# Discrete Prices and the Incidence and Efficiency of Excise Taxes

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**Abstract**

This paper uses UPC-level data to examine the relationship between excise taxes, retail prices, and consumer welfare in the distilled spirits market. We document a nominal rigidity in retail prices that arises because firms largely choose prices that end in ninety-nine cents and change prices in whole-dollar increments. A correctly specified model, like an ordered logit, takes this discreteness into account when predicting the effects of alternative taxes. Explicitly accounting for price points substantially impacts estimates of tax incidence and the excess burden cost of tax revenue. Meaningful non-monotonicities in these quantities expand the potential considerations in setting excise taxes.

**Keywords:** Excise Tax, Incidence, Market Power, Price Adjustment, Nominal Rigidities.

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## 1. Introduction

Pass-through describes how changes in costs relate to changes in prices and conveys the extent to which cost shocks are borne by consumers or firms. As a measure of incidence, pass-through determines the welfare implications of cost shocks such as exchange rate fluctuations, commodity price spikes and taxes. Higher retail pass-through rates mean that firms are better able to shift the burden of cost shocks on to consumers while low pass-through rates indicate that the incidence of a cost shock is largely borne by firms.

In this paper we examine the pass-through of recent increases in state excise taxes on distilled spirits. We focus on taxes on distilled spirits for three main reasons. First, distilled spirits are one of the most heavily taxed commodities in the United States with the combined state and federal tax burden comprising as much as 30-40% of the retail price. Second, the recent availability of high-quality scanner data across a number of retail establishments and unique wholesale price data allow for better measurement of price changes in this product sector than before. Finally, in the last decade alcohol taxes have been subject to numerous proposed and enacted policy changes with many states raising alcohol taxes while at the federal level the Tax Cuts and Jobs Act of 2017 reduced federal excise taxes on alcohol. Understanding the welfare implications of existing excise taxes will help inform future reforms.

We first provide descriptive evidence of price responses to tax increases and to match the prior literature estimate pass-through rates using linear regression. Like prior studies, we find evidence of over-pass-through, particularly for smaller products which experienced smaller tax increases, though estimates vary over different horizons. Examining price changes we next document the pricing behaviors that underlie these responses. We find that the majority of price changes are made in large, fixed increments – most frequently in whole-dollar amounts – to one of a handful of favored *price points* like prices ending in \$0.99. Retailers do not react to taxes by smoothly increasing prices but instead either leave a price unchanged or increase the price sharply most often by \$1 or \$2. In light of the pricing behaviors we document and the rigidities they imply, we estimate discrete choice models to better approximate the pricing patterns we see in the data. Finally, we use these estimates to predict how prices will change in response to tax increases of different magnitudes and simulate the resulting incidence and social cost of tax revenue. The non-linear nature of the price responses to tax increases means that modestly smaller or larger taxes can lead to sharply different pass-through rates with very different incidence and welfare costs. For example, our simulations show that increasing the tax by \$0.52 per liter rather than \$0.375 per liter leads to a ten-fold increase in the deadweight loss per dollar of tax revenue raised.

We take a different, though complementary, approach from the literature on optimization frictions. Instead of exploiting discontinuities in the tax schedule as a source of *exogenous* variation to recover a frictionless, long-run structural elasticity, we explicitly model the *endogenous* but discontinuous pricing strategies of firms in response to taxes. Our goal is not to recover the structural relationship between prices and taxes that would arise in a frictionless world, but rather to model how pricing rigidities would respond to alternative tax policies, and to understand the welfare implications of tax increases in such a world.

Pass-through rates exceeding unity have been estimated by previous studies focused on a smaller number of alcoholic beverage products. Cook (1981) found that the median ratio of annual price change to tax change for leading brands in the 39 state-years that had tax changes between 1960 and 1975 was roughly 1.2. Young and Bielinska-Kwapisz (2002) followed the prices of seven specific alcoholic beverage products and estimated pass-through rates ranging from 1.6 to 2.1. When Alaska more than doubled its alcohol taxes in 2002, Kenkel (2005) reported that the associated pass-through was between 1.40 to 4.09 for all alcoholic beverages, and between 1.47 to 2.1 for distilled spirits. All three studies report substantial product-level heterogeneity in the degree of pass-through. The over-shifting of taxes is not limited to taxes on distilled spirits, nor are all excise taxes over-shifted. For sales taxes Poterba (1996) found that retail prices of clothing and personal care items rise by approximately the tax amount while Besley and Rosen (1999) could not reject full pass-through for some goods, but found evidence of over-shifting for more than half of the goods they studied. In another retail setting where price points may be important, Besanko et al. (2005) found that 14% of wholesale price-promotions were passed on at more than 100% into retail prices.[1] In fuels, where price increments are very small (often one cent) relative to tax changes, studies have found that gasoline and diesel taxes are fully passed through to consumers though prices may not fully adjust when supply is inelastic or inventories were high (Marion and Muehlegger, 2011) and that gas tax holidays are pass-though quickly but only partially to consumers (Doyle Jr. and Samphantharak, 2008). Harding et al. (2012) found that cigarette taxes were less than fully passed through to consumers, while DeCicca et al. (2013) could not reject full pass-through of cigarette taxes on average.

Intuition suggests that excessive pass-through indicates that a market is characterized by imperfect competition. However, pass-through rates greater than unity generally require not only market power among suppliers but also curvature restrictions on demand. Fabinger and Weyl (2012) derive a convenient expression relating pass-through, $\rho$, to market characteristics under symmetric imperfect competition with linear costs:

$$\rho = \frac{1}{1 - \theta\mu'(p)}$$

where $\mu(p) = -\frac{Q'(p)}{Q(p)}$, and $\theta$ is similar to a conduct parameter ($\theta = 1$ corresponds to monopoly, and $\theta = 0$ is perfect competition).[2] As $\theta \to 0$, $\rho \to 1$, but whether the pass-through rate approaches 1

[1] It is worth noting that price changes at the time of tax changes may be less costly for retailers because consumer awareness of the tax change may lower 'customer antagonization' costs (Anderson and Simester, 2010).

[2] The definition of $\mu(p)$ comes from the monopolist or cartel's profit maximization problem which yields $(p - c) = -\frac{Q'(p)}{Q(p)}$.

from above or below depends on $\mu'(p)$, the log-curvature of demand.

Most results showing excessive pass-through like Katz and Rosen (1985), Seade (1985), and Stern (1987) employ a single-product homogenous good framework and rely on Cournot competition with conjectural variations in addition to curvature restrictions. Besley (1989) and Delipalla and Keen (1992) employ a Cournot model with free entry and exit, and rely taxes pushing out competing brands to generate overshifting.[3] Because Cournot competition may not be a realistic assumption for many taxed goods including distilled spirits, Anderson et al. (2001) develop similar results under differentiated Bertrand competition. The common thread of all of these studies is that demand must be sufficiently (log)-convex in order to generate overshifting. As demand becomes too convex, however, for example convex enough to generate the pass-through rates of 3 or 4 estimated for some states and product sizes here, Anderson et al. (2001) point out marginal revenue curves may no longer be downward sloping. Thus theoretical attempts to justify over-shifting of the degree we observe may lead to unrealistic restrictions on demand curves.[4]

In a recent and notable departure from this theoretical literature, Hamilton (2009) finds that excise taxes can be overshifted when demand is sufficiently *concave* rather than convex but requires strategic complementarities between prices and variety and that higher taxes lead to reduced variety of product offerings. As we observe over-shifting, but not brand exit in response to the tax this long-run explanation of over-shifting is also not well matched to our data. Instead, we show that a nominal rigidity like price points can generate over-shifting or under-shifting of taxes without restrictions on the curvature of the underlying demand curve or reduced product variety.

The focus on price points among retailers is not unique to our setting. A literature which documents the presence of price points as a source of nominal rigidities in macroeconomics includes: Kashyap (1995), Knotek (2016) and Levy et al. (2011).[5] Other work has focused on the role of "convenient prices" – round prices that coincide with monetary denominations (Knotek, 2008), (Knotek, 2010).[6]

[3] This literature is nicely summarized in Fullerton and Metcalf (2002).

[4] Fabinger and Weyl (2012) categorize the pass-through rate and marginal revenue properties of several well-known demand systems, and show that satisfying both properties is difficult but possible under certain forms of Frechet and almost ideal demand systems (AIDS) Deaton and Muellbauer (1980).

[5] A deeper question is: "Why do we observe ninety-nine cent prices?" One potential explanation is that consumers exhibit "left digit bias" and do not fully process information. This idea is explored in Lacetera et al. (2012). Another explanation might be that firms consider only a smaller number of discrete price points for cost or information processing reasons. For further discussion of just-below prices please see Schindler (2011). Basu (2006) demonstrates that in oligopolistic markets with fully rational consumers who nonetheless exhibit left-digit bias firms benefit when consumers ignore the last digits of a price, even under Bertrand competition. In recent work Shlain (2018) uses Nielsen data to show that consumers respond to a one cent increase from a 99-ending price as if it were a 15 to 25 cent difference and firms respond to this bias with high shares of 99-ending prices and missing low-ending prices, though they do not fully exploit the profit potential of left-digit bias. While interesting, these "why" explanations are beyond the scope of our paper. Other work shows that left-digit bias can benefit firms. Krishna and Slemrod (2003) suggest that tax authorities themselves may exploit left-digit bias in setting tax rates like for example the 39.6% top tax rate that prevailed from 1993 until 2001.

[6] Like "convenient prices", "price points" are an equilibrium outcome rather than a primitive of the retailing environment, though we do not model the full equilibrium.

Ours is first examination of the implications of price points for tax incidence and efficiency. The phenomenon of price points extends beyond distilled spirits. Tabulations of the Nielsen data demonstrate that prices are concentrated at a handful of price points in many product markets. Approximately 40.1% of all prices are set at at one of the four most common price points for each product category. At the product category level, in more than 49% of the 1,113 product categories of the Nielsen data, at least half of all prices in each category are set at one of the category's four most common price points. The pricing patterns that we observe are not unique to spirits; retailers utilize price points in many product markets, making our findings potentially relevant for considerations of broader excise taxes.

## 2. Alcohol Taxation and Industry Background

Our paper focuses on *state excise taxes*, which are remitted by wholesalers and usually levied by volume rather than ethanol content. In addition to state taxes the federal government taxes distilled spirits by ethanol content at $13.50 per proof-gallon, or $4.99 for a 1.75L bottle of 80-proof vodka.[7] The statutory incidence of federal excise taxes falls on the producers of distilled spirits or is due upon import into the United States while wholesalers remit state excise taxes. As such posted prices at the retail and wholesale levels include both state and federal excise taxes. In some states, there is an additional sales tax tacked on to the retail price that applies only to alcoholic beverages, while in others alcoholic beverages are exempt from the general sales tax.

As a consequence of the 21st Amendment, states are free to levy their own taxes on spirits, as well as regulate the market structure in other ways. There are 18 *control states*, where the state has a monopoly on either the wholesale distribution or retailing of alcohol beverages (or both).[8] Connecticut, Illinois, Louisiana, and 29 other states are *license states.* License states follow a three-tier system where vertically separated firms engage in the manufacture, wholesale distribution, and retailing of alcohol beverages. Almost all license states have restrictions that prevent distillers from owning wholesale distributors, or prevent wholesale distributors from owning bars or liquor stores. In the three states we study, wholesalers and retailers are fully distinct.[9]

All of these taxes are of course levied in part to address the negative health and public safety externalities of alcohol. Governments, however, also tax alcohol for the explicit purpose of raising revenue.[10] Few states had changed their alcohol taxes over the prior decade, but following the onset

[7]Taxes are stated in customary units of gallons, though products are sold internationally in standardized metric units of 750mL, 1L, and 1.75L bottles. A proof-gallon is 50% alcohol by volume (100 Proof) at 60 degrees Fahrenheit.

[8]The monopoly applies to all alcohol beverages in some states, and in others to distilled spirits but not wine or beer. Control states can adjust markups or taxes to raise revenue. A few control states, such as Maine and Vermont, nominally control the distribution and sales of spirits but contract with private firms which set prices. Control states have been the subject of recent empirical work examining the entry patterns of state-run alcohol monopolies Seim and Waldfogel (2013) and the effects of uniform markup rules Miravete et al. (2018).

[9]States have other restrictions on the number of retail licenses available, or the number of licenses a single chain retailer can own. States also differ on which types of alcoholic beverages, if any, can be sold in supermarkets and convenience stores.

[10]For example, in 2015 Governor Sam Brownback of Kansas proposed raising alcohol and tobacco taxes to help close

of the Great Recession, eight states passed legislation affecting alcohol taxes. We report those tax changes in Table 1.

Our analysis investigates tax changes in three states: Connecticut, Illinois and Louisiana. We focus on these three states because unlike Kentucky, Maryland and Massachusetts which only adjusted their *ad valorem* sales taxes, Connecticut, Illinois and Louisiana changed their unit excise taxes. Further, our primary dataset, the Kilts Nielsen Scanner data, provides sufficient coverage of these states. We lack sufficient data to study the 2013 excise tax increase (and sales tax decrease) in Rhode Island or the 2009 excise tax increase in New Jersey, in part because those states only allow spirits to be sold in stand alone liquor stores.

Prior to July 1, 2011, the state of Connecticut levied a tax on the volume of distilled spirits (independent of proof) of \$4.50 per gallon, which worked out to \$2.08 per 1.75L bottle.[11] After July 1, 2011, the tax increased to \$5.40 per gallon, or \$2.50 on a 1.75L bottle, for an increase of \$0.24 per liter. In September 2009, Illinois increased its excise tax from \$4.50 per gallon to \$8.55 per gallon, or an additional \$1.07 per liter. Louisiana raised taxes in April 2016 only slightly from \$2.50 to \$3.03 per gallon or \$0.14 per liter. The Louisiana tax increase was initially legislated to be temporary but was made permanent before its expiration.

It should be noted that Connecticut and Louisiana also raised their sales taxes from 6% to 6.35% and from 4% to 5%, respectively, at the same time that they increased their alcohol excise taxes. Our empirical analysis examines the impact of the specific tax increase on sales-tax-exclusive retail prices. As sales taxes are levied at the time of retail sale and added onto the posted price, any pass-through of the sales tax increases would lead to lower retail prices. Thus the pass-through rates we report for Connecticut and Louisiana potentially under-estimate the true excise tax pass-through rates. We also estimate pass-through rates using sales-tax-inclusive prices; our estimates are mechanically larger but statistically indistinguishable from the results presented here.

Our empirical exercise focuses more specifically on the July 2011 tax increase in Connecticut for a few reasons that exploit institutional details around the Connecticut tax increase. First, the Connecticut state regulator forbids wholesalers or retailers from engaging in temporary sales, coupons, price promotions, or giveaways; retail "sales" must be registered with the Department of Consumer Protection in advance, and are limited to a small number of clearance items. The retail price data reveal few if any temporary sales; ignoring the first week of the month (which may cover two months), there is virtually no within product-store-month price variation in Connecticut. Because weekly prices in the Nielsen data are calculated as revenue divided by unit sales, this means we can say with some confidence that the prices observed in our data accurately describe the prices observed by consumers in Connecticut. It also means that we do not need to distinguish

the state's \$648 million budget shortfall. For more details see `http://www.kansas.com/news/politics-government/article6952787.html`. In 2016, Governor Jon Bel Edwards of Louisiana proposed a similar tax increase which would raise \$27 million, as part of reducing a \$900 million deficit, see `http://www.nola.com/politics/index.ssf/2016/03/house_passes_new_alcohol_tax_h.html`.

[11] Many states levy lower tax on lower-proof ready-to-drink products, or lower-proof schnapps and liqueurs.

between general price changes and short-term markdowns.[12] A second important provision of the Connecticut tax increase ensured that the tax was uniform on all units sold after the tax increase. Retailers (and wholesalers) were subjected to a *floor tax* on unsold inventory as of July 1, 2011. By making the tax impact immediate for all units, this means that we can be certain all units sold at retail after July 1 were subject to the higher tax rate.[13]

The institutional details for the Illinois and Louisiana tax increases are a bit different. Both states allow temporary sales, loyalty card discounts, and coupons on distilled spirits. This means we should be cautious about interpreting weekly variation in average prices paid (particularly small changes) as actual price changes by retailers. Likewise, we cannot find evidence either way for whether a *floor tax* was employed in Illinois and Louisiana, so there may have been identical products on the retailer's shelf taxed under different regimes, and thus the effect of tax changes on retail prices may have been less immediate.

## 3. Data

Our primary data source is the Kilts Nielsen Scanner dataset. The Nielsen data are a substantial improvement over previous price data in the alcohol tax literature; much of the prior literature relies on the ACCRA Cost of Living Index data, which survey a small number of products and stores in each state. Nielsen provides weekly scanner data, which track revenues and unit sales at the UPC (universal product code) level for a (non-random) sample of stores in all 50 states, though in practice we only have sufficient data on distilled spirits from 34 states.[14] These weekly data are available from 2006-2016, and include data from both stand-alone liquor stores as well as from supermarkets and convenience stores.

Participation in the Nielsen dataset is voluntary, and not all stores participate. The data contain many more supermarkets than stand-alone liquor stores, and many stores in the sample are affiliated with a larger chain. This leads to better coverage for states where spirits are sold in supermarkets. In Connecticut, we observe 34 (mostly larger) stand-alone liquor stores. Because spirits are also available in supermarkets in Illinois and Louisiana, we observe 884 and 310 stores respectively. While the raw data are organized weekly, for our analyses we aggregate our data to the store-product-month level or the store-product-quarter level. For prices, we use the price from the last full week entirely within that month or quarter.[15]

[12] How one handles temporary sales is one of the principal challenges in the empirical macroeconomics literature on estimating menu costs. See Levy et al. (1997), Slade (1998), Kehoe and Midrigan (2007), Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Eichenbaum et al. (2014).

[13] The floor tax meant that any product not in the hands of consumers would be subjected to the new tax rate rather than the old tax rate, and prevented retailers from evading the tax by placing large orders in advance of the tax increase. It did not, however, prevent consumers from stockpiling alcoholic beverages in advance of the tax increase, though we find no evidence of an anticipatory price effect.

[14] We lack sufficient data from 16 states, many of which are control states (in *italics*): *Alabama*, Alaska, Hawaii, *Idaho*, Kansas, *Montana, New Hampshire*, New Jersey, *North Carolina*, Oklahoma, Oregon, *Pennsylvania*, Rhode Island, Tennessee, *Utah, Vermont, Virginia*.

[15] For additional details on aggregation, please consult Appendix C.

We weight all regressions by a product's annual sales in the same store for the calendar year prior to tax change. This means we weight products in Connecticut based on 2010 sales, Illinois based on 2008 sales, and Louisiana based on 2015 sales.[16] We use these weights because price changes are more important for more popular products.[17] One downside of this choice of weights is that products with no sales during these years are effectively dropped from the sample. To address differences in the number observations for each state, we normalize our weights so that each state receives equal weight in our overall sample.[18]

We exclude 1L bottles from Illinois and Louisiana because we have fewer than 8,000 such observations and they represent a very small fraction of sales; we keep them for Connecticut where they represent around 8% of the market. For more detailed summary statistics please see Appendix A.

For the state of Connecticut only, we are able to use a special dataset we constructed of the (tax inclusive) prices that wholesalers charged retailers from August 2007 to August 2013.[19]. As one might expect, and as our results will indicate, wholesale prices serve as an important state variable for retailer pricing decisions. For some welfare calculations, we assume a markup of $\mu = \frac{p}{mc} \in \{1.25, 1.5, 2.0\}$, with 1.5 being close to the average markup we estimate in our other work Conlon and Rao (2015).

## 4. Descriptive Evidence and Linear Pass-Through Estimates

### 4.1. Monthly Price Changes

We first summarize observed price changes in each state by month and year, highlighting the month when taxes increased. Figure 2 plots unweighted mean monthly retail price changes averaging over all years and for the year of the tax change for Connecticut, Illinois, and Louisiana. The plots demonstrate three facts. First, there is a regular, seasonal component to price changes with prices increasing in some months like January and July and decreasing in others like February. Second, in both Connecticut and Illinois retail prices immediately and sharply increased in the month of the tax hikes with mean retail price increases of \$0.316 in Connecticut and \$0.651 in Illinois, which are substantially larger than price increases in those months in other years, and larger than the average tax increase. In Louisiana where taxes were increased by \$0.15 on average, prices increased only modestly by \$0.186 in the month of the tax change. We find evidence of delayed responses with an even larger response of \$0.787 in Illinois in the month following the tax change and a smaller than typical May price decline in Louisiana. Finally, we don't find much evidence (except perhaps

[16]Our weighting is meant to mimic the Laspeyres price index. We don't weight using contemporaneous sales (Paasche), because we expect that demand curves slope downwards and we don't want to systematically underweight products with larger price increases.

[17]In total we observe 6,785 products many of which have extremely low sales. We consider restricting the sample to the top 1000 or top 500 products and it has almost no effect on any of the estimates we report.

