable (High Excise Tax) to indicate location near the border on the higher excise tax side (locations in TN near the TN–AL–GA border and locations in AL and GA near the FL–AL–GA border). We treat AL and GA as one side of the border in both cases, because the excise tax is nearly identical in these states (US$0.57 per six-pack in GA and US$0.59 per six-pack in AL). The RDD will only work for estimating the incidence of the excise portion of the tax, as it is that part of the tax, which changes abruptly at the state border. Sales tax rates differ across cities, counties, and states in our sample but only change modestly at the borders we examine.[4] The RDD specification is

$$\begin{aligned} P_{itj} = {} & \alpha + \beta_1 (D = 1 \text{ if High Excise Tax State})_i \\ & + \sum_{k=1}^{N} \left[\delta_{1k} (\text{distance})_i^k + \delta_{2k} (D = 1 \text{ if High Excise Tax} \times \text{distance})_i^k \right] \\ & + \mathbf{Z}_t' \delta + \mathbf{CP}_j' \varphi + \varepsilon, \text{ if } -b \leq \text{distance} \leq b, \end{aligned} \tag{3}$$

where distance is miles from individual store i to the border where the excise tax switches. We include fixed effects (CP) for each county pair

(j) to control for the longitudinal position along each border as well as the census tract demographic information in some specifications. b is the bandwidth on either side of the border where stores are included in the estimation, and N is the order of polynomial of the control function, which shows the relationship between price and distance to the state border moving toward the border. We estimate equation (3) using the excise tax inclusive price of a six-pack of beer as the dependent variable.

We are interested in the β_1 coefficient, which in the RDD specification describes the discontinuous change in alcohol prices that occurs at the border where tax policy changes. We compare the β_1 coefficients in equation (3) with the tax difference between the states to determine incidence. At the TN– GA–AL border, the alcohol tax increases by US$0.27 moving into TN from GA and by US$0.25 moving into TN from AL. At the FL–GA–AL border, alcohol taxes increase by US$0.30 moving into GA from FL and by US$0.32 moving into AL from FL. The weighted average (by the number of stores in our sample nearest each border) change in excise tax moving into the high tax state is US$0.28.

Table 1 shows the average sales tax (measured in percentage points) imposed on stores in our sample located in the border counties of each state, along the borders where we estimate the RDD. The major difference in sales tax is between TN and GA, with TN showing a higher average sales tax at the border. TN also has a higher alcohol tax, so to the extent that sales taxes are passed on to consumers, this difference should be reflected in a larger price drop going into GA and may possibly bias our results toward finding more of the incidence of the alcohol tax falling on consumers.

Table 1. Sales Tax Differential at State Border.

	Mean	Standard Deviation
TN		
TN stores in border counties along the AL border	0.096	0.002
TN stores in border counties along the GA border	0.097	0.002
AL		
AL stores in border counties along the TN border	0.087	0.009
AL stores in border counties along the FL border	0.087	0.007
GA		
GA stores in border counties along the TN border	0.07	0
GA stores in border counties along the FL border	0.07	0
FL		
FL stores in border counties along the AL border	0.071	0.005
FL stores in border counties along the GA border	0.073	0.002

Note: Sales tax rates reflect all city, county, and state sales taxes that apply to alcohol. The mean is given for all store observations residing in counties along each state border listed. AL = Alabama; FL = Florida; GA = Georgia; TN = Tennessee.

Data, Selection, and Summary Statistics

Our primary source of data is telephone surveys of alcohol retailers in our study area. We use Internet searches (yellowpages.com and google.com) to generate a list of alcohol retailers in this area, searching for ''grocery,'' ''convenience,'' and ''liquor'' stores across the geographic region. We also use Google Maps to search for locations near the border of the states in our sample. When contacting stores, we use a standard script, requesting information on the posted price for a six-pack of twelve-ounce Bud Light cans and a six-pack of twelve-ounce Miller Lite cans. We then verify that the price reported did not include sales tax.

We generate a list of 4,314 different retail stores to request price information, 2,114 provided price information on at least one of the products we requested. We collect price data from stores over a thirteen-week period, during which time there were no changes in alcohol or sales taxes in the area of study. The majority of stores for which we are not able to obtain price information simply stated that they did not sell alcohol (836). All of these are grocery or convenience stores in our searches. We are not able to obtain information from other stores we contacted because no one answered the phone call after three attempts (434), the listed phone number was incorrect or disconnected (369), or the clerk actively refused to offer price information (173). We deem 34 responses unreliable based on our judgment of how

Table 2. Selection in Price Data Refusal to Offer Price Information.