[18]Later we also balance our weights so that each state and product size combination receives equal weight.

[19]For more details on this dataset and how it is constructed, please consult Appendix C

for Connecticut's $0.133 June increase) of prices increasing in anticipation of the tax change, even though the laws were passed months prior.

These average price changes don't tell the entire story and are driven in part by more frequent price changes. Figure 3 plots the sales-weighted fraction of retail products experiencing price changes and price increases each month in each state. There is a substantial spike in the frequency of price adjustment (and especially price increases) commensurate with the tax increases in Connecticut (July 2011) and Illinois (September 2009). The spike in Connecticut is more evident in part because the state bans temporary sales resulting in lower baseline adjustment frequencies. In Louisiana, however, the April 2016 tax change is associated with an increase but not a large spike in the frequency of price changes or increases. Instead price changes and increases spike three months later in July 2016, a month generally associated with price increases in Louisiana. In total these patterns suggest we should analyze the price impact of a potential tax change over a longer window of time (such as three months) rather than simply examining the immediate impact.

### 4.2. Linear Regression Estimates of Pass-Through

Following the large literature on pass-through, we measure the pass-through rate using a linear regression of price changes $\Delta p_{jst}$ on tax changes $\Delta \tau_{jst}$ where $j$ denotes product, $s$ denotes store, $t$ denotes month and the $\Delta$ operator denotes the difference taken over time within a store and product. We let $\Delta$ denote a $(1,3,6)-$ month difference. We follow the convention for excise tax pass-through and measure both changes in dollars per bottle. Thus the pass-through rate, $\rho(\cdot)$, describes the expected price increase (in dollars) for a \$1 tax increase.

We estimate the pass-through parameter with fixed effects for UPC, as well as month-of-year and year.

$$\Delta p_{jst} = \rho_{jst}(\mathbf{X}, \Delta\tau) \cdot \Delta\tau_{jt} + \beta \Delta x_{jst} + \gamma_j + \gamma_t + \epsilon_{jst} \quad (1)$$

We have written the pass-through rate $\rho_{jt}(X, \Delta\tau)$ as a general function that might depend on $(j,t)$ as well as other covariates $\mathbf{X}$, or the size of the tax change itself, $\Delta\tau$. Most of the literature assumes that for "small" tax changes, pass-through is approximately constant. For example, Besley and Rosen (1999) and Harding et al. (2012) assume a single pass-through rate $\rho_{jt}(X, \Delta\tau) = \rho$, or product specific pass-through $\rho_{jt}(X, \Delta\tau) = \rho_j$ respectively.

We estimate the regression (1) pooling observations from all three states, but interacting $\rho_{jt}(\cdot)$ with each state and package size (750mL, 1L, 1.75L) which we report in Table 2. This is a semi-parametric regression in the sense that for each observed value of $\Delta\tau_{jt}$ we estimate a distinct pass-through rate. We report seven estimates (we drop 1L bottles in Illinois and Louisiana) for one-month, three-month, and six-month horizons to address the concern that retail prices may not respond immediately.[20] We provide two sets of estimates in separate panels. The top panel reports

[20]For example, Figure 2 indicates retail prices may vary with a predictable schedule not aligned with tax changes.

the pass-through rates estimated from the full sample, while the bottom reports the pass-through estimates conditional on a price changes. Under the hypothesis that all tax changes are smoothly passed on through price changes, we would expect these two sets of parameter estimates to be identical.

There are some important patterns which emerge from Table 2. The first is that pass-through is nearly immediate in Connecticut where the one-month and three month estimates are nearly identical; while pass-through is slower in Illinois and Louisiana. This is consistent with the patterns observed in Figure 2. This may be because the timing of the tax change in Connecticut was commensurate with the month when retailers traditionally adjusted prices, or it may be because of the *floor tax*. Later, at the six month window pass-through estimates often (though not always) attenuate. In part this may be because retailers adjust prices for other reasons in addition to the tax change, this is particularly true in Louisiana where large price changes are more frequent (see Figure 2 and Figure 3).[21]

When we focus on three-month pass-through rates, we see that five of the seven state-size combinations have estimated pass-through rates which are statistically $> 1$ and are closer to 2 than to 1. Consistent with prior work on taxation of distilled spirits, this suggests that tax changes are *overshifted*, or that a \$1.00 tax change is met with a more than \$1.00 price change.[22] In general, the pattern also suggests that larger tax changes are met with smaller pass-through rates. To see this relationship more explicitly we plot the seven pass-through estimates for three-month price changes in the left panel of Figure 4. When we pool the data for all states and estimate the pass-through rate as a weighted linear function of the tax change we find that $\rho(\Delta\tau) = 1.76 - 0.51 \cdot \Delta\tau$, which we also plot on Figure 4.[23] This implies that the pass-through rate of an infinitesimal tax increase would be 176% and for a \$1.00 tax increase would be 125%.

If we compare the left and right panes of Table 2, we see pass-through estimates conditional on any price changes are substantially larger than overall estimates of pass-through. This suggests that tax changes were not smoothly passed on into price changes but instead that a large number of products experience no price change in response to the tax, while other products experience a larger price change than the average pass-through rate suggests. These conditional estimates along with the pass-through rates implied by a \$1 and \$2 price change are plotted in the lower panel of Figure 4. If the observed tax changes resulted in price changes of exactly \$1, estimated pass-through rates would lie on the first dotted line; if all prices changed by \$2, the estimates would lie on the second dotted line. What we observe is that both Louisiana estimates and the Connecticut estimate for

While Section 2 discusses that absent an explicit *floor tax* Louisiana and Illinois retailers may hold inventories not subjected to higher tax rates for several months.

[21]Also recall that we include state-product specific fixed effects (trends) in (1) which are generally positive.

[22]While some of this overshifting could reflect a combination of sticky retail prices and forward-looking expectations of future marginal cost increases, these factors do not account for the heavy use of price points we document in Section 5.

[23]We consider higher order functions of $\Delta\tau$. Both the quadratic and cubic function are indistinguishable from the linear function.

750mL products lie very close to the \$1 line while the Illinois estimate for 1.75L products lies close to the \$2 line and IL estimate for 750mL products suggests a mix of \$1 and \$2 price changes. The other Connecticut estimates for 1L and 1.75L products at three-months are somewhat lower than implied by a strict \$1 price change rule though the one-month conditional estimates (3.29 and 2.00) would line up well.

This suggests the correct way to think about the pass-through rate may not be as a constant applied to any size tax change, but rather that the pass-through rate we measure may be a mechanical relationship between large price change increments and the size of the tax.

## 5. Price Points and Pass-Through

The analyses in the previous section suggest that three-months is a more appropriate interval to analyze retail responses to tax changes. Therefore, we document several facts by examining the frequency of price endings and categorizing price changes using *quarterly data*. We focus on the idea that retailers choose from a small number of *price points* and that the bulk of price changes are in increments of \$1.00.

Later, we write down a dynamic model of price adjustment with discrete price points. We show how to estimate the policy function from the dynamic pricing model using an ordered logit. Using the ordered logit estimates, we re-calculate pass-through, welfare, and deadweight loss and compare them to estimates from the linear (constant pass-through) model.

### 5.1. Observed Price Points

We begin by documenting the relatively small number of *price points* used by distilled spirits retailers in the Nielsen scanner dataset. From 5,479,724 observations of quarterly prices we construct a transition probability matrix using just the cents portion of price. A product which sold for \$10.99 for two quarters in a row would be recorded as a price that previously ended in \$0.99 cents and still is priced at a price ending in \$0.99, as would a product which increased in price to \$11.99. Table 3 presents transition frequencies for each state detailing how the cents portions of prices compare from quarter to quarter.

As these matrices show, retailers set prices at and change prices to a small set of price points that account for a large share of overall prices. The most common price ending is 99 cents and it accounts for 78% of prices in Louisiana, 80% in Illinois, and 91% in Connecticut. Not all retailers use 99 cents as their default price ending, one chain in Illinois uses 97 cents and two chains in Louisiana use 49 cents instead. We aggregate price endings outside of the ten most common into the *other* category, which ranges from 1.35% in Connecticut to 5.93% in Illinois.[24]

[24] If we normalize the rows of each matrix to sum to one, we can treat these as Markov Transition Probability Matrices. In the long-run (ergodic) distribution we find that the share of prices outside of the ten most common price points would be 1.22%, 5.77% and 3.46%, meaning that the long-run stationary distribution of prices and the marginal distribution of prices are highly similar.

We expect that Table 3 understates the actual concentration of price points, even though the two most common price endings account for at least 85% of prices in every state. In addition to alternative conventions among a few chains, some retailers appear to use other price points (such as 19 cents or 95 cents) as internal tracking for sale or clearance items. Further, as we discuss in Section 3, Nielsen reported prices, particularly in Illinois and Louisiana where sales and discounts are more common, may not coincide with any transacted prices when prices change midweek.[25] We try to address these issues by reverse engineering transaction prices when possible, and describe the steps we take in Appendix D.2, but they remain.

The key consequence of this small number of price points is that when firms adjust prices they will generally adjust them in larger increments ($1.00, $2.00, $3.00, etc.) We categorize price changes in Table 4. We report the share of *price changes* which are whole dollars, and half dollars. When we focus on (quarterly) price changes during the period of the tax change we see that in Connecticut 76% of price changes are in whole dollar increments. This share is somewhat lower in Illinois and Louisiana (around 67% and 64% respectively). The share of *half dollar* price changes is also significant (ranging from 6.2% in Connecticut to 12.1% in Louisiana) during this period. The overwhelming majority of *half dollar* price changes are $\pm\$0.50$ rather than $\pm\$1.50, 2.50$, etc.[26] It is likely that some of the price changes labeled as *Other* or *Very Small* outside of Connecticut in Table 4 are the result of midweek price changes, coupons, or loyalty card discounts. Table 4 also indicates, even during the period of the tax change, a large number of prices are unchanged (almost 60% in Connecticut and nearly 40% in Louisiana and 15% in Illinois). This is consistent with our regression evidence that prices don't always respond to tax changes, but when prices do respond, they respond in large increments.

### 5.2. A Model of Price Changes with Price Points

The evidence from the previous section suggests that retailers rely on *price points* and often adjust prices in *whole dollar increments*. As a starting point, we consider (a modified version of) the dynamic price adjustment model of Knotek (2016) where retailers receive flow payoffs:[27]

$$\pi_t(\mathbf{p_t}, \mathbf{mc_t}) = \sum_j (p_{jt} - mc_{jt}) q_{jt}(\mathbf{p}) - \phi \cdot \mathbf{I}[p_{jt} \neq p_{j,t-1}] - \kappa \cdot \mathbf{I}[p_t \notin \mathcal{P}]$$

The retailer sells product $j$ in period $t$ at price $p_{jt}$, has a marginal cost $mc_{jt}$ and faces demand $q_{jt}(\mathbf{p})$. Here retailers deviate from static profit maximization in two important ways: they pay a

[25]This also helps explain why 99 to 99 transitions are more common in Connecticut than in other states. As we note in Section 2, Connecticut also does not allow coupons, loyalty cards, and makes temporary sales very difficult.

[26]We provide a full accounting of price change increments in Appendix Table D5 in Appendix D.2.

[27]Our version is modified in that we express static profits in terms of prices, marginal costs, and demand $q(p)$ rather than quadratic distance from the target markup $\left(\frac{p_t}{mc_t} - \mu_t\right)^2$ as in more common in the New Keynesian framework. This distinction is of no consequence for our empirical implementation.

menu cost $\phi$ in order to adjust prices between $t-1$ and $t$ and they pay a penalty $\kappa$ for deviating from the set of *price points* $\mathcal{P}$. In our main specification, we define the set $\mathcal{P}_t$ in terms of *price changes* so that $\mathcal{P}_t = p_t + \Delta p_t$ where $\Delta p_t \in \{-\$1, 0, +\$1, +\$2, +\$3\}$.[28]

The retailer solves a dynamic problem by choosing a sequence of price vectors $\mathbf{p_t} \in \mathbb{R}^J_+$ to maximize:

$$\max_{\mathbf{p_t} \in \mathbb{R}^J_+} \sum_{t=0}^{\infty} \beta^t \pi_t(\mathbf{p_t}, \mathbf{mc_t})$$

which we can write in recursive form where $\Omega_t$ denotes the state space:

$$V(\mathbf{p_t}, \Omega_t) = \max_{\mathbf{p_t} \in \mathbb{R}^J_+} \quad \pi_t(\mathbf{p_t}, \mathbf{mc_t}) + \beta E_{t+1}[V(\mathbf{p_t}, \Omega_{t+1} | \Omega_t)]$$

We consider a simplified version of the problem above. We restrict the set of feasible prices that the retailer can choose to the price points $\mathbf{p_t} \in \mathcal{P}_t$. One way to interpret this is by taking $\kappa \to \infty$ in the model above. This is clearly a simplifying assumption. Given our evidence in Tables 3 and 4 approximately 90% of observations conform to this grid of whole dollar price changes (once we include zero price changes).[29] This seems like a better assumption than assuming that $\kappa = 0$ and $\mathbf{p_t} \in \mathbb{R}^J_+$ is unrestricted, which allows prices to adjust continuously as the linear model implicitly assumes.

We focus on a specific set of counterfactuals which depend only on the *policy functions* in the language of Bajari et al. (2007).[30] This avoids ever solving for an equilibrium of the pricing problem, but it means we cannot separately identify the menu costs $\phi$ or price point costs $\kappa$.[31] Because we have a small number of tax changes, it also means we are limited in our ability to consider changes in the state variables $\Omega_t$ or their transition $f(\Omega_{t+1}|\Omega_t)$. We consider a policy function of the form $Pr(\Delta p_{jt} | \Delta \tau_{jt}, \Omega_t)$ and ask: "How would prices respond if we held everything else fixed, but varied the size of the tax change?" This means if we estimate policy functions using three-month changes, we are explicitly considering how other tax changes would affect three-month price changes. We are not modeling what might happen in the longer run if higher taxes *cause* retailers to price differently

[28] In our empirical specification, we consider robustness tests that expand this set to $\Delta p_t \in \{-\$2, -\$1, 0, +\$0.5, +\$1, +\$2, +\$3, +\$4, +\$5\}$.

[29] Absent the assumption that $\kappa \to \infty$ a model such as Knotek (2016) implies that $\Delta p_{jt}$ follows a distribution that is neither discrete nor smooth and continuous. Instead it has a finite number of mass points at the points in $\mathcal{P}_t$. Just estimating such a density would be quite challenging.

[30] The approach of Bajari et al. (2007) (BBL) is as follows: (a) implicitly assume that an MPE exists, and only one equilibrium is played (even though there could be multiple equilibria); (b) Estimate the policy functions of the agents: $\hat{\sigma}_r(\Delta p_{jt}, \Omega_t)$, and the transition densities of the exogenous variables: $\hat{f}(\Omega_{t+1}|\Omega_t)$. (c) consider deviations from the policy functions to recover the parameters of the payoff function including the adjustment costs $(\phi, \kappa)$.

[31] When prices are chosen among a discrete set, the first-order conditions need not hold exactly, leading to a large number of potential solutions and no good algorithm to find them. The multiproduct pricing problem is further complicated by the large state space, as we must keep track of both $\mathbf{p_t}$ and $\mathbf{p_{t-1}}$ for each product offered, while only a small number of states are actually observed in the data.

years later. Likewise, we should be cautious about the interpretation of long-run behavior of agents outside the model (such as if manufacturers reduce annual price increases in response to the tax change). If there are menu costs, agents take them into account when making decisions, but we cannot separate them in welfare calculations.

### 5.3. Pass-Through with Price Points

In the simplest example of discrete pricing, the firm can either increase its price by a single unit, or keep the same price:

$$\Delta p_{jt} = \begin{cases} 1 & \text{if } \Delta\tau_{jt} \geq \overline{\tau}_{jt}(\mathbf{X}) \\ 0 & \text{if } \Delta\tau_{jt} < \overline{\tau}_{jt}(\mathbf{X}) \end{cases} \tag{1}$$

For a large enough tax increase, the firm will always increase its price, and for a small enough tax increase the firm will keep its existing price. For each product there is a threshold level of the tax increase, $\overline{\Delta\tau}_{jt}$, beyond which the price is increased. This would imply that the true function $\rho_{jt}(X, \Delta\tau) = \delta_{\overline{\tau}_{jt}(\mathbf{X})}(\Delta\tau_{jt})$ where $\delta_z(\cdot)$ is the Dirac delta function with point mass at $z$. Then for each product we can compute its product specific pass-through rate as $\hat{\rho}_j = \frac{1}{\Delta\tau_{jt}} \int_0^{\Delta\tau_{jt}} \delta_{\overline{\tau}(X)}(\Delta\tau_{jt})$. This pass-through rate takes on only two values for each $j$: $\frac{1}{\Delta\tau_{jt}}$ or 0. Ignoring other covariates, the OLS estimates of the pass-through rate from (1) are a weighted average of product level pass-through $\hat{\rho} = \sum_{jt} w_{jt}\hat{\rho}_j$.

This demonstrates how it is possible to generate either incomplete pass-through or over-shifting. For example, if $\Delta\tau = 0.25$ and products are equally weighted, $w_j = \frac{1}{J}$, then $\hat{\rho}$, our OLS estimate of pass-through, would be a weighted average of $\rho_j = 4$ and $\rho_j = 0$. As long as more than $\frac{1}{4}$ products increase their price in response to the tax, it is possible to estimate $\hat{\rho} \geq 1$ without imposing special conditions on the demand function, while if fewer products increase their price we will find incomplete pass-through ($\hat{\rho} < 1$).

Figure 5 illustrates the price response with a binary logit. Because the x-axis represents the tax change, and the y-axis represents the price change, the OLS estimate of the pass-through rate is the slope of a ray intersecting the sinusoidal curve, $\hat{\rho} = \frac{\Delta p}{\Delta\tau}$. The complete pass-through $\rho = 1$ line is in yellow for reference. For a small tax increase (red line), it might be that very few products change prices so that the estimated pass-through rate is small. For a very large tax increase (blue line) the price of most products may increase, but this might be smaller (or larger) than the denominator, $\Delta\tau$. Some intermediate tax increase may be just large enough to be a tipping point where firms adjust the prices of many products, leading to a large change in average prices relative to a modest change in $\Delta\tau$ and a high estimated pass-through rate. If we plot the slope of each ray to the same S-shaped curve, we would find that the implied pass-through rate is U-shaped: rising during the steep part of the S-curve and falling over the flat parts. If we expanded the support of potential tax changes (and the potential outcomes of our price change model), price changes would follow a series of S-shaped curves, and pass-through would follow a series of U-shaped curves.

In general we do not expect the econometrician to observe $\overline{\Delta\tau}_{jt}(\mathbf{X})$ directly, and instead it must be estimated. If we allow for some econometric error in $\overline{\Delta\tau}_{jt}(\mathbf{X})$ that is IID and type I extreme value: then this suggests that the correct estimator for $\hat{\rho}_{jt}(X, \Delta\tau)$ is the predicted probability from a logit (divided by the tax increase): $\frac{Pr(\Delta p=1|\mathbf{X},\Delta\tau)}{\Delta\tau}$. Our empirical specification extends this model to an ordered logit and allow for larger price increases (or price decreases).

With enough variation in the support of $\Delta\tau$, the linear model from (1) can trace out any relationship between tax changes and price changes $\rho_{jt}(X, \Delta\tau)$, including a nonlinear relationship with discrete price changes such as an (ordered) logit. A stylized fact is that most price changes are in whole-dollar increments. This motivates our choice to impose a discrete distribution on price changes, and allows us to obtain more reasonable estimates for the relationship between price changes and tax changes. This is helpful because the support $\Delta\tau$ is limited. This is especially important when we want to forecast for tax changes not observed in the data. If we estimate a large pass-through rate for an observed tax increase, the linear model would apply that pass-through rate to a larger increase; the nonlinear model might interpret a large pass-through rate as the top of the U-shaped curve and anticipate less pass-through for larger tax changes. This is crucial for measuring the welfare cost of these taxes, because declining pass-through rates mean not only that taxes fall more on firms than on consumers, but also that they generate less deadweight loss per dollar of government revenue.

### 5.4. Estimating Pass-Through with Price Points

To address whole-dollar price changes, we estimate ordered logit models of the form:

$$\begin{aligned} \Delta p_{sjt} &= k \text{ if } Y^*_{sjt} \in [\alpha_k, \alpha_{k+1}] \\ Y^*_{sjt} &= f(\Delta\tau_{jt}, \theta_1) + g(w_{jt}, p_{sjt}, \theta_2) + h(p_{sjt}, p_{-s,jt}, \theta_3) + \beta X_{sjt} + \gamma_t + \varepsilon_{sjt} \end{aligned} \tag{2}$$

where we restrict $\Delta p_{sjt} \in \{-\$1.00, 0, +\$1.00, +\$2.00, +\$3.00\}$ and assign observed price changes outside of this range to the nearest price point.[32] The choice of covariates is informed both by the firm dynamic optimization problem of Section 5.2 and the regression results of Section 4.2. We allow the tax change to flexibly influence $\Delta p_{sjt}$ through $f(\cdot)$. Through $g(\cdot)$ we allow the cumulative change in the wholesale price since the last change in the retail price, $\Delta w_{jt}$, to flexibly enter equation (2), this is meant to measure pressure on the retailer to increase (decrease) prices. Specifically, we include both a polynomial in the cumulative $\Delta w_{jt}$ and an indicator for whole price changes less than or equal to zero.[33] We also proxy for competitive pressure with $h(p_{sjt}, p_{-s,jt}, \theta_3)$ which includes indicators for being the highest or lowest priced seller of a product and a polynomial

[32] We provide extensive details on the assignment of prices changes to the discretized grid in Appendix D.2 as well as robustness to different grids of price points.

[33] Once we control for $g(\cdot)$, additional controls for duration between price adjustments are not significant.

in the difference between the firm's price and the median competitor price for the same product.

The ordered logit models also include additional covariates like lagged prices (to capture price changes of "cheap" vs. "high-end" products), annual sales of the product at that retailer (to capture which products are important for overall profitability), total annual unit sales of the retailer (to capture "large" vs. "small" retailers). We do not include product specific fixed effects, because we worry about the incidental parameters problem in the nonlinear model.[34] We interact all of the covariates (except those in $f(\cdot)$) with indicator variables for each state, and treat Connecticut as our base case. This allows us to sidestep the unavailability of wholesale price data in Illinois and Louisiana. We weight the sample by the quantity sold during the calendar year prior to each state's tax change, but normalize weights such that every state-size is given the same overall weight. We also give equal weight to quarters with or without a tax change.[35]

We report key parameter estimates in Table 5; the full set of estimates can be found in Appendix Table G7. Most of these terms have the anticipated sign: products which have experienced large wholesale price changes since the prior retail adjustment are more likely to see price increases, products priced high (low) relative to competitors are less (more) likely to see price increases, just as in the linear regression in Appendix Table B2.

In Table 5, we report the parameter estimates for several different choices of orthogonal polynomials $f(\Delta\tau_{jt})$ (Cubic, Quartic, and Quintic). For purposes of comparison we also include a cubic spline with a single knot point at $\Delta\tau_{jt} = 1$.[36] When we estimate the model we hold out 20% of the data and then use the withheld data to select the order of the polynomial. Out of sample likelihood and BIC prefer the quartic polynomial model. This also agrees with the fact that 4th order term is significant at 1%, while the 5th order term is not.[37] We provide additional details regarding in sample fit in Appendix Figure D1.

The predicted price change as a function of the tax change, $(\widehat{\Delta p_{sjt}}|\Delta\tau_{jt}, X_{sjt})$, is the main calculation of interest and is easier to interpret than the coefficients themselves. There are several important considerations when making predictions. The first is to restrict $\widehat{\Delta p_{jt}}$ to a discrete prediction, as the ordered logit does.[38] Second, we report responses in terms of statutory tax changes $\Delta t_t$ (ie: dollars per liter) rather than in $\Delta\tau_{jt}$ (dollars per bottle). The relationship between the two is straightforward: $\Delta\tau_{jt} = \Delta t_t \cdot z_{jt}$ where $z_{jt}$ is the size of product $j$ in liters. This avoids a situation where products are taxed at two different rates.[39] Third, because the ordered logit

[34] For this reason we also cannot include store fixed effects in our nonlinear model. Omitting product fixed effects from the linear models in Section 4.2 tends to affect the $R^2$ of the regression, but not pass-through estimates.

[35] This is a common technique in statistics and machine learning to deal with the fact that we are only interested in predicting cases when $\Delta t > 0$, and those cases represent a small fraction of our overall data.

[36] Varying the location of the knot point has no discernable effect on the estimates.

[37] This measure is only meaningful because we use *orthogonal polynomials*.

[38] We cannot expect to understand the implications of *price points* if $\Delta p_{sjt}$ is allowed to take on continuous values such as 0.82.

[39] In theory a state could elect to charge a different tax rate on 1.75L bottles than 750mL bottles, though we are unaware of any state that does so.

model is nonlinear, this means that the effects of $\Delta\tau_{jt}$ on $\Delta p_{jt}$ will depend on other covariates. All of our predictions are restricted to the period of the tax change in Connecticut. We predict $\widehat{\Delta p_{sjt}}$ separately for each store and product, and then take a weighted average where we weight the sample by $w_{jt}$, the annual sales for that product and store in the year prior to the tax increase.[40] The average is taken over the distribution of the covariates $x_{sjt}$.

$$E_x[\widehat{\Delta p}_{jst}|\Delta t] = \sum_j [\widehat{\Delta p}_{jst}|\Delta\tau_{jt} = z_{jt}\cdot\Delta t, x_{jst}]\cdot w_{jst}$$

Finally, because we are interested in the causal impact of excise taxes, we do not report the level of the predicted price change, but the *difference* between the predicted change of a tax increase of some positive $\Delta t = a$ and the predicted price change of no tax increase $\Delta t = 0$:

$$g(a) = E_x[\widehat{\Delta p}_t|\Delta t = a] - E_x[\widehat{\Delta p}_t|\Delta t = 0]$$

We report the average predicted price changes $g(a)$ and implied pass-through rates in Figure 6 using our preferred quartic polynomial in $\Delta\tau_{jt}$. While each predicted price change is a discrete change to a price point, the mean predicted change and mean pass-through rate plotted in Figure 6 (as well as in Figure 7 and 8) average over thousands of products and thus appear to be continuous functions of $\Delta\tau_{jt}$. We plot tax changes between zero and \$1.07/Liter, which is the largest tax change we observe in the data. Considering a larger tax increase requires *extrapolating* beyond the data which we do not recommend.[41] In all graphs vertical lines denote the observed tax increase of \$0.14/L in Louisiana, \$0.237/L in Connecticut and \$1.07/L in Illinois. The quartic, quintic and spline specifications yield extremely similar average predictions while the cubic yields somewhat oversmoothed but qualitatively similar predictions.

A state considering its next change in distilled spirits taxes might be interested to understand how pass-through varies over larger and smaller tax increases for products of different sizes. In the Appendix we plot implied pass-through rates by tax per bottle for each bottle size. Pass-through rates are very similar for all three bottle sizes, which is unsurprising since model predictions are nearly identical for $\Delta P$ as a function of $\Delta\tau$ by size. The main source of discrepancy in predicted price changes arises from differences in state variables such as relative prices and wholesale prices, which are not tremendously different on average across package sizes. We focus on tax per liter plots here because states set tax rates in per liter terms; no state has levied different volumetric tax rates on products of different sizes.

[40] We use the same weighting for the linear regressions in Table 2. This coincides with the Laspeyres price index. We also constructed the same figures using the Paasche index and obtain imperceptibly different results. This is because the change in quantity weighting is small relative to the large and discrete nature of price changes. Other weighting measures such as equal weighting across store products yields qualitatively similar results.

[41] Recall from Figure 4 the largest $\Delta\tau = \$1.87$ is per bottle for 1.75L bottles in Illinois. We could in theory predict larger tax changes than \$1.07/L for 750mL bottles, but not for 1.75L bottles.

The main takeaway from Figure 6 is that $\widehat{\Delta p_{sjt}}$ follows an S-shaped curve as a function of $\Delta\tau_{jt}$, and the implied pass-through rate depends on the size of the tax. We find relatively low pass-through $\rho < 0.5$ for taxes below \$0.40/L and much higher pass-through $\rho > 1.5$ for tax increases above \$0.50/L.

As a robustness test, we expand the set of price points to include +\$0.50 price increases; predicted price changes are nearly indistinguishable from our main specification. We consider further expanding the set of price points to include −\$2.00 and +\$4.00. As one might expect this leads to somewhat lower pass-through for small tax changes and somewhat higher pass-through for larger tax changes, but is still highly similar to our main specification. By including relatively rare additional outcomes we reduce the bias of our predictions (from rounding), but at the expense additional variance from mis-categorization. We report those results in Appendix D.2.

### 5.5. Measuring Incidence and Excess Burden

We focus on two key welfare measures: the incidence, which measures the extent to which the tax burden is borne by consumers or firms; and the social cost of taxation, which measures how much deadweight loss is generated per dollar of government revenue. Unlike the standard framework where prices continuously respond to tax changes we show that with price points both incidence and the social cost of taxation can be increasing or decreasing in the size of the tax. It is important to note that the following welfare analysis assumes that prices are exclusively characterized by price points and all price changes are made in whole-dollar increments. If some prices are changed in other increments, then the welfare implications of excise taxes would be some mix of the following and more traditional excess burden measures.

Let $(P_0, P_1)$ and $(Q_0, Q_1)$ denote the price and quantity before and after a tax increase of $\Delta\tau$ respectively, with $\Delta Q = Q_1 - Q_0$ and $\Delta P = P_1 - P_0$. We use the traditional linear approximations and constant marginal costs $(MC)$ as illustrated in Figure 1, where supply is characterized by (single-product) monopoly, to derive the following expressions. These expressions are approximations in the sense that the demand curve need not be linear. The incidence and social cost of additional tax revenue are given by:

$$I(\Delta\tau) = \frac{\Delta CS(\Delta\tau)}{\Delta PS(\Delta\tau)} \approx \frac{\Delta P \cdot Q_1 + \frac{1}{2}\Delta P \cdot \Delta Q}{(\Delta P - \Delta\tau) \cdot Q_1 + (P_0 - MC) \cdot \Delta Q} \tag{3}$$

$$SC(\Delta\tau) = \frac{\Delta DWL(\Delta\tau)}{\Delta GR(\Delta\tau)} \approx \frac{(P_0 - MC) \cdot \Delta Q + \frac{1}{2}\Delta P \cdot \Delta Q}{\Delta\tau \cdot Q_1} \tag{4}$$

where $\Delta CS(\Delta\tau)$ and $\Delta PS(\Delta\tau)$ are the change in consumer and producer surplus, $\Delta GR(\Delta\tau)$ represents the change in government revenue, and $\Delta DWL(\Delta\tau)$ is the change in deadweight loss attributable to the tax change. To estimate the surplus losses to consumers and producers, the deadweight loss and revenue raised by taxes, we draw on a combination of data, parameter estimates and assumptions. Our main input is the predicted price change at different tax levels $\widehat{\Delta P_{sjt}}(\Delta\tau_{sjt})$ which we obtain from our ordered logit model. We use the observed store-product-month level price and quantity $(P^0_{fjt}, Q^0_{fjt})$ from the Nielsen data in the quarter prior to Connecticut's July 2011 tax increase (2011Q2). In order to predict counterfactual quantities under different prices, $Q_1(\Delta P(\Delta\tau))$, we need an estimate of the demand elasticity $\epsilon_D$.

We assume an own-price elasticity of demand of $\epsilon_d = -3.5$ which is consistent with the typical *product-level own price elasticity* reported in Conlon and Rao (2015) and Miravete et al. (2018). As a robustness test we consider $\epsilon_d \in \{-2.5, -3.5, -4.5\}$ which spans the range of own-elasticities reported for individual products in the literature.[42] Because all of these elasticities exceed unity and we consider markets characterized by single product monopoly, producer surplus losses will always outpace consumer surplus losses and the incidence will be less than unity.

Consistent with a constant elasticity framework we assume that $\frac{P_{jt}}{MC_{jt}} = \mu$ and apply a common markup to all products, using the implied marginal cost estimates in our welfare calculations. For our main specification we assume $\mu = 1.5$ or $\frac{P-MC}{P} = 0.33$ which is consistent with the combined retailer-wholesaler markup observed in Connecticut. As a robustness test we also consider markups of $\mu = 1.2$, $\frac{P-MC}{P} = 0.16$ and $\mu = 2$, $\frac{P-MC}{P} = 0.5$, which give qualitatively similar predictions though larger (smaller) markups increase (decrease) $\Delta PS$ and $\Delta DWL$.[43]

Because we consider joint retailer-wholesaler surplus our welfare calculations for producers apply to all in-state firms. We do not include distillers or manufacturers in our surplus calculations in part because they are largely multinationals and are out-of-state businesses. The more pressing concern is that we have little to no information on the production function for distilled spirits.

To better understand the implications of price points for tax incidence and efficiency we estimate $\Delta PS, \Delta CS, \Delta GR, \Delta DWL$ as a function of $\Delta\tau$ for each store-product, compute the expressions from equations (3) and (4) and aggregate across products using weights as we did for Figure 6. We also include vertical lines at the observed tax changes for each state in \$/Liter. For purposes of comparison, in Figure 7 we also report the same welfare measures computed under the least squares estimates of pass-through for Connecticut $\rho = (2.94, 2.094, 0.800)$ for 750mL, 1L, and 1.75L bottles respectively.[44]

[42]Product-level own price elasticities tend to be larger in magnitude than category level elasticities for spirits, which are often inelastic; including those reported in the meta-analysis by Wagenaar et al. (2009). There are a large number of individual products and cross-price elasticities among competing brands are posisitive. We implicitly assume the own-price elasticity captures the full impact of price changes on quantities without any cross-price effects. The assumption of zero cross-price elasticities will matter only to the degree that the welfare gain from switching products varies substantially with the size of the tax change. For robustness we compute $\Delta CS$ and $\Delta PS$ using the structural demand model from Conlon and Rao (2015). In general we find lower incidence on consumers than in the constant elasticity framework, but the way incidence (and efficiency) vary with respect to $\Delta\tau$ remains qualitatively similar.

[43]We are able to observe Connecticut wholesale prices for most products in our dataset, and the prices paid by wholesalers to manufacturer/distillers for a subset of products. When we estimate markups in our other paper (Conlon and Rao, 2015), we obtain similar quantities though we typically estimate smaller markups on low-end products and larger markups on high-end products rather than a single markup.

[44]These results come from quarterly regressions which we report in Table D4. They are highly similar to the

Accounting for the discreteness of the price points has some important economic implications. In the linear (constant pass-through) model the social cost of tax revenue $\frac{\Delta DWL}{\Delta GR}$ is a linearly increasing function of the tax. Once we incorporate price points, it is an increasing series of U-shaped curves. For a small tax change, there are very few predicted price changes as firms absorb the cost with the exception of a few products right on the boundary of price adjustment. After the products right on the boundary adjust, the social cost of tax revenue actually declines as firms continue to absorb the tax increases. Around $\$0.50/L$, which represents an \$0.88 tax increase for 1.75L bottles, we see a spike in price increases in Figure 6 and in the social cost of tax revenue in Figure 7. Increasing the tax by $\$0.52/L$ generates roughly 10 times the deadweight loss per dollar of tax revenue raised than a tax of $\$0.375/L$. After a wave of mostly 1.75L bottles adjust prices, the social cost of tax revenue declines from \$0.55 to \$0.80, until it increases again around $\$1.00/L$ or around \$0.75 per 750mL bottle.

In comparison, the linear model tends to over predict the social cost of small tax increases and under-predict the social cost of large tax increases. We see a similar pattern for the relative incidence $I = \frac{\Delta CS}{\Delta PS}$ in Figure 7. Here the linear model (weakly) over-predicts the relative share of taxes borne by consumers. This is particularly true for small tax increases which are borne mostly by firms. For larger tax increases, the two measures roughly coincide with $I \approx 0.8$. Just like in the social cost of taxation calculations, we observe one of a series of U-shaped curves in the incidence calculation.

In Figure 8, we show how our welfare results respond to different assumptions regarding elasticities. We see that the incidence of small tax changes is relatively insensitive to the elasticity, but for larger tax changes we generally find that as demand becomes more elastic, consumers bear a smaller fraction of the burden ($I \approx 0.5$ for a large tax increase at $\epsilon = -4.5$ and $I \approx 1.5$ for $\epsilon = -2.5$). This is consistent with our usual intuition that as the demand side becomes more elastic they bear less of the tax. However, the predicted incidence is still non-monotonic, though for large tax changes the curve flattens as demand becomes more elastic.

Figure 8 also shows how the social cost of taxation responds to the elasticity. Again, consistent with our usual intuition more elastic demand leads to a larger quantity response and more deadweight loss per dollar of tax revenue. Here we have preserved the U-shaped curve as in Figure 7 but merely stretched (or compressed) them over the y-axis. This shows that the main qualitative finding (that the social cost of taxation is not a linearly increasing function of the tax but rather a non-monotone relation) is insensitive to the choice of the elasticity.

We also report comparisons between our ordered logit price points predictions and the OLS estimates for individual elasticties (similar to Figure 7) in Appendix D.2 in Figures E2 and E3. Qualitatively the findings are similar, the linear model over-predicts the social cost of small tax changes and under-predicts the social cost of large ones. The linear model also over-predicts the

3-month results reported in Table 2. We use the same formulas from equations (3) and (4) rather than $I = \rho$ or $I = \frac{1}{\rho}$ formulas which explicitly rely on smooth changes.

consumer burden of large tax increases and gives broadly similar predictions for larger tax increases.

### 5.6. Discussion of Results

With price points there are intervals where the ratio of excess burden per dollar of tax revenue actually declines —revenue increases outpace surplus losses. Specifically, following a threshold where many prices are adjusted, even as taxes rise, fewer prices are increased leading to small average quantity responses but additional revenues. This suggests a close relationship between the incidence of taxes and the efficiency of taxes when both vary with the size of the tax change. In short, taxes that do not trigger price increases: (1) are paid by firms, (2) cannot generate deadweight loss because without price changes quantity remains unchanged.

The fact that the efficiency cost of tax revenues declines over some ranges suggests that states deciding on tax changes would do better on the efficiency front if they consider how prices are changed when they set tax increases. Larger tax increases in some cases may actually entail a lower cost of public funds on average. While finding the local minimum of a curve like that in Figure 7 may be difficult, avoiding the local maximum may be somewhat easier, and the potential savings (roughly 30% of the social cost of tax revenue) are large. The challenge for policymakers is estimating how far from the boundary $\overline{\tau}_{jt}(\mathbf{X})$ each product is. We think this exercise is easier than it looks, at least for a single bottle size. In our case, the tax increase to avoid is the 50-60 cent per liter tax, which translates to an increase of \$0.80-\$1.05 for the most popular 1.75L bottle size. We don't think it is coincidental that the social cost of taxation is highest when the tax change and the price increment are similar.

We see that policymakers in Connecticut and Louisiana pursued very different strategies for tax efficiency, but both were successful in avoiding the local maximum. In Connecticut, policymakers implemented a relatively small tax of \$0.24 per liter that triggered a relatively small number of \$1.00 price increases. Likewise in Louisiana, they implemented an even smaller tax increase of \$0.14 per liter, which triggered a very small number of \$1.00 price changes. In Illinois, policymakers implemented a very large tax of \$1.07 per liter that triggered a large number of \$1.00 and \$2.00 price increases, leading to a high pass-through rate, relatively more consumer incidence and a less efficient tax. A tax increase of \$0.75 would have been a more efficient tax and borne to a greater degree by producers. Where the exercise becomes more complicated is that tax increases that are good for one package size may be bad for others; but by focusing attention on the most popular bottle sizes, it may be possible to mitigate this problem.

## 6. Conclusions

We empirically document an important rigidity in the pricing of distilled spirits that affects how taxes pass-though to prices. We demonstrate that retailers set the vast majority of prices of spirits products at only a handful of price points in terms of the cents portion of the price. In the three states we study, at least 89% of prices have one of three endings. Price points and their associated rigidities mean that firms withstand cost shocks, including tax increases, until they are sufficiently far from their optimal price that moving to the next price point leaves them better off, resulting in infrequent but large prices changes in set increments.

We show that theoretically these pricing rigidities can rationalize both incomplete or excessive pass-through without placing restrictions on the demand curve. As a result of these rigidities, using parameter estimates from a linear regression of change in price on change in tax can be misleading when evaluating alternative tax policies. Linear regression of price changes on tax changes presumes that price adjustment can happen in a smooth and continuous manner. An ordered logit model can instead account for the discreteness of price changes and be used to recover the pass-through rate, incidence, and efficiency of alternative tax policies. We demonstrate that with price points and the resulting pattern of price changes pass-through, incidence, and tax efficiency are non-linear and non-monotonic functions of the tax and that nominal rigidities like price points or menu costs have potentially important implications for excise tax policy.

We document that price increases in response to tax changes can be concentrated around certain levels of tax increases. Further increases beyond these levels may not generate many further price increases, but instead come out of firm profits, leading to minimal changes in quantity. As such the incidence and social cost of government revenue are tightly linked. Taxes are most efficient when the consumer incidence is minimized, and sometimes larger taxes can produce a lower average cost of public funds. This strongly contrasts with the conventional wisdom that tax efficiency is linearly decreasing in the amount of tax revenue raised.