Excise tax	0.000 (0.0155)		0.023 (0.0217)
Sales tax		−0.242 (0.2362)	−0.484 (0.3302)
Observations	3,851	3,851	3,851
R^2	.000	.000	.000

Note: Standard errors clustered at city level in parentheses. The number of observations reflects the loss of observations from stores where we do not have city or county location. All of these were from stores in the sample that either did not answer the phone or had a disconnected line.

store clerks responded, and research assistants do not code a specific reason for non-response in 354 cases, most of which are the result of an incorrect or disconnected phone number.

The issue of sample selection may come into play if refusing to report price is correlated with both the actual price of the product and alcohol or sales taxes in an area. To address this issue, we estimate a model of refusal as a function of the tax parameters (sales and alcohol), as shown in equation (4):

$$R_{isco} = \propto + \beta_1 (\text{Excise Tax})_s + \beta_2 (\text{Sales Tax})_{sco} + \mathbf{X}_i' \lambda + \varepsilon, \qquad (4)$$

where R varies at the store level and is equal to 1 if a store actively refused to give price information and equal to 0 otherwise. Excise taxes differ at the state level, s, and sales taxes differ at the state, city (c), and county (o) level. Table 2 shows the results of estimating equation (4) using sales tax and excise tax separately and jointly. These models all show that tax rates are not a meaningful determinant of refusal. We are therefore not concerned that our sample is biased by a correlation between prices, refusal, and tax rates.

Table 3 shows summary statistics for the retail stores that we have price data on and appear in our sample. We have the largest sample of stores from GA (34.6 percent) and the smallest sample from TN (15.9 percent). In terms of the store type, convenience stores make up the largest proportion (38.3 percent), followed by liquor (35.3 percent) and grocery stores (26.4). Census tracts in our sample have majority white residents (53.8 percent), although the large standard deviation shows that we have a mix of racial groups in the census tracts in our sample. The average unemployment rate is (10.5 percent) higher than the national average at the time (9.5 percent). Census tract level control variables are obtained from the Brown University Longitudinal Data Base (2010).

Table 3. Sample Characteristics.

$N = 2{,}114$	Percentage of Stores	
Store level		
Location in Georgia	34.6	
Location in Alabama	18.9	
Location in Florida	30.6	
Location in Tennessee	15.9	
Grocery	26.4	
Convenience	38.3	
Liquor	35.3	
National chain	12.7	
	Mean	**Standard Deviation**
Distance to border (miles to nearest state border)	78.9	80.3
Sales tax (US$ per unit)	0.47	0.08
Excise tax (US$ per unit)	0.52	0.19
Price Bud Light (10 miles, high tax)	6.11	0.553
Price Bud Light (10 miles, low tax)	6.26	0.579
Price Miller Lite (10 miles, high tax)	6.05	0.545
Price Miller Lite (10 miles, low tax)	6.14	0.609
Census tract level		
Percentage white	53.87	28.59
Median income (US$)	42,148	16,005
Unemployment	10.5	5.3
Residents over 18	3,544	1,485
Percentage bachelor's degree	23.5	14.3
County level		
Number of large universities	0.42	0.66
Major metropolitan area	0.12	0.33

Note: Store-level data are author collected using yellow pages and Google Internet searches. Census tract level data are from the 2010 Census and American Community

Survey accessed through the Brown University Longitudinal Tract Data Base at http://www.s4.brown.edu/ us2010/Researcher/Bridging.htm.

Alcohol Tax Incidence Estimates

OLS—Combining Sales and Excise Tax

Table 4 shows the estimation results for equation (1) using separate regressions for the two products and for specifications with store-level and census tract level control variables. The first three columns show results for Bud Light prices, and columns (4) to (6) show results for Miller Lite prices. The positive sign on all of the Total

Table 4. Tax Incidence Estimates: Excise and Sales Tax Combined.

	Tax Inclusive Price: Bud Light			Tax Inclusive Price: Miller Lite		
	(1)	(2)	(3)	(4)	(5)	(6)
Total tax (in dollars)	.116 (.0908)	.117 (.0974)	.265* (.1467)	.343*** (.1022)	.430*** (.1055)	.533*** (.1496)
Distance to state border (in miles)		.001*** (.0003)	.001*** (.0006)		.001*** (.0003)	.001*** (.0006)
$D = 1$ if liquor store		−.240*** (.0423)	−.211*** (.0597)		−.204*** (.0506)	−.2083*** (.0704)
$D = 1$ if grocery store		−.127*** (.0419)	−.128*** (.0627)		−.181*** (.0566)	−.159** (.0754)
$D = 1$ if National chain		.192*** (.0515)	.261*** (.0597)		.248*** (.0729)	.291*** (.0830)
Percentage of white residents			.004* (.002)			.006*** (.0023)
Median income			.000 (.0000)			.000 (.0000)
Unemployment rate			.007 (.0118)			.02 (.0135)
Population 18 and older			.000 (.0000)			.000 (.0000)
Percentage with bachelor's degree or higher			−.001 (.0084)			.006 (.0073)
Number of large colleges			.084 (.0610)			.047 (.0592)
$D = 1$ if metropolitan county			.106 (.1371)			.129 (.1667)
Observations	2,074	2,073	1,381	1,546	1,545	1,036
R^2	.002	.053	.090	.014	.072	.117

Note: Standard errors are clustered at city level in parentheses.

*p < .1.
**p < .05.
***p < .01.

Tax coefficients suggests that prices rise with the amount of the tax. The magnitude of the results generally shows that while some of the alcohol tax is passed on to consumers, the majority of the tax is borne by retailers. The results show that for a US$1 increase in alcohol taxes, prices will rise by between US$0.11 and US$0.53, or that consumers pay between 11 percent and 53 percent of the total alcohol tax. These results are statistically significant at the 1 percent level for all Miller Lite regressions but only marginally statistically significant for one Bud Light regression.

The biggest difference in the results is between brands of beer. In the specifications using Bud Light prices, consumers pay between 11 percent and 26 percent of the total alcohol tax. In the specifications using Miller Lite prices, consumers pay between 34 percent and 53 percent of the total alcohol tax. We reestimated our regressions using a seemingly unrelated regression (SUR) model to obtain the proper covariance matrix between Bud and Miller prices so that we could test whether the levels of pass- through were statistically different from each other. Using a chi-square test with the SUR results confirms that the Bud and Miller Lite pass- through results are statistically different from each other. Because these are both national brands, it is doubtful that supply elasticities differ enough to make measurable differences in incidence. It seems more likely that demand for Miller Lite is more inelastic than the demand for Bud Light in the region, possibly due to differences in regional preferences or advertising.

These estimates are generally smaller in magnitude compared to previous estimates in the literature. Most previous studies find alcohol excise taxation is overshifted onto consumers. For instance, Young and Bielinska-Kwapisz (2002) use multistate variation in alcohol excise taxation and prices over time as a means to identify the incidence of the excise tax. Their estimates indicate a US$1 excise tax increase on beer increases prices by US$1.71. Barzel (1976) also finds overshifting of taxes on consumers in the market for alcohol. Kenkel (2005) uses phone surveys just before and one year after a onetime alcohol excise tax increase in Alaska to measure the degree of pass-through for excise taxes. He finds a wide range of tax incidence estimates for beer showing average excise tax pass-through rates between —0.848 and 4.26 for eight different types of beer products. Carbonnier (2013) finds alcohol excise taxes are overshifted onto consumer prices by as much as three times the per unit tax.

OLS—Separating Sales and Excise Tax

Table 5 shows the estimation results for equation (2), which separates the sales and excise portions of the alcohol tax into different variables. This allows us to examine the incidence of each portion of the tax, each of which may have different salience for consumers. The results in table 5 show that the excise and sales tax portions of the alcohol tax have different levels of pass-through. We easily reject the null hypothesis that $\beta_1 = \beta_2$ for every specification. Perhaps most intriguing is that the results show negative pass-through to consumers for the alcohol excise tax, while sales taxes are passed through to consumers to some degree.