Our estimates center on 3-month pass-through rates, raising the question of how relevant our conclusions are over different time horizons. Large price changes following a tax increase may forestall future price increases, meaning that high pass-through rates may dissipate over time. Our perspective is that the short-run may not be such a short period of time. First, we observe qualitatively similar results when we repeat our exercise over 6-month and 1-year horizons. Second, as indicated in Figure 3, in 2014 (well after the Connecticut tax increase) retail prices increase less than once per year on average, and often with a predictable seasonal pattern. It is not unreasonable to think that a well timed tax increase could have a relevant horizon of 2-3 years. When paired with the potential to reduce the social cost of excise taxation by up to 30%, this seems relevant.

Our simulations raise the possibility of better policy design. By considering pricing patterns and the optimization frictions they create explicitly, policymakers can improve the efficiency of excise tax increases. For example, in recent years several U.S. cities have enacted new taxes on sugar sweetened beverages ranging from $0.01 to $0.02 per ounce, or $0.68 to $1.35 per two-liter bottle and $1.44 to $2.88 per 12-pack. Our results suggest that policymakers interested in minimizing the efficiency cost of these taxes should prefer tax increases that are either considerably smaller or larger than typical price change increments of the most commonly sold package size.

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Table 1: Changes in Distilled Spirits Taxes in License States, 2007-2016

| State | Old Tax | New Tax | Effective Date | Notes |
|---|---|---|---|---|
| Connecticut | $4.50/gal + 6% sales tax | $5.40/gal + 6.35% sales tax | July 1, 2011 | |
| Illinois | $4.50/gal + 6.25% sales tax | $8.55/gal + 6.25% sales tax | Sept 1, 2009 | plus Cook County and Chicago excise taxes |
| Louisiana | $2.50/gal + 4% sales tax | $3.03/gal + 5% sales tax | April 1, 2016 | legislated to end 07/2018; made permanent |
| Kentucky | $1.92/gal | $1.92/gal + 6% sales tax | April 1, 2009 | sales tax newly applied to off-premise sales |
| Maryland | $1.50/gal + 6% sales tax | $1.50/gal + 9% sales tax | July 1, 2011 | sales tax increase on alcohol only |
| Massachusetts | $4.05/gal | $4.05/gal + 6.25% sales tax | Sept 1, 2009 | ended Jan 1, 2011 |
| New Jersey | $4.40/gal + 7% sales tax | $5.50/gal + 7% sales tax | Aug 1, 2009 | |
| Rhode Island | $3.75/gal + 7% sales tax | $5.40/gal + 0% sales tax | Dec 1, 2013 | |

Note:
The table above describes the nature and timing of the tax changes for each of the eight states that altered their alcohol-specific taxes since 2007. In addition to these changes in alcohol taxes, 5 license states increased their general sales taxes which also apply to alcohol: California in 04/2009 (1 percentage point), Washington DC in 07/2011 (1 p.p), Indiana in 04/2008 (1 p.p.), Maryland in 01/2008 (1 p.p.), and Minnesota in 07/2009 (0.375 p.p.). Further, in 2012 Washington state privatized both the distribution and retailing of spirits and now even allows producers to sell directly to retailers. Concomitant with the privatization, Washington also raised taxes on spirits.

Table 2: Pass-Through: Taxes to Retail Prices

| Dependent Variable: Price Change | All Observations 1 month | 3 month | 6 month | Δ Retail Price ≠ 0 1 month | 3 month | 6 month |
|---|---|---|---|---|---|---|
| | Connecticut July 1, 2011 Tax Increase of $0.24/L | | | | | |
| Tax Change (750mL) | 2.740* | 2.816* | 2.283* | 5.824* | 4.508* | 3.393* |
| | (0.662) | (0.509) | (0.586) | (1.500) | (0.976) | (1.147) |
| Tax Change (1000mL) | 1.659* | 1.841* | 1.741* | 3.291* | 2.231* | 2.007 |
| | (0.366) | (0.434) | (0.406) | (1.170) | (0.852) | (0.854) |
| Tax Change (1750mL) | 0.986* | 0.802* | 0.483* | 1.997* | 1.212 | 0.705 |
| | (0.291) | (0.232) | (0.259) | (0.717) | (0.484) | (0.549) |
| | Illinois Sept 1, 2009 Tax Increase of $1.07/L | | | | | |
| Tax Change (750mL) | 0.655* | 1.547* | 2.007* | 0.979* | 1.982* | 2.357* |
| | (0.125) | (0.114) | (0.094) | (0.204) | (0.156) | (0.104) |
| Tax Change (1750mL) | 0.401* | 0.822* | 0.858* | 1.108* | 1.150* | 1.016* |
| | (0.053) | (0.075) | (0.114) | (0.129) | (0.099) | (0.129) |
| | Lousiana Sept 1, 2009 Tax Increase of $0.14/L | | | | | |
| Tax Change (750mL) | 1.230 | 3.776* | 1.685* | 2.146 | 6.331* | 0.612 |
| | (0.942) | (0.961) | (0.916) | (1.827) | (1.497) | (1.213) |
| Tax Change (1750mL) | 0.321 | 2.253* | 0.683* | 0.454 | 3.581* | 0.142 |
| | (0.508) | (0.476) | (0.400) | (0.915) | (0.692) | (0.530) |
| Observations | 7,049,524 | 6,859,112 | 6,678,483 | 2,821,502 | 3,759,221 | 4,239,584 |
| Adjusted $R^2$ | 0.021 | 0.040 | 0.042 | 0.050 | 0.075 | 0.070 |

Note: The table above reports OLS estimates of the pass-through of taxes into spirits prices in each state over different horizons by product size. Each state and horizon is a separate regression. The reported coefficients can be interpreted as the pass through in dollars for a one-dollar increase in tax. The left panel includes all observations while the panel on the right conditions on a non-zero change in the retail price. Products are sold in three main sizes: 750mL, 1000mL and 1750mL with state taxes varying by product volume regardless of alcohol concentration. Only 750ml and 1750mL products are included in Illinois and Louisiana because relatively few 1000mL bottles are sold in these states. The dependent variable is the change in price for a given product at a given store over a one month, three month or six month horizons. Each regression includes fixed effects for UPC, month of year, and year (all interacted with state). All regressions are weighted by annual sales for the UPC and store during the calendar year prior to each state's tax change. Standard errors are clustered at the state-UPC level. We provide quarterly results in Appendix Table D4.
* Significant at the 1 percent level.

Table 3: Quarterly Retail Price Transitions by State, Cents Only

Connecticut

| from/to | 0.49 | 0.59 | 0.65 | 0.69 | 0.79 | 0.89 | 0.93 | 0.95 | 0.98 | 0.99 | other |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.49 | 2.26 | 0.02 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.73 | 0.03 |
| 0.59 | 0.04 | 0.98 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.29 | 0.02 |
| 0.65 | 0.00 | 0.00 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.01 |
| 0.69 | 0.02 | 0.01 | 0.00 | 0.18 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.01 |
| 0.79 | 0.01 | 0.02 | 0.00 | 0.00 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.01 |
| 0.89 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.41 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 |
| 0.93 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.61 | 0.01 | 0.00 | 0.30 | 0.03 |
| 0.95 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.00 | 0.20 | 0.02 |
| 0.98 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.63 | 0.20 | 0.01 |
| 0.99 | 0.72 | 0.32 | 0.02 | 0.07 | 0.08 | 0.17 | 0.07 | 0.17 | 0.13 | **88.55** | 0.72 |
| other | 0.03 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.01 | 0.01 | 0.82 | 0.49 |
| total | 3.08 | 1.38 | 0.10 | 0.26 | 0.21 | 0.60 | 0.71 | 0.27 | 0.77 | **91.26** | 1.35 |
| long-run | 3.04 | 1.42 | 0.08 | 0.22 | 0.19 | 3.96 | 0.26 | 0.25 | 0.54 | 88.82 | 1.22 |

Illinois

| from/to | 0.19 | 0.29 | 0.39 | 0.49 | 0.59 | 0.79 | 0.89 | 0.97 | 0.98 | 0.99 | other |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.19 | 0.06 | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.25 | 0.04 |
| 0.29 | 0.00 | 0.15 | 0.00 | 0.03 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.18 | 0.03 |
| 0.39 | 0.00 | 0.00 | 0.07 | 0.02 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.30 | 0.04 |
| 0.49 | 0.02 | 0.04 | 0.03 | 2.03 | 0.02 | 0.06 | 0.02 | 0.03 | 0.01 | 2.14 | 0.38 |
| 0.59 | 0.01 | 0.00 | 0.00 | 0.03 | 0.11 | 0.01 | 0.00 | 0.00 | 0.00 | 0.28 | 0.04 |
| 0.79 | 0.01 | 0.01 | 0.01 | 0.05 | 0.01 | 0.23 | 0.01 | 0.00 | 0.00 | 0.65 | 0.07 |
| 0.89 | 0.00 | 0.00 | 0.00 | 0.02 | 0.00 | 0.01 | 0.07 | 0.00 | 0.00 | 0.22 | 0.03 |
| 0.97 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 3.24 | 0.00 | 1.29 | 0.09 |
| 0.98 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 1.07 | 0.07 | 0.15 |
| 0.99 | 0.19 | 0.16 | 0.27 | 2.14 | 0.24 | 0.61 | 0.20 | 1.43 | 0.12 | **71.43** | 3.09 |
| other | 0.04 | 0.04 | 0.04 | 0.40 | 0.05 | 0.06 | 0.03 | 0.13 | 0.14 | 3.38 | 1.97 |
| total | 0.33 | 0.40 | 0.42 | 4.76 | 0.43 | 1.02 | 0.33 | 4.84 | 1.34 | **80.19** | 5.93 |
| long-run | 0.31 | 0.39 | 0.41 | 4.68 | 0.41 | 1.00 | 0.32 | 5.28 | 1.41 | 80.02 | 5.77 |

Louisiana

| from/to | 0.19 | 0.29 | 0.39 | 0.49 | 0.59 | 0.69 | 0.79 | 0.89 | 0.95 | 0.99 | other |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.19 | 0.48 | 0.01 | 0.01 | 0.02 | 0.01 | 0.02 | 0.01 | 0.01 | 0.00 | 0.10 | 0.03 |
| 0.29 | 0.01 | 0.76 | 0.02 | 0.04 | 0.01 | 0.01 | 0.02 | 0.01 | 0.00 | 0.13 | 0.02 |
| 0.39 | 0.01 | 0.02 | 0.61 | 0.04 | 0.01 | 0.02 | 0.02 | 0.01 | 0.00 | 0.16 | 0.03 |
| 0.49 | 0.03 | 0.05 | 0.05 | 5.75 | 0.06 | 0.06 | 0.05 | 0.08 | 0.01 | 2.98 | 0.23 |
| 0.59 | 0.01 | 0.01 | 0.01 | 0.04 | 0.67 | 0.02 | 0.02 | 0.01 | 0.00 | 0.12 | 0.02 |
| 0.69 | 0.01 | 0.01 | 0.02 | 0.07 | 0.02 | 0.80 | 0.03 | 0.01 | 0.00 | 0.12 | 0.02 |
| 0.79 | 0.01 | 0.01 | 0.02 | 0.07 | 0.01 | 0.02 | 0.68 | 0.02 | 0.00 | 0.13 | 0.02 |
| 0.89 | 0.01 | 0.01 | 0.02 | 0.07 | 0.01 | 0.02 | 0.02 | 0.74 | 0.00 | 0.10 | 0.03 |
| 0.95 | 0.00 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 1.19 | 0.46 | 0.37 |
| 0.99 | 0.15 | 0.22 | 0.23 | 3.02 | 0.20 | 0.21 | 0.21 | 0.20 | 0.70 | **71.53** | 1.40 |
| other | 0.02 | 0.03 | 0.02 | 0.28 | 0.02 | 0.02 | 0.02 | 0.03 | 0.12 | 1.81 | 1.41 |
| total | 0.74 | 1.13 | 1.01 | 9.43 | 1.02 | 1.20 | 1.08 | 1.12 | 2.02 | **77.64** | 3.58 |
| long-run | 0.89 | 1.48 | 1.26 | 9.61 | 1.33 | 1.56 | 1.41 | 1.42 | 1.90 | 75.69 | 3.46 |

Note: The table above describes quarterly price transitions for each state where prices move *from* prices listed by row *to* prices listed by column. Each entry reports the unweighted share of all prices accounted for by each transition. For example, 2.26% of all prices in Connecticut now end $0.49 and also ended in $0.49 last quarter while 0.72% of all Connecticut prices now end in $0.49 but ended in $0.99 last quarter. The 'other' row cumulates all unlisted price endings, meaning that 0.03% of all current Connecticut prices now end in $0.49 but had an unlisted price ending like $0.96 in the prior quarter. The 'total' row reports the share of prices at each price point. The 'long-run' row at the bottom of each state panel reports the long-run stationary distribution of prices $\pi$ implied by each state's transition matrix $\pi = \pi P$. The most frequent transition pattern in each state is bolded along with the corresponding total share.

Table 4: Quarterly Retail Price Increments

| | All Weeks | | | Month of Tax Change | | |
|---|---|---|---|---|---|---|
| | CT | IL | LA | CT | IL | LA |
| Whole Dollar | 71.08 | 61.57 | 64.75 | 75.96 | 67.15 | 63.72 |
| Half Dollar | 6.59 | 8.61 | 13.25 | 6.20 | 8.83 | 12.12 |
| Small Change | 2.72 | 4.91 | 3.11 | 1.12 | 1.60 | 2.04 |
| Large Change | 4.11 | 1.71 | 1.97 | 2.38 | 1.46 | 1.87 |
| Other | 15.50 | 23.19 | 16.92 | 14.33 | 20.96 | 20.25 |
| Zeros | 78.28 | 46.25 | 53.56 | 58.67 | 14.67 | 38.88 |

Note: The table above reports the unweighted share of quarterly price changes that are in whole dollar, half dollar and other increments. Price changes larger than $8 or smaller than $0.25 in magnitude are labelled *Very Large* and *Very Small*, respectively. *No Change* reports the share of prices that are unchanged.

Table 5: Ordered Logit Estimates $\Delta p \in \{-1, 0, +1, +2, +3\}$

| | Cubic | Quartic | Quintic | Spline(1) |
|---|---|---|---|---|
| Tax Change | 498.114* | 523.324* | 523.353* | 1.841* |
| | (28.189) | (28.034) | (27.995) | (0.535) |
| Tax Change$^2$ | -104.691* | -130.026* | -129.352* | -6.094 |
| | (27.446) | (28.134) | (28.172) | (3.227) |
| Tax Change$^3$ | -46.388* | -28.202 | -33.103 | 29.941* |
| | (16.433) | (17.116) | (18.926) | (8.990) |
| Tax Change$^4$ | | -39.447* | -32.614 | 3.220* |
| | | (13.420) | (17.393) | (0.238) |
| Tax Change$^5$ | | | -7.496 | |
| | | | (14.520) | |
| Wholesale price change <= 0 | −0.444* | −0.435* | −0.437* | −0.434* |
| | (0.162) | (0.163) | (0.163) | (0.162) |
| Wholesale Price Change | 96.227* | 96.032* | 96.172* | 96.570* |
| | (18.534) | (17.940) | (17.899) | (17.904) |
| Wholesale Price Change$^2$ | −55.762* | −44.598 | −43.672 | −44.772 |
| | (20.628) | (20.013) | (20.176) | (20.019) |
| Wholesale Price Change$^3$ | −29.598 | −22.685 | −22.226 | −23.457 |
| | (18.614) | (18.300) | (18.533) | (18.348) |
| Total Product Sales | −0.022 | 0.042 | 0.045 | 0.043 |
| | (0.061) | (0.056) | (0.055) | (0.056) |
| Total Store Sales | 0.214* | 0.232* | 0.233* | 0.230* |
| | (0.041) | (0.040) | (0.039) | (0.040) |
| log Lag Price | −0.185 | −0.145 | −0.141 | −0.144 |
| | (0.106) | (0.114) | (0.116) | (0.115) |
| High Price | −0.224 | −0.242 | −0.249 | −0.277 |
| | (0.103) | (0.108) | (0.109) | (0.108) |
| Low Price | 0.426* | 0.406* | 0.404* | 0.454* |
| | (0.124) | (0.129) | (0.128) | (0.129) |
| Relative Price | −268.986* | −186.646* | −169.923* | −306.066* |
| | (7.735) | (7.843) | (7.903) | (8.010) |
| Relative Price$^2$ | 216.632* | 322.345* | 339.913* | 46.209 |
| | (30.202) | (30.587) | (30.451) | (30.859) |
| Relative Price$^3$ | 251.597* | 488.293* | 503.261* | 107.108* |
| | (4.622) | (4.802) | (5.056) | (4.628) |
| Observations | 2,371,792 | 2,371,792 | 2,371,792 | 2,371,792 |
| State-UPCs | 3,567 | 3,567 | 3,567 | 3,567 |
| Out of Sample Likelihood | 1,025,925 | 1,025,797 | 1,025,900 | 1,024,963 |
| BIC | 2,052,727 | 2,052,498 | 2,052,731 | 2,050,829 |

Note: The table above reports estimates from ordered logistic regressions of quarterly price changes on quarterly tax changes with different parameterizations of the tax change and a number of controls. The first column employs a cubic orthogonal polynomial of the tax change while columns 2 and 3 use quartic and quintic orthogonal polynomials of the tax change, respectively. The final column uses a spline with a knot point at tax change = 1 and its coefficients are not polynomial order. The controls measure the change in wholesale price since the last change in retail price, total sales by product over all stores, total sales by store over all products, the natural log of the price for the product the prior quarter at the same store, whether that store sold the product at the highest or lowest price the prior quarter and the difference between the price last quarter and the median price across all stores last quarter. All regressions also include state-varying controls; specifically, they include state fixed effects and interactions between state dummies and Total Product Sales, Total Store Sales, log Lag Price, High Price, Low Price and the Relative Price cubic polynomial. All four regressions are weighted by product-store sales in the year prior to the tax change. Weights are balanced by state, bottle size and tax change indicator. * Significant at the 1 percent level. All standard errors are clustered at state-UPC level.

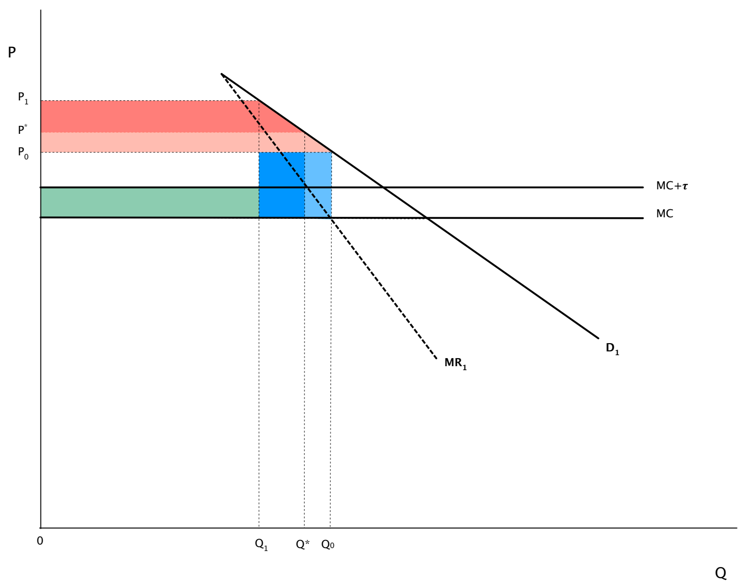


Figure 1: Change in Surplus When Price is Changed

Note: The figure above illustrates the lost surplus due to over-pass through of a tax with a monopolistic supplier. If the tax was pass-through at the lower long-run rate then price and quantity would shift from $P_0$ and $Q_0$ to $P^*$ and $Q^*$ and the lighter shaded regions would represent the lost surpluses to consumers and producers. With over-pass-through price and quantity are instead $P_1$ and $Q_1$, leading to larger surplus losses.