The magnitude and statistical significance of negative pass-through to consumers is quite consistent across brands and robust to the inclusion of store and census tract level control variables. The results suggest that for a US$1 increase in the alcohol excise tax (which is reflected in posted prices and highly visible to consumers), retail prices decline by between US$0.11 and US$0.15. The negative pass-through result is statistically significant at the 1 percent level in all specifications. The level of pass-through for sales taxes is larger than the estimates for the combined tax. Between 40 percent and 45 percent of the sales tax on alcohol is passed through to consumers. Negative pass-through to consumers is rare in the literature on alcohol tax incidence. The only other finding of negative pass-through of which we are aware is for Busch beer by Kenkel (2005). Besley and Rosen (1999) also find some of the evidence of negative pass-through rates on retail products for sales taxes.

A possible explanation for negative pass-through to consumers is that consumers overreact to the excise tax. As explained in Chetty, Looney, and Kroft (2009), it is possible to have negative pass-through if product demand is more sensitive to a price increase caused by taxes than an equivalent price increase caused by other factors (a general price increase). Chetty, Looney, and Kroft (2009) summarize the role of attention or salience in tax incidence in equation form, where the incidence on consumers is from Chetty, Looney, and Kroft (2009, 1168):

$$\text{Consumer Incidence} = \frac{(q/p)\varepsilon_{S,p} + (1-\theta)\varepsilon_{D,q|p}}{(q/p)\varepsilon_{S,p} + \varepsilon_{D,q|p}},$$

where q and p represent price and quantity, $\varepsilon_{S,p}$ is a standard price elasticity of supply, and $\varepsilon_{D,q|p}$ represents the price elasticity of demand evaluated at a given price and tax amount. The parameter θ represents tax salience or the amount of attention that consumers pay to a tax increase relative to an equivalent price increase. A θ less than one indicates that consumers react less to a tax increase than a general price increase, while a value of θ greater than one means consumers react more strongly.

For a perfectly inelastic supply curve ($\varepsilon_{S,p} = 0$), the incidence of a tax on consumers will be negative if consumers react to a change in the price caused by a tax increase more strongly than they do a general price increase, or if θ is greater than one. Our empirical results can be interpreted as consumer's overreaction to the excise tax, resulting in a value for θ between 1.11 and 1.15 for a perfectly inelastic supply curve. As supply becomes more elastic, the corresponding θ that would produce overshifting on to producers

Table 5. Tax Incidence Estimates: Excise and Sales Tax Separated.

	Tax Inclusive Price: Bud Light			Tax Inclusive Price: Miller Lite		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales tax (in dollars)	.413*** (.0248)	.408*** (.0260)	.453*** (.037)	.431*** (.0292)	.431*** (.0313)	.454*** (.0434)
Excise tax (in dollars)	−.119*** (.0076)	−.117*** (.0078)	−.142*** (.012)	−.138*** (.0292)	−.131*** (.0101)	−.155*** (.0155)
Distance to state border (in miles)		.000 (.0000)	.001* (.0000)		.000 (.0000)	.000 (.0000)
$D = 1$ if liquor store		−.007 (.0058)	−.007 (.0079)		.005 (.0079)	−.001 (.0005)
$D = 1$ if grocery store		.008 (.0054)	.002 (.0075)		.008 (.0078)	.003 (.0100)
$D = 1$ if national chain		.018*** (.0054)	.021*** (.0059)		.025*** (.0076)	.025*** (.0086)
Percentage of white residents			−.001*** (.0004)			−.001** (.0005)
Median income			.000** (.0000)			.000 (.0000)
Unemployment rate			−.001 (.0024)			−.001 (.0028)
Population 18 and older			.000 (.0000)			.000 (.0000)
Percentage with bachelor's degree or higher			.000 (.0009)			.000 (.0012)
Number of large colleges			−.000 (.0107)			−.004 (.0130)
$D = 1$ if metropolitan county			−.019 (.0216)			−.025 (.0279)
Observations	2,074	2,073	1,381	1,546	1,545	1,036
R^2	.464	.473	.517	.439	.447	.471

Note: Standard errors are clustered at city level in parentheses.

*p < .1.
**p < .05.
***p < .01.

would need to be proportionally larger than one, for any given demand elasticity value. Given recent estimates of beer demand elasticity in Wagenaar, Salois, and Komro (2009) of -0.46, combined with our empirical estimates and a modest supply elasticity of 0.1, our results imply a θ between 1.35 and 1.40.[5]

Although our empirical results may seem somewhat counterintuitive without considering salience, and they are relatively new to the literature on tax incidence, we believe there are several reasons why they are plausible in the environment we study. First, we are examining prices at individual retailers in a relatively compact geographic area, not state-level averages as is typical in the literature. Consumers are likely to be well aware of tax and price differentials in this setting and can easily travel to retail outlets in other states. Second, retail outlets may have large cross-price elasticities for their products, and, if customers are particularly sensitive to (posted) beer prices, then sellers may keep them low to maintain sales of other products with higher-profit margins. Last, consumers may be uniquely sensitive to the product (beer) and brands (Miller and Bud) that we examine due to the amount of advertising (in store, television, radio, etc.) they are exposed to. We expect that, if the compact geographic area of the stores in our sample is important for our estimates, then the RDD will produce even larger estimates of negative pass-through.

An alternative explanation to the salience of the tax is that negative pass-through is generated through a market structure other than perfect competition. Dutkowsky and Sullivan (2014) explore how a model of monopolistic competition can produce either overshifting or negative pass-through. The magnitude and direction of tax incidence in their model depends not only on the elasticities but also on cost-shifting factors for firms. The assumptions used by Dutkowsky and Sullivan (2014) relate to goods sold by the individual retail outlet so that their model appears to be an appropriate one to use as an alternative explanation with our data.

RDD

Table 6 shows RDD estimation results for equation (3) using linear and quadratic control functions, and each product price as the dependent variable separately. These equations use the excise tax inclusive price as the dependent variable, as it is the excise tax that changes abruptly at a state border and not the sales tax. RDD estimation shows an even larger rate of negative pass-through than OLS estimation, as shown in Table 6. The coefficients are not directly comparable to those in table 5, as the RDD estimate is the price effect of crossing the border, not for a US$1 increase in tax as in the OLS results. To interpret the RDD coefficients, they need to be compared to the tax change that occurs at the state border (moving from the low tax to the high tax side, as equation [3] is set up to do). The average tax change at borders in our sample (FL into GA or AL and GA/AL into

TN) is US$0.28. Therefore, the coefficients in table 6 show the posted price change for an excise tax increase of US$0.28. For example, the specification using Bud Light prices with a linear control function, estimated without controls, using a bandwidth of ten miles around the border shows a price drop of US$0.20 (0.198) moving into the high tax state. This implies that the alcohol tax has a negative pass-through rate of 72.8 percent, which equates to a value for consumer overreaction, θ in the Chetty, Looney, and Kroft (2009) model, of 1.728 (for perfectly elastic supply), or a θ of 2.1 using the Wagenaar, Salois, and Komro (2009) demand elasticity and a supply elasticity of 0.1.

The estimates in table 6 all suggest much higher levels of pass-through and consumer overreaction to excise taxes than the OLS results, although these results are somewhat sensitive when using the ten-mile bandwidth and to a lesser extent the choice of control function. Most of the estimates produce statistically significant results, and all produce negative results, suggesting that prices rise on the lower tax side of a border.

Robustness and Validity

Although the RDD method is an improvement on OLS in terms of what assumptions we need for unbiased results, there are still several other concerns both with that method and with our general sample that we address here.

Robustness

The primary assumption of the RDD estimation is that the excise tax on alcohol is the only factor changing at the border that matters for beer prices. We can partially test this assumption by looking at the

Table 6. Regression Discontinuity Estimation Results for Price Change at Border.

	<10 Miles	<20 Miles	<30 Miles	<40 Miles	<50 Miles
Bud Light					
No controls	*n* = 169	*n* = 441	*n* = 567	*n* = 707	*n* = 772
RDD (linear)	−.198 (.1273)	−.430*** (.0333)	−.455*** (.0731)	−.402*** (.0340)	−.363*** (.042)
RDD (quadratic)	−.179 (.1575)	−.418 (.2571)	−.324** (.1177)	−.447*** (.1318)	−.489*** (.1478)
All controls	*n* = 77	*n* = 247	*n* = 318	*n* = 378	*n* = 417
RDD (linear)	−.411*** (.1269)	−.395*** (.0987)	−.400*** (.1323)	−.308** (.1518)	−.247 (.1695)
RDD (quadratic)	−.755** (.2856)	−.762** (.3349)	−.724** (.3021)	−.823** (.2875)	−.677*** (.2068)
Miller Lite					
No controls	*n* = 126	*n* = 332	*n* = 426	*n* = 529	*n* = 580
RDD (linear)	−.333 (.1930)	−.479** (.1398)	−.478*** (.1151)	−.323* (.1023)	−.305** (.0918)
RDD (quadratic)	−.284 (.2800)	−.277 (.2316)	−.349* (.1921)	−.497** (.1875)	−.423** (.1568)
All controls	*n* = 58	*n* = 185	*n* = 237	*n* = 281	*n* = 312
RDD (linear)	−.553** (.2040)	−.411*** (.1379)	−.425** (.1555)	−.251 (.1759)	−.207 (.1769)
RDD (quadratic)	−.458 (.4371)	−.680* (.3124)	−.392 (.2927)	−.685** (.3033)	−.468* (.2307)