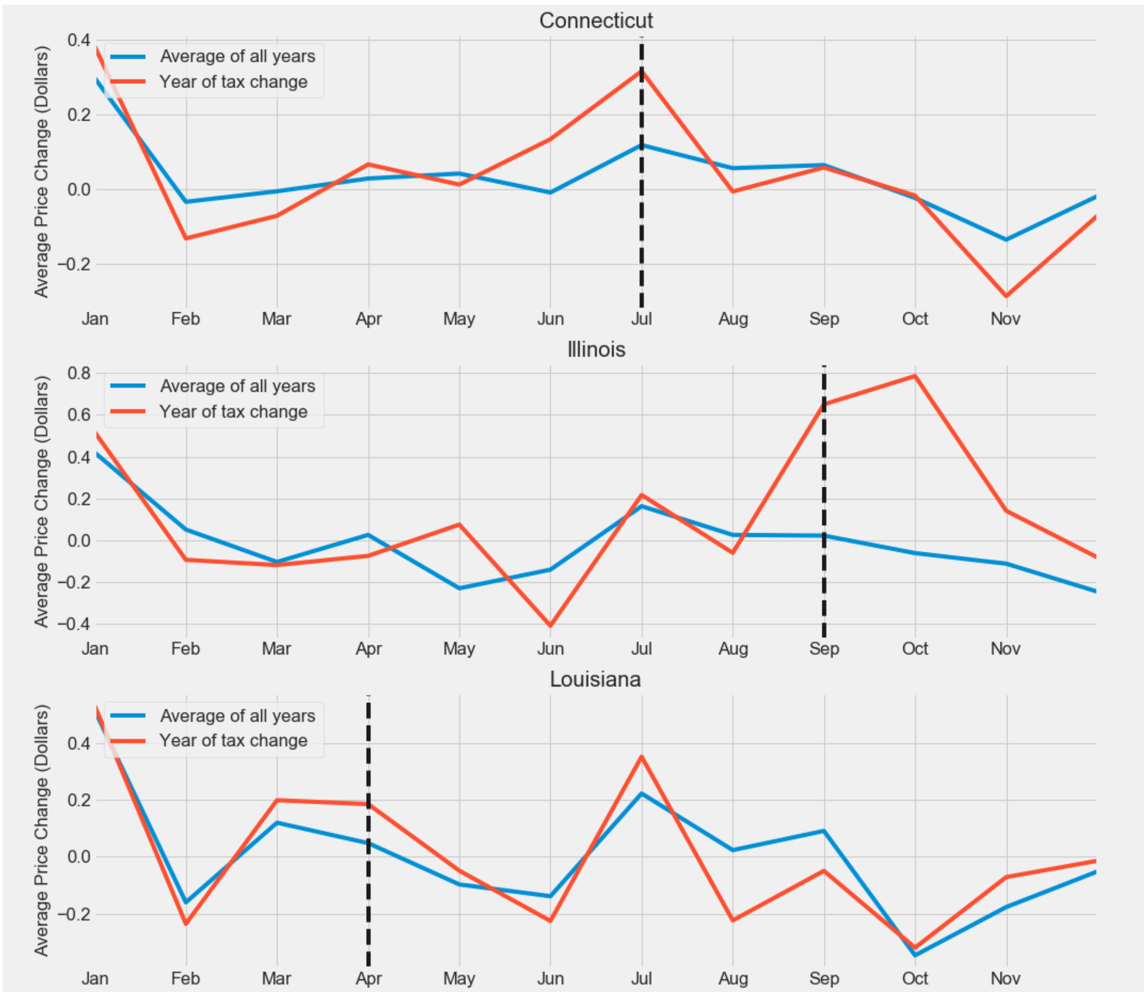


Figure 2: Average Price Change (by Month).

Note: The figure above plots the unweighted mean change in price by month for all years and for the year of the tax change. Vertical lines denote month of tax change. Price is in dollars per bottle.

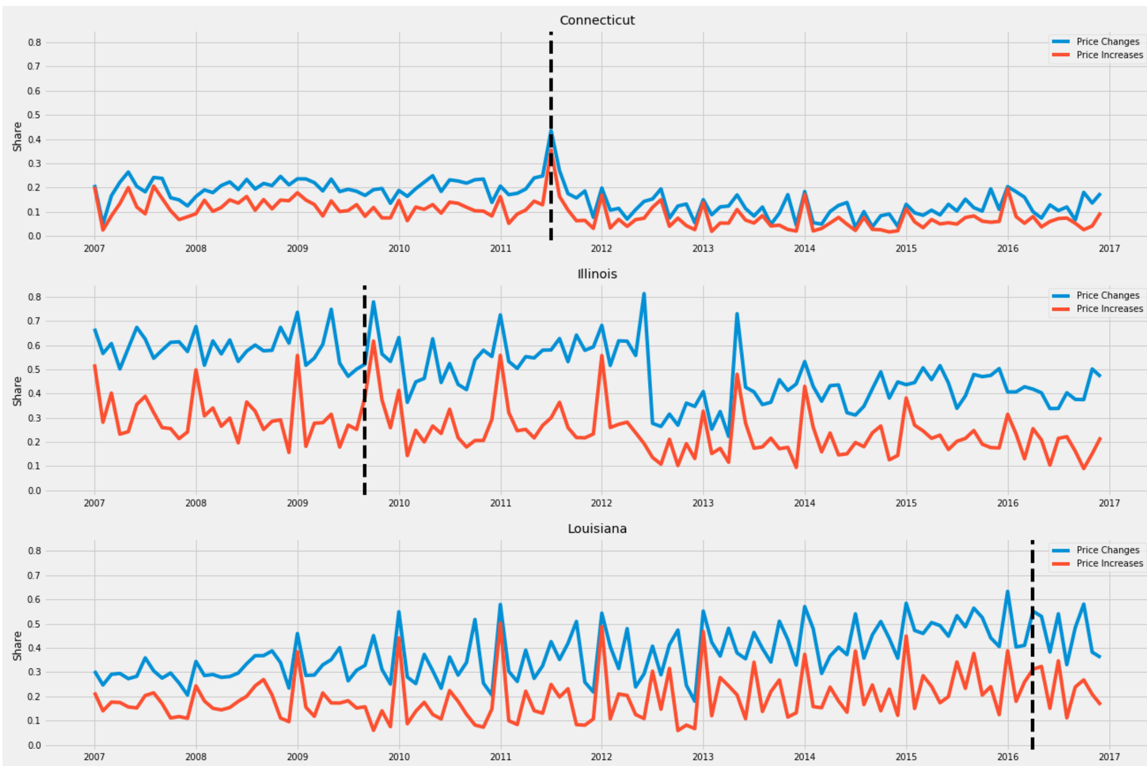


Figure 3: Frequency of Retail Price Adjustments

Note: The figure above plots the share of retail prices that change and that increase in each state for each month between 2007 and 2016, weighted by annual sales for the UPC and store in the calendar year prior to each state's tax change, balanced on package size.

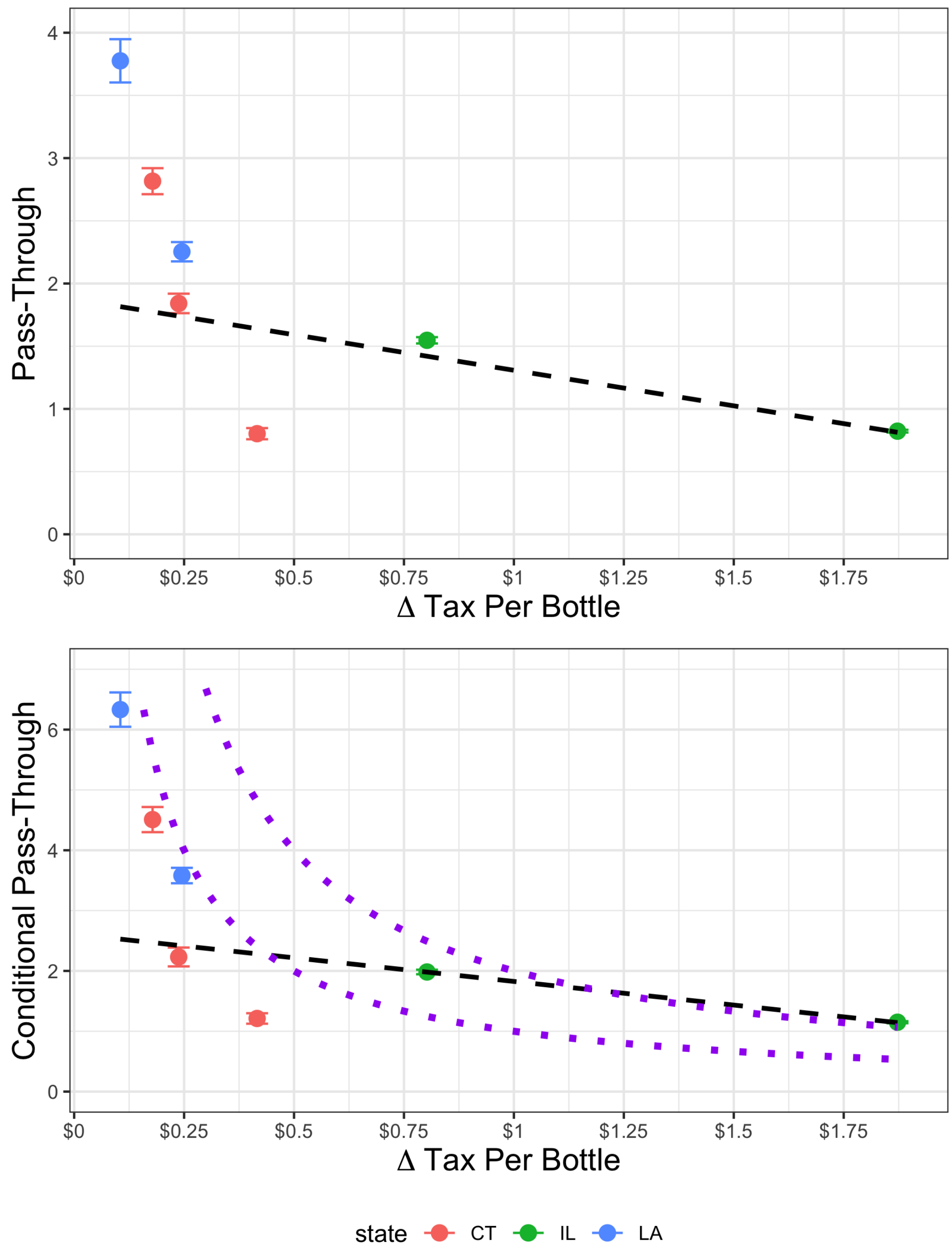


Figure 4: Pass-Through Estimates

Note: The first figure above plots the estimated pass-through rates for different size tax increases. The second figure plots the pass-through estimates conditional on a price change. All regressions are weighted by annual sales for the UPC and store during the calendar year prior to each state's tax change, normalized by size and state. The dashed lines estimate the pass-through rates as linear functions of the tax. For the unconditional left panel the parameters of the best fit line are: $\rho(\Delta\tau) = 1.76 - 0.51 * \Delta\tau$ while for the conditional right panel the best fit line is $\rho(\Delta\tau) = 2.47 - 0.72 * \Delta\tau$. The dotted lines indicate the implied pass through of a $1.00 and $2.00 price change respectively.

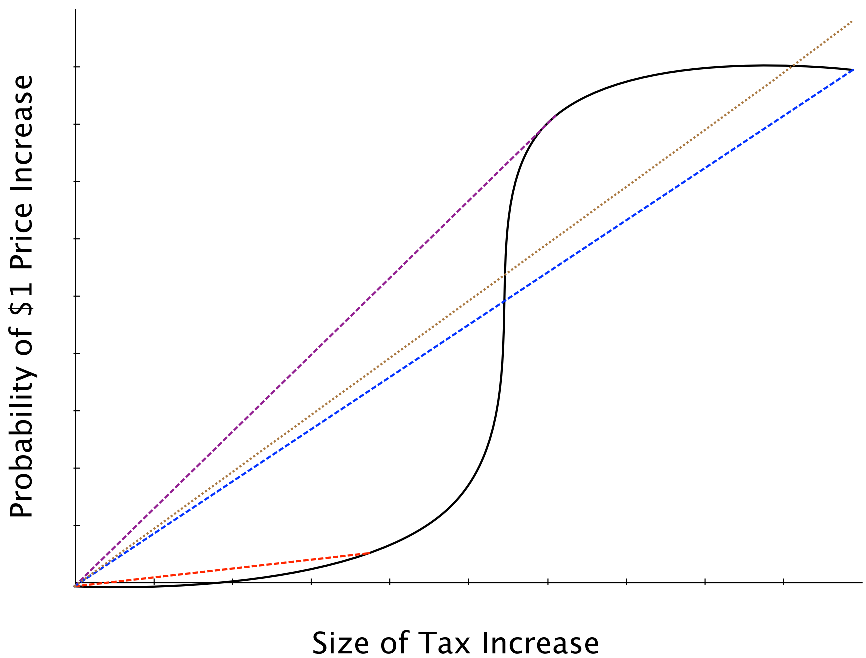


Figure 5: Probability of $1 Tax increase at different tax sizes (illustrative)

Note: The figure above plots the hypothetical price response to a tax increase as a sinusoidal curve. The slopes of the intersecting rays represent hypothetical linear estimates of the pass-through rate of various tax changes. While the true relationship between tax increases and prices is traced out by the curve, different observed tax changes can generate very different linear pass-through estimates.

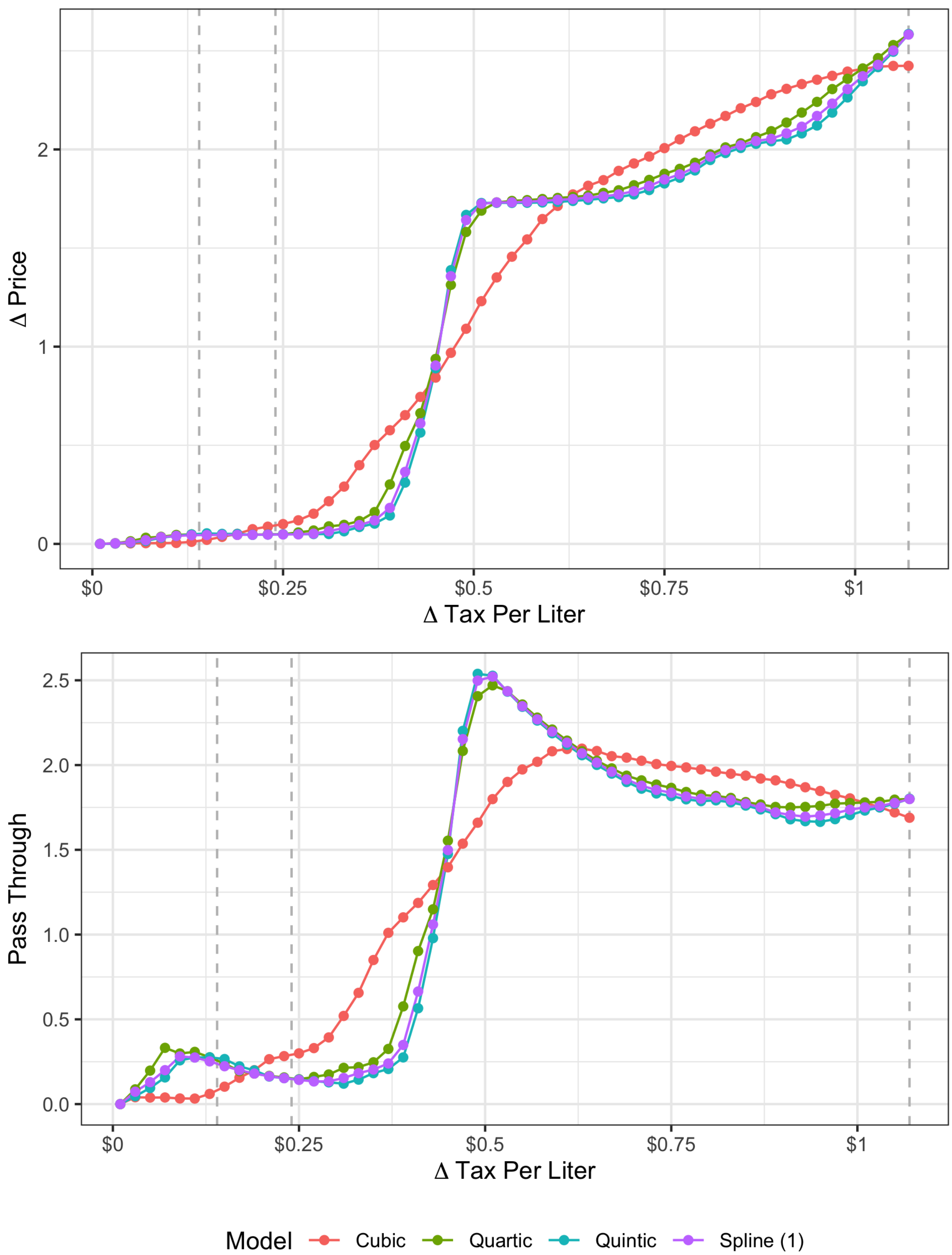


Figure 6: Specification Comparison for Ordered Logit
Top Pane: Predicted Price Change; Bottom Pane: Implied Pass Through Rate.
Vertical Lines at Observed Tax Changes.

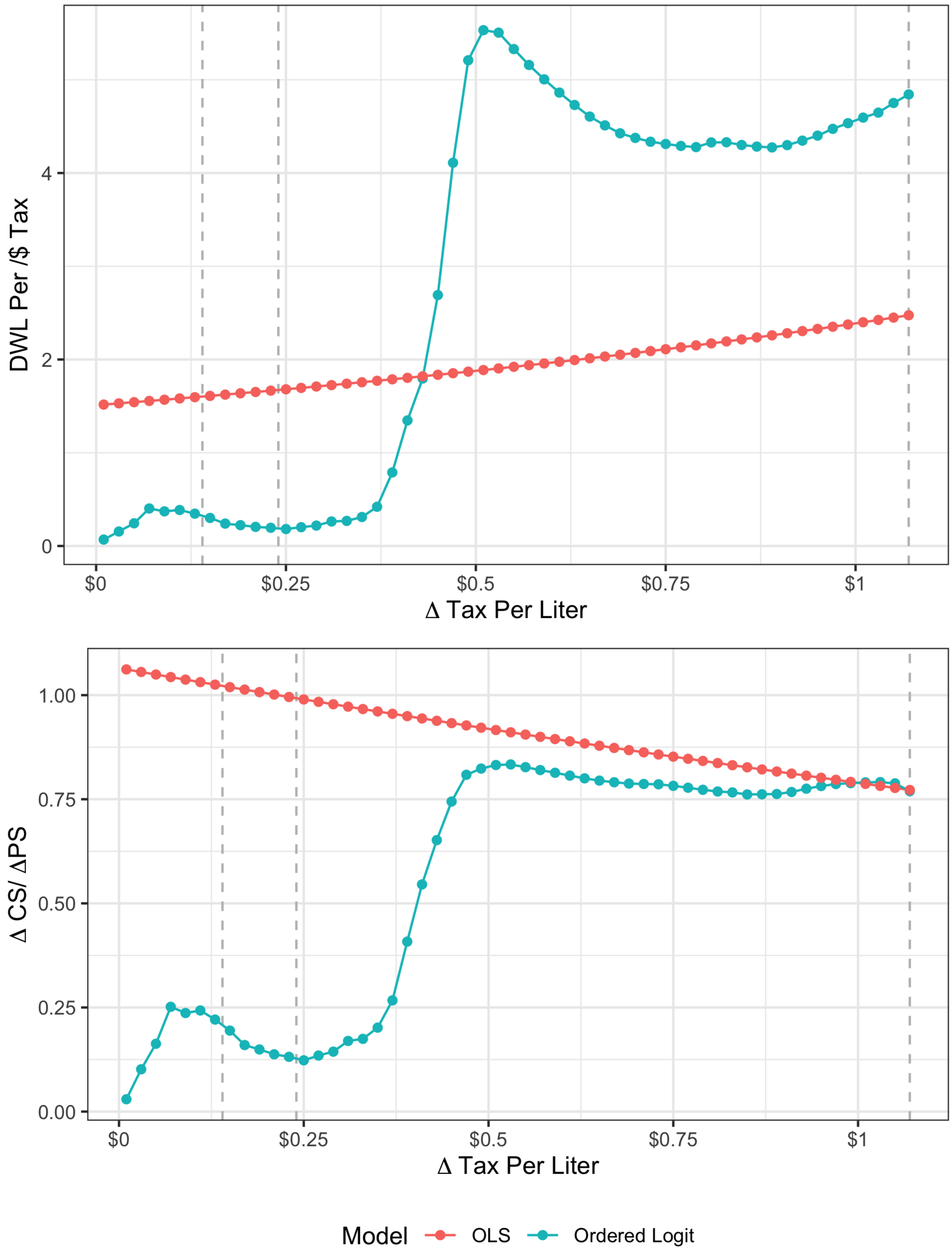


Figure 7: Welfare Predictions: Ordered Logit vs. OLS (Own Elasticity $\epsilon = -3.5$)
Top Pane: Effieciency: DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Vertical Lines at Observed Tax Changes.