Note: Coefficients are shown for the β_1 estimate as in equation (3). All regressions use the excise tax inclusive price (no sales tax) as the dependent variable and include county border-pair fixed effects. Standard errors for no controls in linear RDD specifications are clustered at the state level, and all other standard errors are clustered at the border-pair level. RDD = regression discontinuity design.
*p < .1.
**p < .05.
***p < .01.

Table 7. RDD Estimates for Control Variable Change at Border.

	Linear			Quadratic		
	<10 Miles	<20 Miles	<30 Miles	<10 Miles	<20 Miles	<30 Miles
D = 1 if liquor store	*p* = .868	*p* = .743	*p* = .486	*p* = .369	*p* = .662	*p* = .570
D = 1 if grocery store	*p* = .470	*p* = .372	*p* = .888	*p* = .306	*p* = .599	*p* = .256
D = 1 if national chain	*p* = .899	*p* = .545	*p* = .781	*p* = .187	*p* = .143	*p* = .418
Percentage of white residents	*p* = .975	*p* = .805	*p* = .770	*p* = .541	*p* = .657	*p* = .035**
Median income	*p* = .191	*p* = .172	*p* = .536	*p* = .631	*p* = .611	*p* = .174
Unemployment rate	*p* = .675	*p* = .100*	*p* = .098*	*p* = .265	*p* = .698	*p* = .421
Population 18 and older	*p* = .355	*p* = .514	*p* = .549	*p* = .979	*p* = .380	*p* = .493
Percentage with bachelor's degree or higher	*p* = .101	*p* = .154	*p* = .540	*p* = .420	*p* = .374	*p* = .035**

Note: Standard errors are clustered at the state level in the linear specification, and at the border-pair in quadratic specification, as shown in parentheses. All results are p values for the β_1 discontinuity coefficient in the RDD regression as in equation (3), estimated using control variables as the outcome. All estimates include country-pair fixed effects and the distance control function but no other control variables. RDD = regression discontinuity design.
*p < .1.
**p < .05.

continuity of control variables at the border where excise taxes change, by estimating an RDD model with the control variables as outcomes. Table 7 shows *p*-values from coefficient estimates of the discontinuity parameter (β_1 in equation [3]) for a variety of RDD specifications. Overall, the table 7 results show that other factors that are relevant for beer prices do not change discontinuously at these state borders, lending credibility to the RDD incidence estimates.

Another assumption of the RDD model is that the control function accurately captures changes in the outcome variable moving away from the border. To explore this assumption further, we estimated the RDD results using local linear regression to create the control function following Nichols (2007, 2011). The local linear regression essentially acts like a high-order polynomial specification but uses the data to define how the function looks. This allows for the control function to take on virtually any shape as we move away from the state border. Table 8 shows RDD estimates using the local linear regression control function. Most of these results show coefficient estimates in the middle to low range of the parameterized RDD specifications, and all of them still suggest negative rates of pass-through of alcohol excise taxes for consumers. The results are statistically significant in almost every case, with a few exceptions for the narrowest bandwidth specifications. The magnitude of the results using the local linear control function suggests negative pass-through rates in excess of 100 percent in nearly every case, which equate to values for consumer overreaction, θ in the Chetty, Looney, and Kroft (2009) model, over one for perfectly inelastic supply or values of θ over 2.4 using the Wagenaar, Salois, and Komro (2009) demand elasticity and a supply elasticity of 0.1.