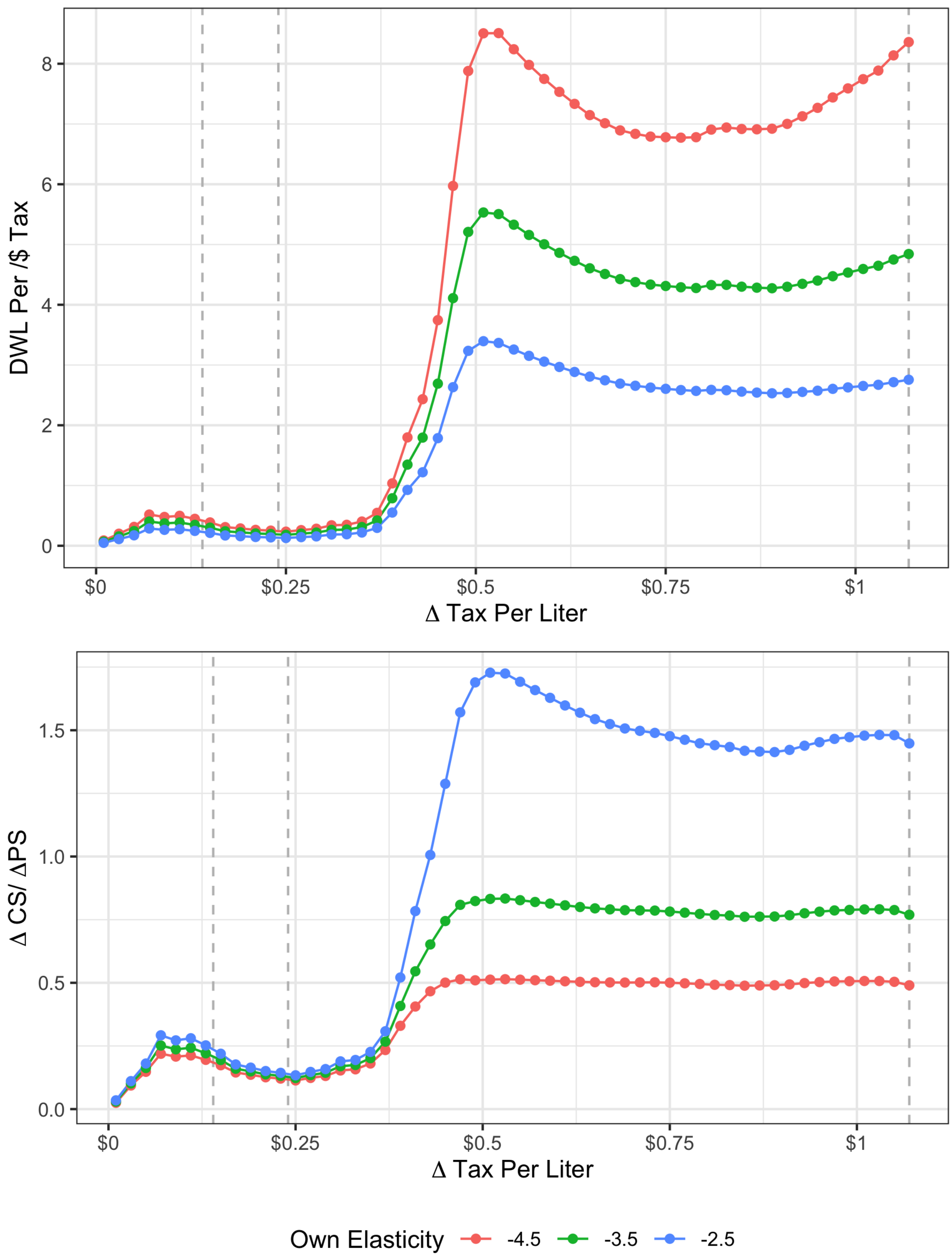


Figure 8: Welfare Predictions: Alternate Elasticities

Vertical Lines at Observed Tax Changes

# Online Appendices

## A. Summary Statistics

We summarize our main (monthly) dataset in Table A1. For each state and product size (750mL, 1L, 1.75L) we report the number of store-product-month observations, the total sales, and the average price paid (total revenue divided by total sales). We exclude 1L bottles from Illinois and Louisiana because we have fewer than 8,000 such observations and they represent a very small fraction of sales; we keep them for Connecticut where they represent around 8% of the market. Additionally, we report the size of the tax increase for each state and product size which ranges from \$0.105 per bottle for 750mL bottles in Louisiana to \$1.87 per bottle for 1.75L bottles in Illinois. We also consider a weighted version of the same sample where we weight products by their annual sales in the same store for the calendar year prior to tax change. We use these weights because price changes are more important for more popular products.[45] The weighted sample has substantially lower prices because mass-market products are cheaper and more popular than high-end niche products.

Table A1: Summary Statistics by State and Size

| | | | Unweighted Sample | | | Weighted Sample | | |
|---|---|---|---|---|---|---|---|---|
| State | Size(mL) | $\Delta\tau$ | # Obs | Total Sales | Price | # Obs | Total Sales | Price |
| CT | 750 | 0.178 | 416,587 | 2,161,852 | 25.64 | 275,585 | 1,553,462 | 22.88 |
| IL | 750 | 0.802 | 6,547,716 | 48,319,333 | 18.53 | 3,459,396 | 31,229,034 | 16.05 |
| LA | 750 | 0.105 | 2,234,366 | 12,371,082 | 19.04 | 1,711,654 | 10,454,975 | 17.56 |
| CT | 1000 | 0.238 | 54,803 | 433,746 | 22.35 | 44,587 | 359,712 | 21.60 |
| CT | 1750 | 0.416 | 244,975 | 2,849,310 | 27.70 | 186,673 | 2,417,044 | 24.95 |
| IL | 1750 | 1.872 | 2,166,896 | 29,223,908 | 23.49 | 1,539,886 | 24,929,312 | 20.11 |
| LA | 1750 | 0.245 | 1,083,667 | 8,833,187 | 24.35 | 882,465 | 7,756,701 | 22.29 |

Note: Observations are store-month-UPC. Weights correspond to annual sales for the UPC and store during the calendar year prior to each state's tax change.

We observe that prices are broadly similar in Louisiana and Illinois, but substantially higher in Connecticut.[46]

## B. Additional Heterogeneity in Pass-Through Rates

The pass-through rates detailed in Table 2 average over all products in each state of the specified size. These averages belie some sources of meaningful heterogeneity in pass-through rates.

Table B2 details the substantial heterogeneity across stores in their response to the tax. Stores that sell products at relatively lower prices (in the prior month) are more likely to raise prices in response to the tax change than those stores with relatively higher prices. We use two different discrete measures of high and low-price stores by product and month: the first column uses dummies for prices above or below the median price, the second column uses dummies for the highest and lowest price retailer (allowing for ties) selling the same product. For both measures we find that at low-price stores the tax is passed on at a rate of roughly 260% to 270% while at high-price stores

[45] In total we observe 6,785 products many of which have extremely low sales. We consider restricting the sample to the top 1000 or top 500 products and it has almost no effect on any of the estimates we report.

[46] We examine the laws which facilitate collusive wholesale pricing in Conlon and Rao (2015).

pass-through point estimates are below 10% and statistically indistinguishable from zero. We also employ a continuous measure of relative price in the third column and again find lower relative prices are correlated with larger pass-through rates.

Table B2: Pass-Through - Taxes to Retail Prices Relative to Other Stores

| | Above/Below Median | Min/Max | Continuous |
|---|---|---|---|
| Δ Tax | 1.045* | 1.132* | 1.128* |
| | (0.270) | (0.237) | (0.221) |
| Δ Tax * High | −0.923* | −1.141* | |
| | (0.352) | (0.366) | |
| Δ Tax * Low | 1.548* | 1.584* | |
| | (0.411) | (0.489) | |
| Δ Tax * Relative | | | −0.177* |
| | | | (0.031) |
| High Price | −0.381* | −0.350* | |
| | (0.050) | (0.042) | |
| Low Price | 0.152* | 0.246* | |
| | (0.029) | (0.031) | |
| Relative to Median | | | −0.034* |
| | | | (0.003) |
| Observations | 427,957 | 427,957 | 427,957 |
| Adjusted $R^2$ | 0.028 | 0.025 | 0.031 |
| Product FE | Yes | Yes | Yes |
| Month+Year FE | Yes | Yes | Yes |
| High Measure | Above Median | Maximum | Continuous |
| Low Measure | Below Median | Minimum | % Deviation |

* Significant at the 1 percent level

Note: The table above reports OLS estimates of the pass-through of taxes into retail prices in Connecticut for low and high-priced stores. All regressions weighted by 2011 Nielsen units (normalized by size) and reported standard errors are clustered at the UPC level. Relative prices are from the *prior* month. Columns (1)+(2) use indicator variables. Column (3) uses percentage deviation from median price.

Table B3 examines how retail price changes are modulated by the cumulative change in the lowest wholesale price of a product since a store's last retail price change. This state variable captures the *pressure* to adjust prices that a retailer faces from the build-up of wholesale price changes. In column 1 of Table B3 we include the wholesale state variable alongside the size-interacted tax change variable; in column 2 we include an interaction between the wholesale state variable and the change in tax and in column 3 we include both the main and interaction terms. In all specifications larger cumulative changes in wholesale prices since the last retail price change lead to larger retail price increases. While the main effect and interaction term are statistically significant on their own (columns 1 and 2) when both are included only the main effect of the wholesale state variable is significant though the point estimate of the interaction term is of the expected positive sign.

Table B3: Pass-Through - Adding Wholesale Price Change State Variable (CT only)

| | (1) | (2) | (3) |
|---|---|---|---|
| Δ Tax (750mL) | 2.949* | 3.028* | 2.887* |
| | (0.815) | (0.818) | (0.820) |
| Δ Tax (1000mL) | 2.024* | 2.014* | 1.953* |
| | (0.575) | (0.581) | (0.581) |
| Δ Tax (1750mL) | 0.672* | 0.510 | 0.592 |
| | (0.391) | (0.404) | (0.402) |
| $\Delta W$ | 0.107* | | 0.106* |
| | (0.018) | | (0.019) |
| $\Delta W \times \Delta T$ | | 0.394* | 0.092 |
| | | (0.105) | (0.109) |
| Observations | 92,553 | 92,553 | 92,553 |
| Adjusted $R^2$ | 0.040 | 0.022 | 0.040 |

* Significant at the 1 percent level.
Note: The table above reports quarterly OLS estimates of the pass-through of taxes into retail prices in Connecticut controlling for the change in the product's wholesale price since the last change in the store's retail price for that product. All regressions weighted by 2010 Nielsen units (normalized by size) and reported standard errors are clustered at the UPC level.

## C. Data

### C.1. Aggregation of Nielsen Weekly Data to Monthly Data

The Nielsen scanner data are recorded weekly, and some weeks span two months. We aggregate the data to the monthly level for the initial analysis for a number of reasons. The first is that in Connecticut, wholesale (and retail) prices are not allowed to vary within a month. This is not necessarily true in Illinois or Louisiana where prices can adjust more flexibly. Second, when tax changes are observed, the occur on the first day of the month. We allocate weeks to months based on the calendar month of the last day of the corresponding week. When we aggregate, we take the last price (Nielsen revenue divided by units) recorded in each month and total sales for each product-store-month. In practice, there is only a single price for 99% of store-month-product observations in Connecticut once we exclude the first week of the month (which may contain data from two months).

### C.2. Consolidation

We consolidate products so that a product is defined as brand-flavor-size such as *Smirnoff Orange Vodka 750mL*. Sometimes a "product" may aggregate over several UPC's, as changes in packaging can result in a new UPC. UPC changes most commonly arise with special promotional packaging such as a commemorative bottle, or a holiday gift set. At other times, the change in UPC may be purely temporal in nature. A product may also be available in both glass and plastic bottles at the same time. We rarely observe price differences for glass and plastic packaging within a product-month, so we also consolidate these UPCs.

In total, these consolidations help us to construct a more balanced panel of products over time, and avoid gaps during holiday periods, or products going missing when packaging changes. This is especially important when our goal is to capture *changes* in prices within a product-store over time.

### C.3. Cleaning Prices

Nielsen data report weekly sales at the store-UPC level. Prices are not observed directly but rather imputed from revenues as $p_t \approx \frac{p_t \cdot q_t}{q_t}$. It is common to adjust or filter prices under a number of scenarios: (1) transitional prices (2) temporary sales (3) clearance/closeouts. For (1) observed prices may not represent transaction prices, but rather the weighted average of two different price points. For (2) and (3) the observed prices may in fact be transaction prices, but those prices may not end in 0.99 as many stores/chains use unusual price endings internally to track sales or clearances.

It is helpful to consider a sequence of prices for a product $[p_{t-2}, p_{t-1}, p_t, p_{t+1}, p_{t+1}]$ and so on. In many cases $p_t$ and $p_{t+1}$ are not adjacent weeks but rather adjacent periods in which a sale is recorded. This is is important because Nielsen does not record any information unless a product was purchased that week.

#### Rule #1: Transitional Prices

If the store changes its prices at the end of a Nielsen-week (Saturday to Saturday) the the recorded price should match the actual transaction price. A more likely scenario is that a store changes its price midweek so that revenues include sales recorded at $p_{t-1}$ and $p_{t+1}$, while no transactions actually take place at the recorded $p_t$. Because we are interested in *price changes* we will replace $p_t$ with the closer of $p_{t-1}, p_{t+1}$, so that our recorded price corresponds to an actual transacted price (rather than a weighted average).

We can detect these transitional prices by when $p_t \in (p_{t-1}, p_{t+1},)$ or $p_t \in (p_{t+1}, p_{t-1},)$ and then we use observed sales $q_t$ to construct a convex set of potential prices where $w = [1, \ldots, q_t - 1]/q_t$ and $p_t \approx w p_{t-1} + (1 - w) p_{t+1}$ to see if $p_t$ lies on the grid of transitional prices.

We apply this rule only to price endings not in the four most commonly used price endings for each chain in our dataset.

We include the code below:

```
def transition_prices(p1,p2,pobs,q):
    # is observed price between (p1,p2)
    if not (((pobs < p1) & (pobs > p2)) | ((pobs > p1) & (pobs < p2))):
        return np.nan
    #convex weights
    w=np.array([x/q for x in range(0,q+1)])
    # grid of possible prices
    possible=w*p1 + (1-w)*p2
    # check if observed price is within 1 cent of rounded grid of possible prices
    # then return the closer price --> otherwise missing
    if any(np.isclose(pobs,np.round(possible,3),atol=.01)):
        if np.abs(p1-pobs) <= np.abs(p2-pobs):
            return p1
        else:
            return p2
    else:
        return np.nan
```

#### Rule #2: Temporary Sales

There is evidence that many stores (or chains) use prices with unusual endings as an internal way to track temporary sales or promotional prices. For example, *reference prices* may end in 0.99 or 0.49 but temporary sales may end in 0.97 or 0.12. This is largely not an issue in Connecticut where regulations make temporary sales relatively rare, but appears to be more common in Illinois and Louisiana where retailers are free to increase and reduce prices at will.

We consider a price a one-week temporary sale if: $p_{t-1} = p_{t+1} = p_{t+2} = p_{t-2}$ and $p_t < p_{t-1}$. For a two week temporary sale, we define the first week as: $p_{t-3} = p_{t-2} = p_{t-1} = p_{t+2} = p_{t+3}$ and $p_t < p_{t-1}$. For both cases we require that the final observed price for a product cannot be considered a "sale" price.

```
def add_temp_sales(df):
   # observed leads and lags are all identical except p_t, p_{t+1} and p_t < p_{t-1}
    x=(df[['p_lag1','p_lag2','p_lag3','p_lead2','p_lead3','p_lead4']].std(axis=1)==0) & ...
            (df['price']< df['p_lag1']) & ~(df['p_lead2'].isnull())
   # p_t == p_{t+1}
    x=x & (df['price'] == df['p_lead1'])

    # Detect the (optional) second week of sale
    y=(df['p_lag1'] == df['price']) & x.shift(1)
    # Detect one week sales
    z=(df[['p_lag1','p_lead1','p_lag2','p_lead2']].std(axis=1)==0) ....
            &(df.price<df.p_lag1)&(~df.p_lead1.isnull())
    df['sales_2wk']=(x|y)
    df['sales_1wk']=z
    return df
```

### Rule #3: Closeouts/Clearance Items

We also find and tag clearance or closeout prices. These are the final price at which a good transacts $p_T$ subject to some conditions. We look for cases where the last price at which a good transacts is otherwise unobserved in the full history of prices $[p_1, p_2, \ldots, p_T]$ except in a sequential run of prices at the end of the dataset. Thus it must be that $p_{t-k} = p_T$ for all $k = 0, 1, \ldots, K$ and some $K \geq 1$. It must also be that $p_{t-K} < p_{t-K-1}$ (the first price beginning the run of clearance prices is lower than the previous price).

This rule is conservative in that if a product starts at 19.99 and is reduced to 14.12 and then later to 12.15 only the 12.15 price is considered a closeout, and 14.15 is also not considered a temporary sale (since the price does not return to 19.99).

```
# return vector same size as p
def np_closeout(p):
    p=p.values
    y=np.zeros(len(p))

    idx=np.where(p==p[-1])
    run_start=idx[0][0]
    #contiguous set of prices that match the final price (without gaps)
    if (np.diff(idx)==1).all() & (p[run_start] < p[run_start-1]):
        y[idx]=1
    return y
```

## C.4. Wholesale Data

We draw on a hand-collected dataset of wholesale prices for the state of Connecticut. Wholesale prices are a key predictor of retail price changes. These prices were scraped by us from the Connecticut Department of Consumer Protection (DCP) from August 2007 to August 2013. These data are available because Connecticut requires that all licensed wholesalers post prices. Wholesalers agree to charge retailers these prices for the entire month, and are legally not allowed to provide quantity discounts or price discriminate.[47] Only 18 wholesale firms have ever sold brands of distilled spirits that we observe in the Nielsen dataset, and more than 80% of sales come from just six major wholesalers. Because Illinois and Louisiana do not require that wholesalers publicly post prices, we do not have wholesale pricing information for these states.

For our welfare calculations we use estimates from Conlon and Rao (2015) of the prices paid by wholesale firms to importers and distillers. These marginal costs are estimated at the product level using a structural model of demand in the approach of Berry et al. (2004).

## D. Quarterly Pass-Through and Price Points

### D.1. Constructing Quarterly Data

We estimate our nonlinear models using quarterly data to avoid the repetitive use of monthly observations. We allocate weeks to quarters using the last day of each week. This works for Connecticut where the tax changes on July 1 (the first day of Q3), and Louisiana where the tax changes on April 1 (the first day of Q2). We have to modify this procedure for Illinois, where the tax changes on September 1. For Illinois, we change the starting month for each quarter so that Q1 begins in December, Q2 begins in March, Q3 begins in June, and Q4 begins in September. This way, the tax change happens at the beginning of of Q4 under our adjusted definition.[48] When we aggregate, we take the last price (Nielsen revenue divided by units) recorded in each quarter and total sales for each product-store-quarter.

For comparison, in the left panel of Table D4 we reproduce Table 2 from the main text using the quarterly data instead of monthly data. We find that the patterns are broadly similar, though we have fewer observations, larger standard errors, and less precise control over seasonality. In all but once case (1750mL bottles in Connecticut) we find evidence that taxes are over-shifted $\rho > 1$ and that conditional on a price change, estimated pass-through rates are higher. The latter effects are muted as one might expect because at the quarterly level price changes are more common overall.

[47] Connecticut is one of 12 states with a set of regulations known as *Post and Hold*, which mandates that all wholesalers post the prices they plan to charge retailers for the following month. Wholesalers must commit to charging these prices for the entire month (after a look-back period when wholesalers can view one another's initially posted prices and adjust their prices downwards without beating the lowest price for the product). For a detailed analysis of these regulations please see Conlon and Rao (2015).

[48] These definitions make it difficult to include quarterly fixed effects in regression specifications, as December (a high sales month) is in Q4 for (CT,LA) and Q1 in IL. For this reason we only ever consider $State \times Quarter$ fixed effects.

Table D4: Pass-Through: Taxes to Retail Prices (Quarterly)

| | Quarterly | | w/ Price Points | |
|---|---|---|---|---|
| | All Observations | Δ Retail Price ≠ 0 | All Observations | Δ Retail Price ≠ 0 |
| | Connecticut July 1, 2011 Tax Increase of \$0.24/L | | | |
| Δ Tax (750mL) | 2.944* | 4.476* | 2.723* | 4.031* |
| | (0.735) | (1.716) | (0.532) | (1.342) |
| Δ Tax (1000mL) | 2.094* | 2.639 | 1.952* | 2.568 |
| | (0.509) | (1.227) | (0.437) | (1.130) |
| Δ Tax (1750mL) | 0.800 | 0.950 | 0.766 | 0.929 |
| | (0.373) | (0.774) | (0.359) | (0.765) |
| | Illinois Sept 1, 2009 Tax Increase of \$1.07/L | | | |
| Δ Tax (750mL) | 2.738* | 3.447* | 2.385* | 3.130* |
| | (0.224) | (0.256) | (0.190) | (0.218) |
| Δ Tax (1750mL) | 1.375* | 1.645* | 1.226* | 1.470* |
| | (0.099) | (0.123) | (0.096) | (0.115) |
| | Louisiana April 1, 2016 Tax Increase of \$0.14/L | | | |
| Δ Tax (750mL) | 1.791 | 3.935 | 1.983 | 4.434* |
| | (1.112) | (1.759) | (1.002) | (1.696) |
| Δ Tax (1750mL) | 1.198 | 2.159 | 1.632* | 3.004* |
| | (0.576) | (0.906) | (0.445) | (0.735) |
| Observations | 3,035,603 | 1,606,649 | 2,948,414 | 1,443,105 |
| Adjusted $R^2$ | 0.052 | 0.094 | 0.074 | 0.141 |

* Significant at the 1% level.

Note: We include fixed effects for UPC, quarter of year, and year (all interacted with state). All regressions are weighted by annual sales for the UPC and store for the year prior to the tax change. Standard errors are clustered at the state-UPC level. Price points are defined in Table D6.

## D.2. Constructing Price Points

When we estimate the ordered logit models, we consolidate several price changes into larger bins. We report the data in relatively narrow intervals in Table D5. Some important patterns emerge. First, the majority of price changes are within a few cents of zero. Second, as we have documented in the main text, the most popular price change intervals are the ones that contain $-\$1.00, +\$1.00, +\$2.00$. There are some other important patterns that are worth mentioning. (1) Connecticut price changes are more likely to be in or around whole dollar increments than price changes in other states. As described in the main text, this is in part because Connecticut regulations prevent mid-month price changes that reduce our ability to accurately measure prices from the revenue and quantity information reported by Nielsen. In addition, Connecticut limits temporary sales which mean that most reported prices coincide with transaction prices. (2) There are a relatively small fraction of very large price changes (both positive and negative) which we will ultimately ignore when estimating our ordered logit models. These may represent undetected closeouts, or substantial departures from previous pricing strategy and often affect low sales high price specialty products (with prices $\geq \$150$). Other non whole-dollar price changes such as 50 cents, represent less than 2% of the observations in the overall data. Thus aggregating over these price changes is relatively innocuous. (3) moderate positive price changes of \$3.00 or more are relatively uncommon except in Illinois during the quarter of the tax change.

We further consolidate the data in Table D5 to a set of price change increments which we use in our ordered logit estimation. As before, we assign each price change to an interval, and report its frequency in the table. We also can assign each interval a value or "Category Value", these values

Table D5: Frequency of Quarterly Price Change Intervals

| | All Quarters | | | Quarter of Tax Change | | |
|---|---|---|---|---|---|---|
| Price Change | CT | IL | LA | CT | IL | LA |
| (-10,-6.03] | 0.51 | 0.85 | 0.57 | 0.30 | 0.82 | 0.74 |
| (-6.03,-5.97] | 0.18 | 0.36 | 0.31 | 0.11 | 0.24 | 0.44 |
| (-5.97,-5.03] | 0.092 | 0.25 | 0.15 | 0.12 | 0.16 | 0.33 |
| (-5.03,-4.97] | 0.31 | 0.60 | 0.64 | 0.44 | 0.30 | 0.77 |
| (-4.97,-4.03] | 0.11 | 0.48 | 0.25 | 0.03 | 0.33 | 0.38 |
| (-4.03,-3.97] | 0.57 | 1.11 | 1.26 | 0.62 | 0.90 | 1.67 |
| (-3.97,-3.03] | 0.19 | 0.81 | 0.49 | 0.21 | 0.54 | 0.57 |
| (-3.03,-2.97] | 0.86 | 2.25 | 2.14 | 0.84 | 1.48 | 2.26 |
| (-2.97,-2.03] | 0.33 | 1.37 | 1.00 | 0.20 | 0.85 | 1.47 |
| (-2.03,-1.97] | 1.50 | 4.84 | 3.95 | 1.63 | 0.94 | 4.01 |
| (-1.97,-1.03] | 0.44 | 2.29 | 1.86 | 0.44 | 1.16 | 2.77 |
| (-1.03,-0.97] | 1.85 | 8.03 | 6.70 | 4.22 | 3.63 | 7.93 |
| (-0.97,-0.53] | 0.15 | 1.24 | 0.93 | 0.14 | 0.67 | 0.90 |
| (-0.53,-0.47] | 0.10 | 1.08 | 1.23 | 0.14 | 0.56 | 1.28 |
| (-0.47,-0.03] | 0.28 | 1.57 | 1.22 | 0.45 | 0.91 | 1.38 |
| (-0.03,0.03] | 77.45 | 43.55 | 50.73 | 58.18 | 14.60 | 38.77 |
| (0.03,0.47] | 0.71 | 1.64 | 1.60 | 0.81 | 1.54 | 1.34 |
| (0.47,0.53] | 0.63 | 1.30 | 1.92 | 1.30 | 1.23 | 3.72 |
| (0.53,0.97] | 0.41 | 1.31 | 0.97 | 1.48 | 1.72 | 1.11 |
| (0.97,1.03] | 5.88 | 9.32 | 8.28 | 14.85 | 13.46 | 11.93 |
| (1.03,1.97] | 0.62 | 2.42 | 2.18 | 1.42 | 6.52 | 3.06 |
| (1.97,2.03] | 2.35 | 4.92 | 4.29 | 4.46 | 16.25 | 4.95 |
| (2.03,2.97] | 0.36 | 1.43 | 1.10 | 0.89 | 4.92 | 0.99 |
| (2.97,3.03] | 1.10 | 2.36 | 2.22 | 1.87 | 9.66 | 2.69 |
| (3.03,3.97] | 0.23 | 0.70 | 0.46 | 0.48 | 2.45 | 0.47 |
| (3.97,4.03] | 0.72 | 1.13 | 1.07 | 1.40 | 4.07 | 1.27 |
| (4.03,4.97] | 0.15 | 0.40 | 0.23 | 0.54 | 1.35 | 0.42 |
| (4.97,5.03] | 0.42 | 0.69 | 0.74 | 0.65 | 4.22 | 0.60 |
| (5.03,5.97] | 0.059 | 0.22 | 0.13 | 0.20 | 1.10 | 0.081 |
| (5.97,6.03] | 0.23 | 0.37 | 0.31 | 0.35 | 0.96 | 0.38 |
| (6.03,6.97] | 0.056 | 0.12 | 0.071 | 0.11 | 0.32 | 0.062 |
| (6.97,7.03] | 0.14 | 0.22 | 0.16 | 0.075 | 0.56 | 0.18 |
| (7.03,10] | 0.39 | 0.31 | 0.29 | 0.30 | 0.75 | 0.36 |
| $\lvert \Delta P \rvert > 10$ | 0.60 | 0.46 | 0.53 | 0.75 | 0.81 | 0.70 |

are *not* used in the ordered logit estimation, however we do use these values when calculating our counterfactuals.

We estimate quarterly pass-through regressions using these transformed values and compare the results to the un-transformed quarterly data in Table D4. The right panel of Table D4 confirms that transforming the data this way has little impact on the estimated pass-through rates. In all cases pass-through estimates using the transformed data are statistically indistinguishable from the quarterly pass-through estimates using the un-transformed data.

We can examine the in-sample fit of the ordered logit by looking at Connecticut during the month of the tax change. This period is important because it is the period we use for all of our counterfactual experiments. In Figure D1 we compare the observed price changes to those predicted under our main ordered logit specification. In general, the fit of the model is good, though we under-predict zero price changes and over-predict both positive and negative price changes. We also see that that the fraction of observations at large price changes $> +\$3$ or $< -\$3$ is fairly small, which suggests restricting the domain of potential outcomes may not be a major problem. Likewise, we see that nearly all price changes adhere to the grid of pre-specified price points with the possible exception of +\$0.50, which we examine in more detail in a robustness test below.

Table D6: Frequency of Quarterly Price Changes with Price Points

| Category Value | Interval | All Periods CT | All Periods IL | All Periods LA | During Tax Change CT | During Tax Change IL | During Tax Change LA |
|---|---|---|---|---|---|---|---|
| -2 | (-5.1,-1.5] | 4.11 | 12.78 | 10.90 | 4.19 | 6.10 | 12.74 |
| -1 | (-1.5,-0.25] | 2.43 | 12.12 | 10.17 | 5.02 | 5.67 | 12.27 |
| 0 | (-0.25,0.25] | 77.97 | 45.23 | 52.32 | 58.68 | 16.04 | 40.03 |
| $+\frac{1}{2}$ | (0.25,0.75] | 1.31 | 2.71 | 3.07 | 2.94 | 2.81 | 5.22 |
| +1 | (0.75,1.5] | 6.45 | 11.59 | 10.38 | 16.27 | 18.29 | 14.52 |
| +2 | (1.5,2.5] | 2.74 | 6.64 | 5.67 | 5.41 | 21.98 | 6.45 |
| +3 | (2.5,3.5] | 1.40 | 3.29 | 2.81 | 2.35 | 12.86 | 3.28 |
| +4 | (3.5,4.5] | 0.89 | 1.63 | 1.37 | 2.05 | 5.91 | 1.72 |
| +5 | (4.5,5.1] | 0.47 | 0.86 | 0.82 | 0.78 | 4.65 | 0.67 |
| | $\lvert\Delta P\rvert > 5.1$ | 2.23 | 3.14 | 2.50 | 2.29 | 5.69 | 3.11 |

We can also look at how incorporating additional price points affects our estimates of predicted price changes and pass-through in the ordered logit specification. We use the same quartic polynomial in $\Delta\tau$ as before, but now instead of restricting $\Delta p \in \{\leq -1, 0, 1, 2, \geq 3\}$, we allow for additional price points at $\Delta p \in \{+0.5\}$ in one specification and further adds $\Delta p \in \{-2, +4\}$ in another. We report the results for predicted price changes in Figure E6. We find that adding the additional price point at fifty cents has a negligible effect on our predicted price changes, and that adding the additional price points at $\{-2, +4\}$, leads to slightly lower predictions for small tax changes (because of the $-2$) and slightly higher predictions for large tax changes (because of the $+4$). The overall qualitative patterns are preserved. We prefer to consolidate the $+\$4, +\$5$ price changes with the +\$3 price change because outside of Illinois during the month of the tax change they are very rare and thus difficult to predict accurately.

## E. Additional Robustness Tests

Here we consider additional robustness tests.

We vary the elasticity of demand used to calculate counterfactual welfare: deadweight loss, producer surplus, consumer surplus, tax revenue, and incidence. We replicate Figure 7 but instead

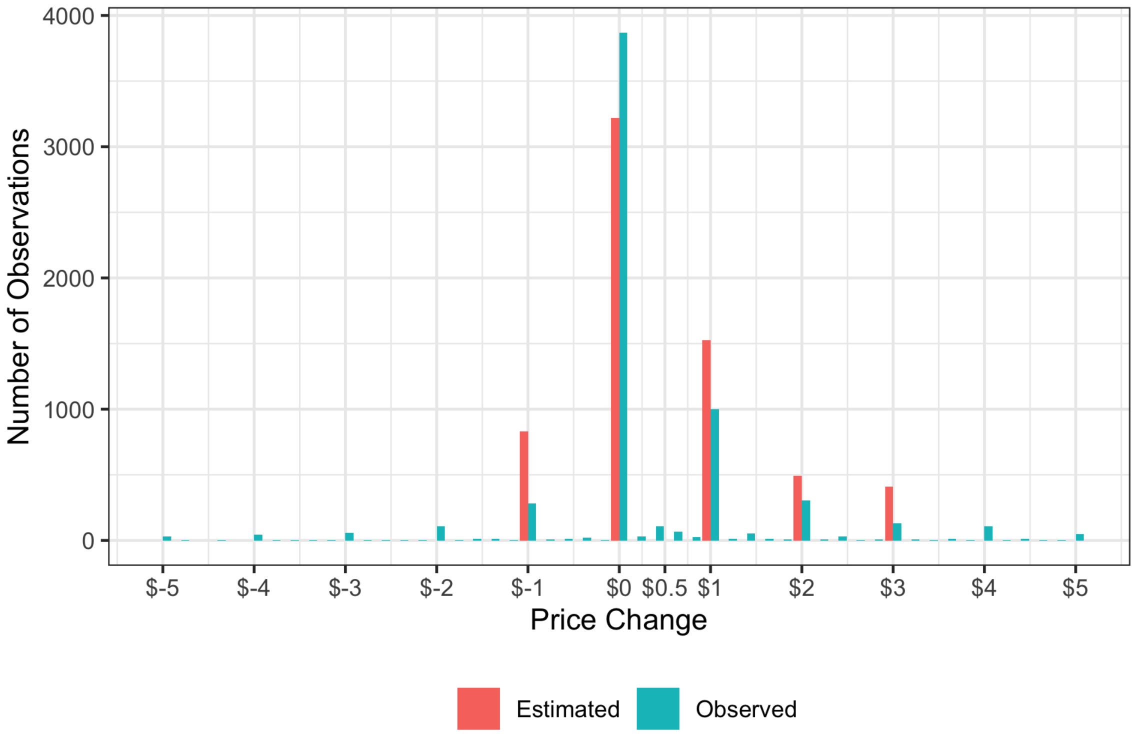


Figure D1: In-sample fit of Ordered Logit

Note: The figure above compares the predictions of our ordered logit model to the price changes observed in Connecticut during the month of the tax change. The predictions correspond to our preferred ordered logit model, which employs a quartic orthogonal polynomial of the tax change. The controls used in the ordered logit model measure the change in wholesale price since the last change in retail price, total sales by product overall stores, total sales by store over all products, the natural log of the price for the product the prior quarter at the samestore, whether that store sold the product at the highest or lowest price the prior quarter and the difference between the price last quarter and the median price across all stores last quarter. The regression also includes state-varying controls; specifically, it includes state fixed effects and interactions between state dummies and Total Product Sales, Total Store Sales, log Lag Price, High Price, Low Price and the Relative Price cubic polynomial. Weights are balanced by state, bottle size and tax change indicator.

use elasticities $\epsilon_d \in \{-2.5, -4.5\}$. These are meant to capture the range of product-level own price elasticities reported in the empirical literature. See Conlon and Rao (2015) or Miravete et al. (2018). We provide those results in Figures E2, E3. As we might expect, as we increase the elasticity of demand, consumers bear less of the burden and firms bear more. The social cost of taxation responds the opposite way in that as demand becomes more elastic, $\Delta DWL$ increases. For the less elastic demand, the linear pass-through estimate lies strictly above the price points/ordered logit estimates, and for more elastic demand it lies (partly) slightly below. In both cases the qualitative patterns remain similar. Both the efficiency and incidence calculations produce a series of U-shaped curves as we increase the size of the tax that qualitatively match our main result.

We also vary the markups used in the welfare calculations to estimate $MC_j$. In the main text we assume $\mu = 1.5$, here we also consider $\mu = 1.2$ and $\mu = 2.0$ in Figures E4 and E5 respectively. Increasing the markup increases $\Delta PS$ at all values of the tax increase, and increases the firm portion of $\Delta DWL$. Again, while the scale of the y-axis varies with the markup term, the qualitative predictions of our model remain the same.

The results are also insensitive to enlarging the set of potential price points. In Figure E6 we plot the change in price predicted by the baseline ordered logit model as well price change predictions from an ordered logit with one additional discrete price change of \$0.50 and an ordered logit with additional discrete changes of \$0.50, -\$2 and +\$4. The addition of the \$0.50 price change does little to change the predicted price changes. Adding larger price changes of -\$2 and +\$4 leads to larger predicted price changes for larger tax increases, particularly for tax increases above roughly \$0.55. While these larger price changes would shift the burden of bigger tax increases towards consumers and increase the social cost of taxes, they do not change the general shape of the predicted price change curve.

Finally, we assess the sensitivity of the results to the exclusion of the change in wholesale price polynomial. Figure E7 plots the change in price and pass-through rate predicted by two ordered logits with a quartic polynomial in the tax rate. One is the baseline model presented in the text and includes all of the control variables, $x_{jt}$; the second excludes all terms of the change in wholesale price cubic polynomial. The coefficients on the $\Delta w$ polynomial terms in the baseline model are large in magnitude and significant in the ordered logit model. Dropping the $\Delta w$ terms reduces the fit of the model as the $AIC$ changes by $5,942,783.71 - 5,912,234.04 = 30,549.67$.

However, when we exclude these terms and examine the key outputs of the ordered logit model in Figure E7 below, we find that there is little to no change in the relevant predictions. Once we average over all of the covariates $x_{jt}$, we find out that the average partial effects are relatively insensitive to the other included covariates. It is reassuring that the relationship between $\Delta p$ and $\Delta \tau$ appears to be robust and not dependent on other covariates (at least once we average over $x_{jt}$). Even the apparent difference in implied pass-through rates is small except for at very small tax changes when a denominator approaching zero magnifies even very small differences.

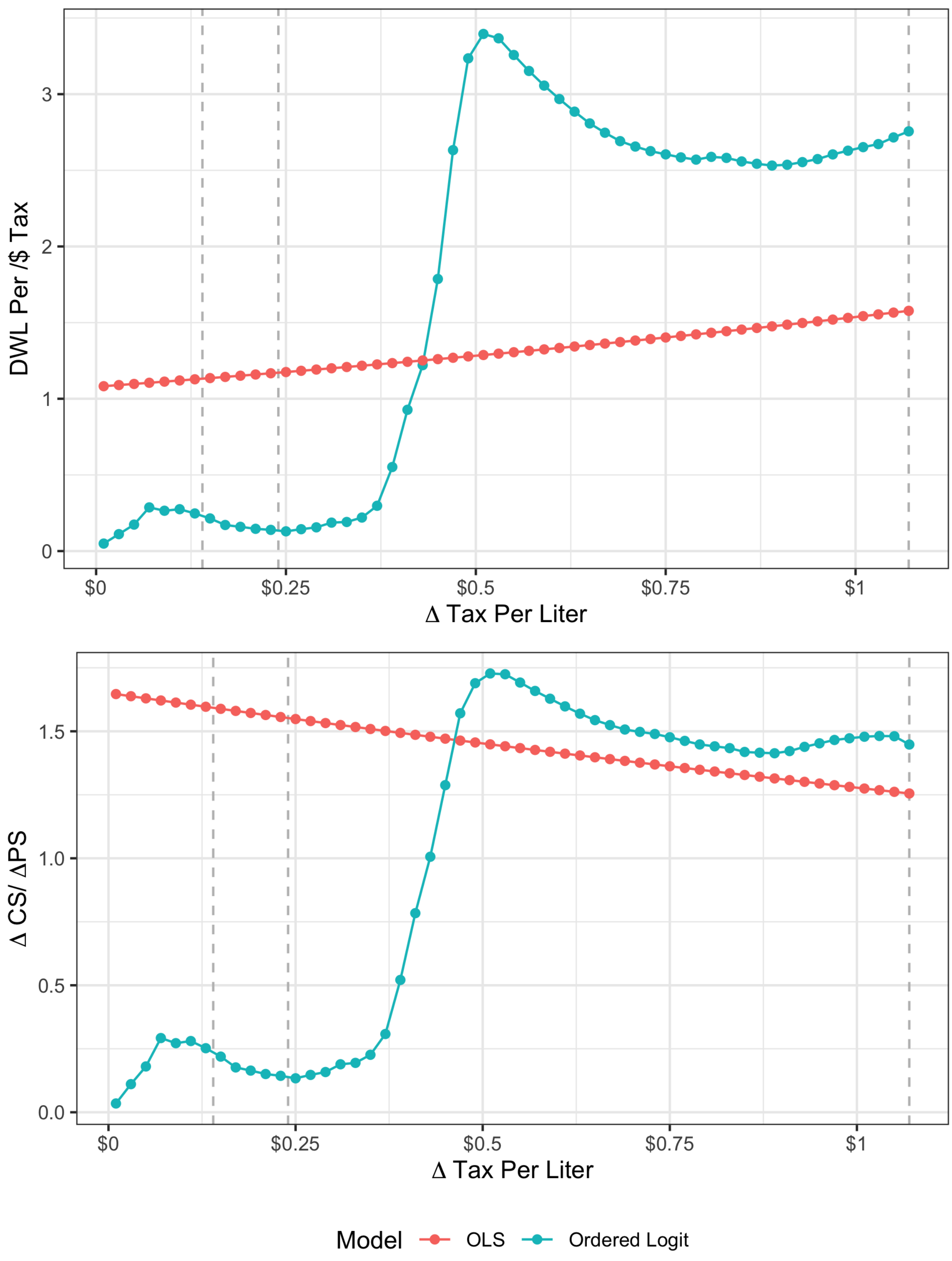


Figure E2: Welfare Predictions: Ordered Logit vs. OLS
Top Pane: Effieciency: DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Own Elasticity $\epsilon = -2.5$

Vertical Lines at Observed Tax Changes.