We recognize that any policy that varies at the state level and is correlated with prices and alcohol taxes would bias even our RDD results. Although these regulations are not the focus of this study, we explore how they could affect our results. All four states in our sample use the same blood alcohol concentration limit for impaired driving in the year of our survey (0.08), and all four states use the same underage drinking and driving blood alcohol concentration limit (0.02). For the sample of states we use and the year of our data, only FL allowed alcohol sales on Sunday. Stehr (2007) indicates that repealing Sunday spirit sale bans causes a large and significant increase in the sale of spirits. As for the effect on beer sales, his point estimates show the repeal of Sunday beer bans cause an increase in the sale of beer; however, the estimates are much smaller in comparison to his spirit results and not as robust. In addition to these differences, AL has an Alcohol Control Board that regulates prices and entry in the retail market, and GA has a keg registration law. The keg registration law requires a purchaser to register a keg of beer at the time of purchase, or be subject to penalty. The keg control law in GA seems to be a small policy difference for the market for six-packs of beer. The Sunday sales law being different in FL and the AL Control Board seem likely to impact the market.

First, to account for the fact that AL has more stringent regulations of this market, we estimate both the OLS and RDD results excluding observations from AL. Second, because FL allows Sunday sales, we estimate both sets of results excluding observations from FL. Lastly, we exclude observations from both of these states. Table 9 shows these results. The restricted sample results largely confirm

Table 8. Regression Discontinuity Estimation Results for Price Change at Border Using Local Linear Regression Control Function.

	<10 Miles	<20 Miles	<30 Miles	<40 Miles	<50 Miles
Bud Light					
No controls	n = 169	n = 441	n = 567	n = 707	n = 772
RDD	−.415*** (.1060)	−.375*** (.1297)	−.442*** (.1267)	−.419** (.1714)	−.367* (.2023)
All controls	n = 77	n = 247	n = 318	n = 378	n = 417
RDD	−.173 (.3907)	−.481 (.3471)	−.643** (.3033)	−.603** (.2890)	−.509* (.2772)
Miller Lite					
No controls	n = 126	n = 332	n = 426	n = 529	n = 580
RDD	−.463** (.1502)	−.344** (.1584)	−.364** (.1511)	−.331** (.1670)	−.269 (.1950)
All controls	N = 58	N = 185	N = 237	N = 281	N = 312
RDD	−.583** (.1903)	−.465 (.3413)	−.543* (.3174)	−.461 (.3012)	−.346 (.2834)

Note: Standard errors are clustered at the state level in the no controls specifications, and at the border-pair in specifications with control variables, as shown in parentheses. RDD = regression discontinuity design.
*p < .1.

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**p < .05.
***p < .01.

Table 9. Alternative Specifications and Robustness Checks.

	Exclude AL	Exclude FL	Exclude AL and FL	Only Chain Stores	Weighted by County Population
OLS sales tax	.592 (.0344)	.334*** (.0308)	.752*** (0.0497)	.452*** (.0489)	.618*** (.0510)
OLS excise tax	−.158*** (.0168)	−.066 (.0458)	−.543*** (.0428)	−.173*** (.0155)	−.181*** (.0182)
RDD 10 miles	−.370*** (.1146)	−.450*** (.1510)	−.343*** (.1279)	−.130 (.3392)	−.403*** (.0503)
RDD 20 miles	−.386*** (.1185)	−.380** (.1946)	−.411*** (.1426)	−.212 (.3398)	−.348*** (.1209)
RDD 30 miles	−.494*** (.062)	−.392 (.3467)	−.568*** (.0812)	−.850** (.3843)	−.403*** (.0503)

Note: Results show the coefficient on tax variables for OLS regressions that include all control variables, β_1 discontinuity parameter for RDD regressions that only include distance controls, and use the nonparametric control function. Standard errors are clustered at city level in OLS regressions, and at state level in RDD regressions, as shown in parentheses. All results are for Bud Light prices. OLS = ordinary least squares; RDD = regression discontinuity design.
**p < .05.
***p < .01.

the findings from the full sample, and we still estimate negative pass-through of the alcohol excise tax to consumers in all specifications. For the OLS regressions, this result remains about the same in magnitude and is statistically significant in all specifications except the case where AL is excluded. The RDD results all show negative pass- through, are similar in magnitude, and are statistically significant in all cases, excepting the thirty-mile bandwidth case where FL is excluded. As a whole, we take these results as evidence confirming the findings of the full sample.

External Validity

Given that our sample is from a region of the United States that has many differences with the country as a whole, we explore the external validity of our results. While using this region provides us with a strong natural experiment on the border of states, reducing concerns of bias, there may be several reasons why these results would not hold for the country as a whole. The demographic characteristics of our sample are quite different than the country as a whole. Our sample includes an area with fewer whites (53.8 percent vs. 72.4 percent for the United States), higher unemployment (10.5 percent vs. 9.5 percent for the United States), lower median income (US$8,000 less than the United States as a whole), and is less educated (23.5 percent with a bachelor's degree vs. 29.9 percent for the United States). Even though we consider these factors as control variables in our model, they may interact with alcohol tax policy in ways that change incidence that we cannot account for. It is also possible that culture or drinking sentiment is different in this part of the country; however, we know of no way to reasonably quantify that notion. Because of these differences, we can only say for sure that our results hold for the sample where our data come from and that future studies should consider examining other markets.

We can, however, address some of the more technical concerns related to the validity of our methodology and attempt to make our sample more representative based on the characteristics we observe. Table 9 shows our results using two alternative specifications intended to address national representativeness. First, we estimate our results using only stores identified as national chains. We expect that although these stores operate locally, they are more likely to adopt national pricing strategies and be more representative of how prices respond to taxes on a national level. These retailers represent a small portion of our sample, so these results suffer from precision problems in the RDD specifications but generally show the same sign and magnitude of our full sample results. Second, we reweight our sample by the county population where each store is located. While this does not make our sample nationally representative, it places more weight on store prices in more densely populated areas, making the point estimates closer to what we might find in a national sample. These results confirm our primary findings in terms of sign, magnitude, and are all statistically meaningful.

Conclusion

Our empirical results using OLS estimation show that between 40 percent and 45 percent of sales taxes are passed on to consumers, while excise taxes actually have negative pass-through rates of between 11 percent and 15 percent. The RDD estimates show an even sharper rate of negative pass-through to consumers, for many specifications the rate is over 100 percent depending on the interaction between salience and the supply elasticity. These results imply that consumers are extremely sensitive to excise taxes on alcohol and that they react to them more strongly than a general price increase.

Consumers being particularly sensitive to tax increases may be helpful information for reducing negative externalities from alcohol consumption, but this likely means a coordinated effort across states or a national tax on alcohol may be most effective. Our results show that consumers are particularly sensitive in areas near state borders, where they can likely easily substitute to other retailers. Future work on this topic might consider exploring some of the reasons why negative pass-through is possible in this particular market. It would also be interesting to consider other products where consumers may be particularly sensitive to tax increases, possibilities include products where prices are particularly noticeable (such as gasoline) or that are heavily advertised (like automobiles).

Authors' Note

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Notes

1. Similar results are found for cigarette tax incidence, with estimates ranging from finding a zero effect of taxation on prices to some showing that prices increase by more than double the amount of a tax increase. See Hanson and Sullivan (2009) and Sullivan and Dutkowsky (2012) for a review of this literature.

2. Our requests for price information are for a standard twelve-ounce product in aluminum cans. We chose the brands Bud Light and Miller Lite because they are consistently ranked in the top four beer brands for market share (Beer Marketer's INSIGHTS 2014) in the United States.

3. Florida has a 6-percent state sales tax rate, and county-level rates ranging from 0 percent to 5 percent. Georgia has a 4 percent state sales tax and county sales taxes ranging from 2 percent to 3 percent. Alabama has a 4 percent sales tax rate at the state level. Alabama counties have sales tax rates (in addition to state sales taxes) ranging from 0 percent to 5 percent and city-level sales tax rates ranging from 0 percent to 5 percent in our survey. Tennessee has a standard 7 percent state sales tax rate on beer, county-level sales tax rates in our sample for Tennessee stores range from 1.5 percent to 2.75 percent, and city-level sales tax rates range from 0 percent to 0.75 percent.

4. Agrawal (2015) finds that local governments smooth sales tax differentials at state borders. Although sales taxes differ across municipalities in our sample area, there are no local governments that impose an excise tax on alcohol that is different from the state-level tax.

5. We use the supply elasticity of 0.1 from Chetty, Looney, and Kroft (2009) as a benchmark. For a supply elasticity of 0.5, the implied y parameter is between 2.3 and 2.4. The implied y for a supply elasticity of 0.05 ranges between 1.23 and 1.27.

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