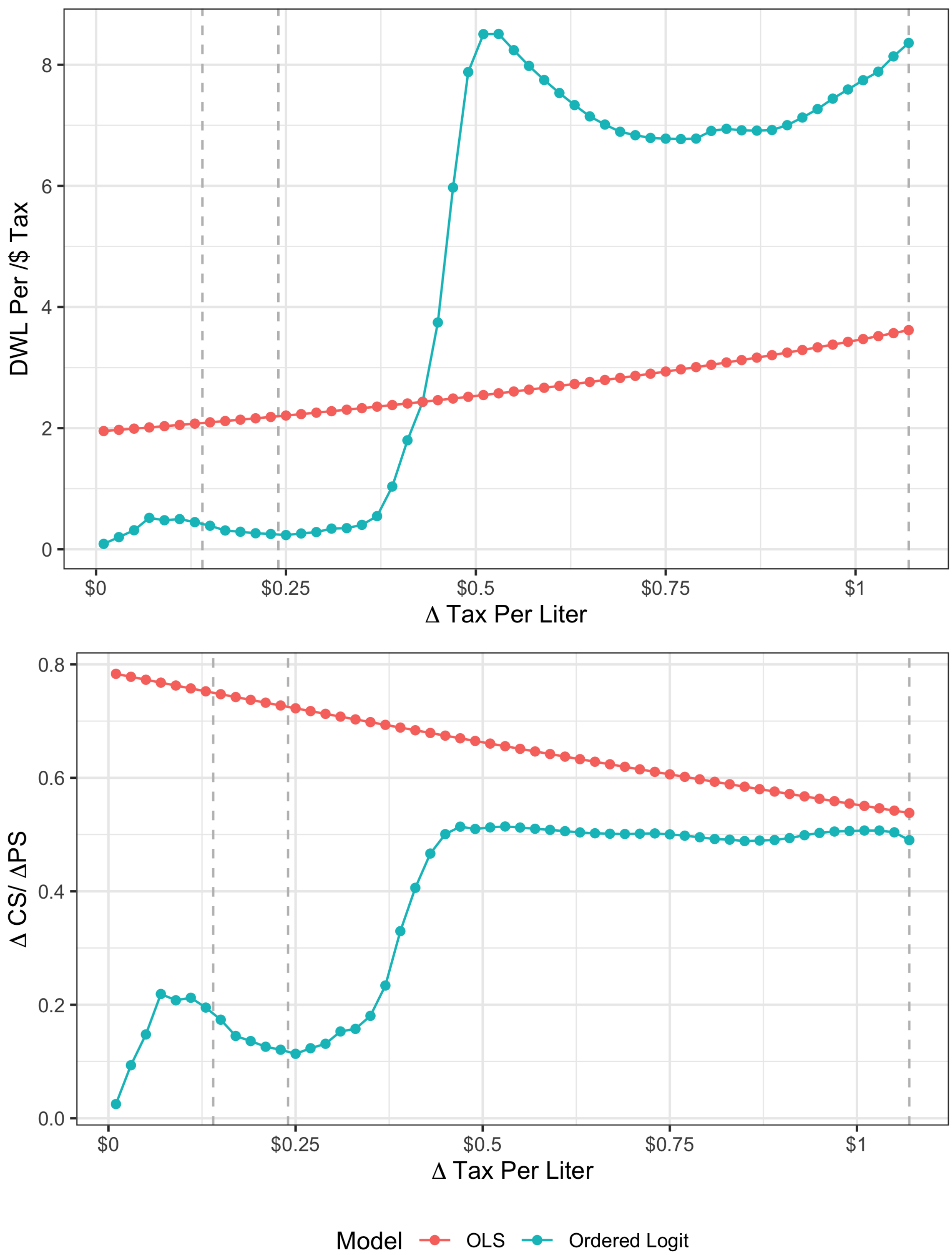


Figure E3: Welfare Predictions: Ordered Logit vs. OLS
Top Pane: Effieciency: DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Own Elasticity $\epsilon = -4.5$
Vertical Lines at Observed Tax Changes.

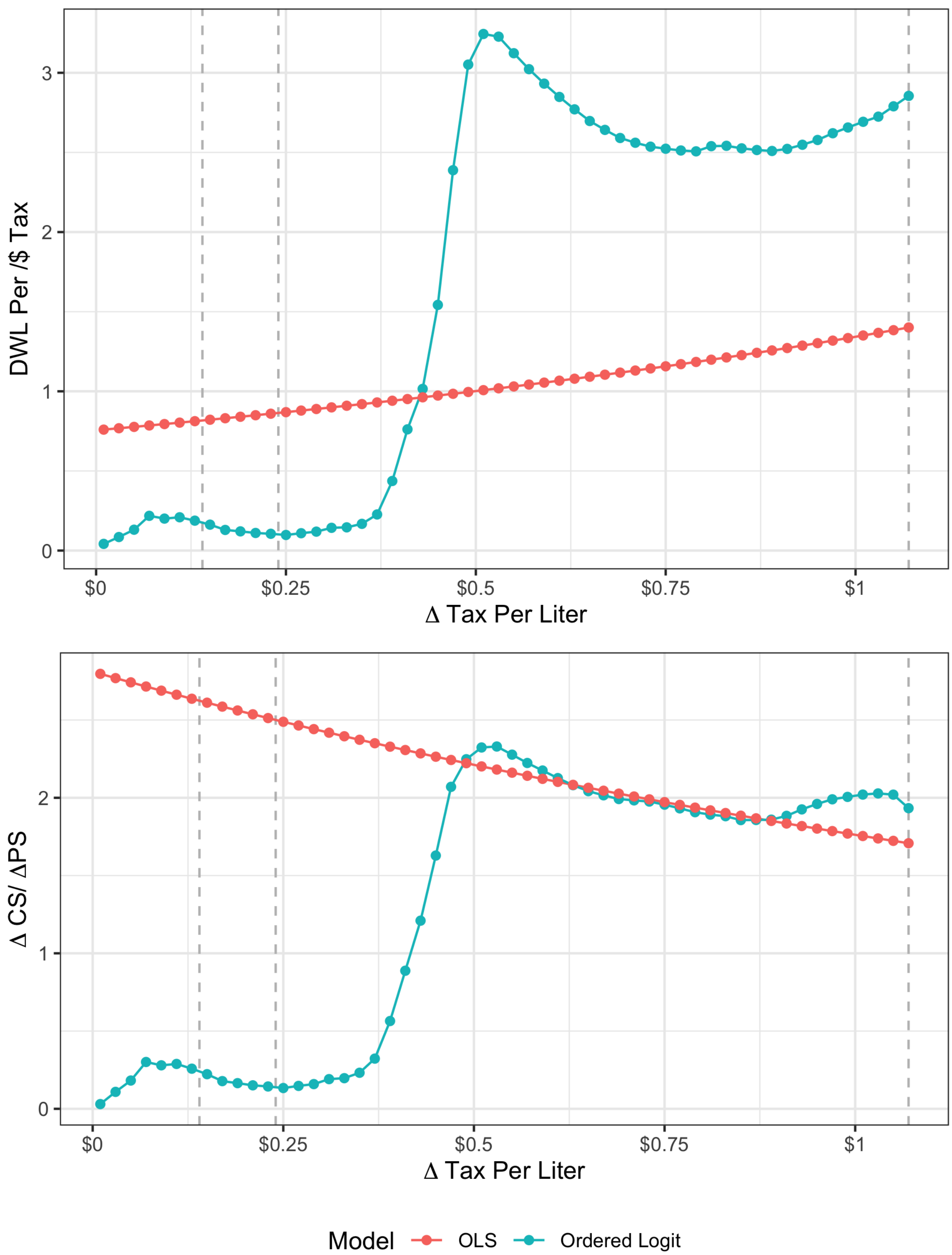


Figure E4: Alternative Markups $\mu = 1.2$: Ordered Logit vs. OLS
Top Pane: Effieciency: DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Own Elasticity $\epsilon = -3.5$

Vertical Lines at Observed Tax Changes.

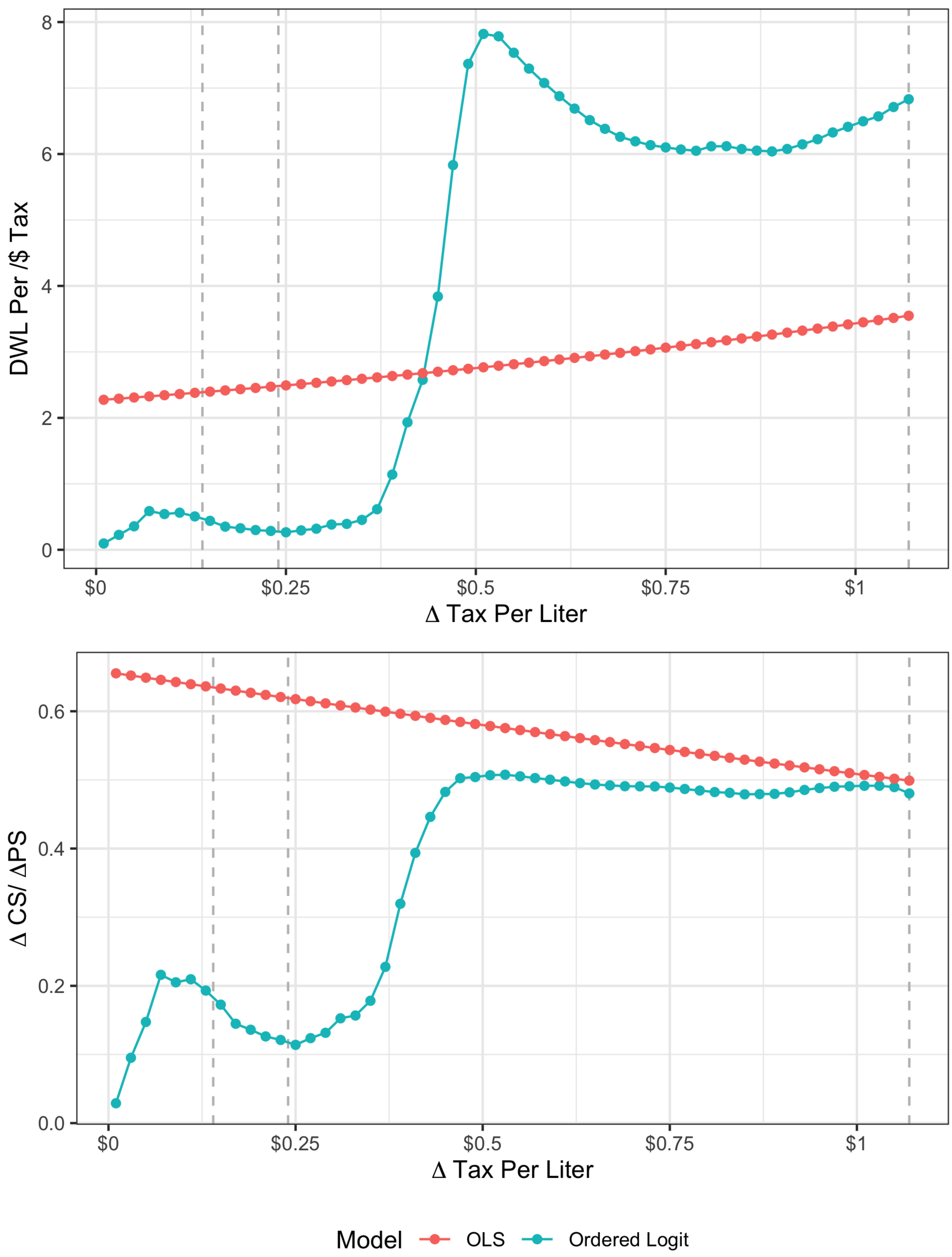


Figure E5: Alternative Markups $\mu = 2$: Ordered Logit vs. OLS
Top Pane: Effieciency: DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Own Elasticity $\epsilon = -3.5$
Vertical Lines at Observed Tax Changes.

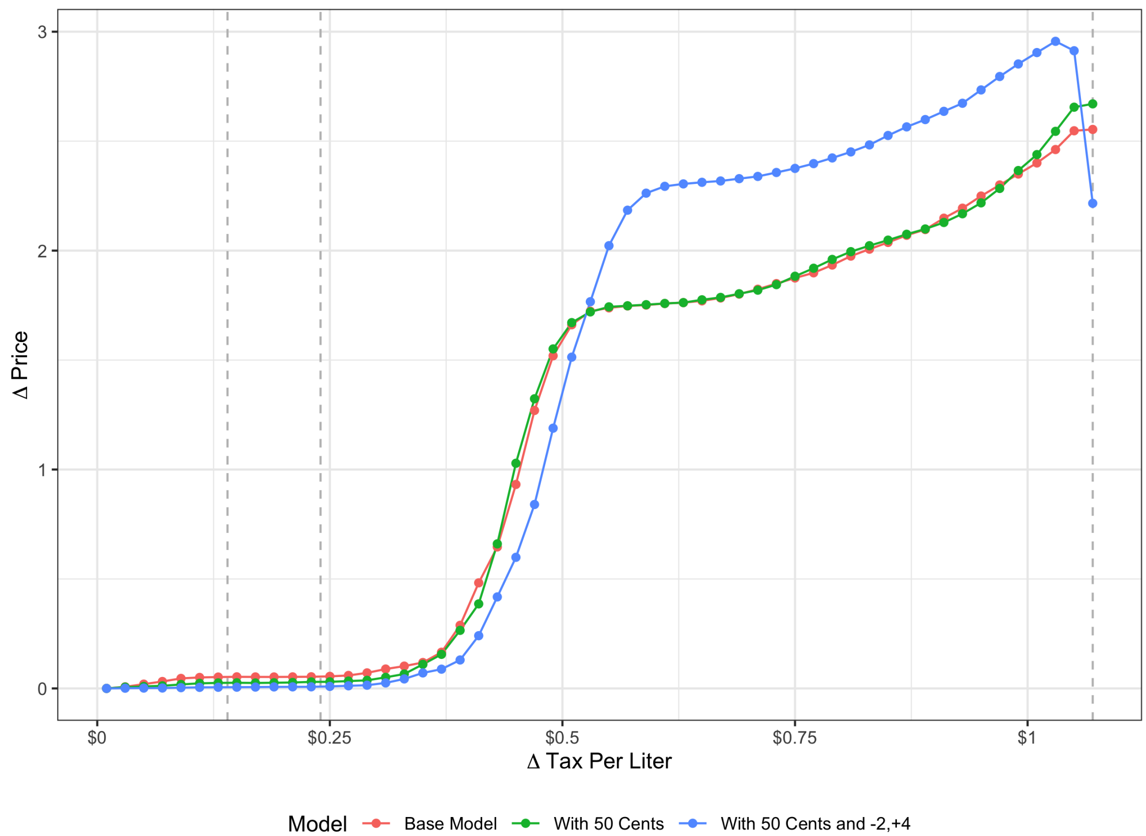


Figure E6: Robustness to Additional Price Points

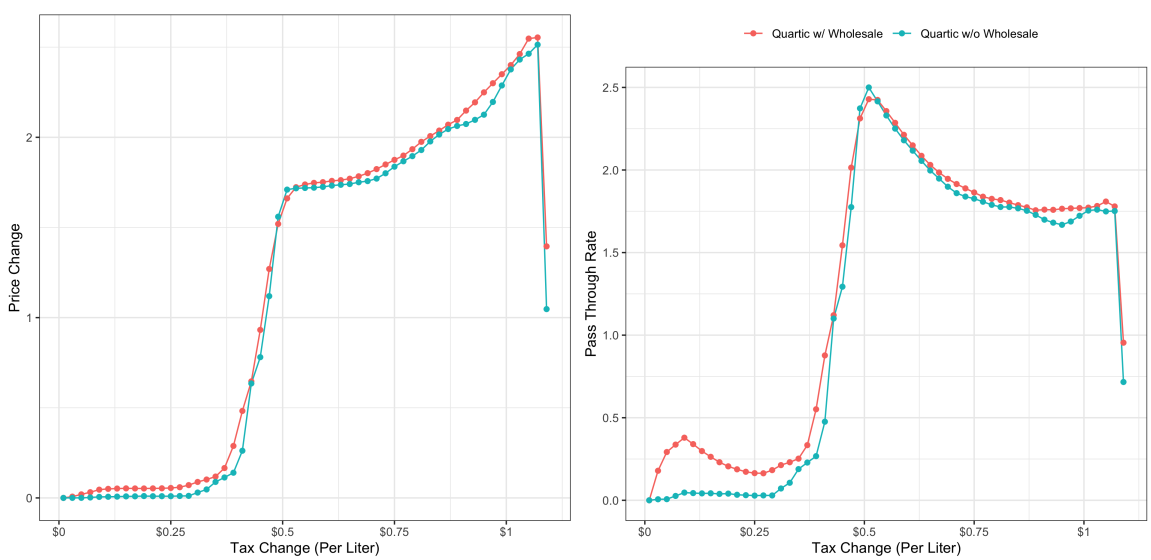


Figure E7: Robustness to Dropping Wholesale Price Terms

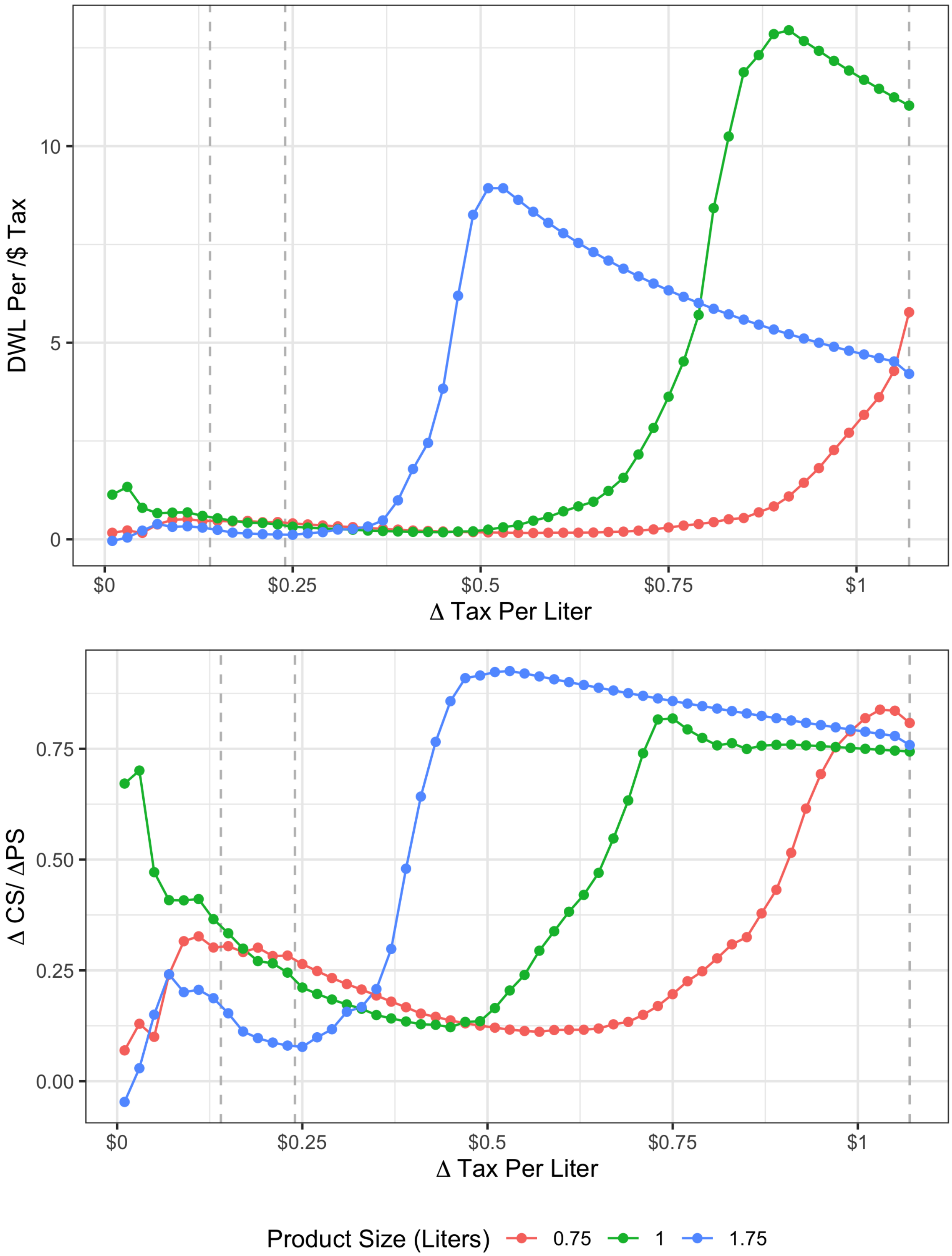


Figure E8: Counterfactual Welfare by Product Size
Top Pane: Efficiency - DWL per Dollar of Tax Revenue; Bottom Pane: Incidence $\Delta CS/\Delta PS$.
Own Elasticity $\epsilon = -3.5$
Vertical Lines at Observed Tax Changes.

## F. Pass-Through by Tax Per Bottle

In Figure 6 we report summary pass-through measures averaged over all products and reported in terms of tax per liter. Below we break-out implied pass-through rates by bottle size. In general pass-through rates for different tax increases are similar across bottle sizes. This is as we would expect since model predictions are nearly identical for $\Delta P$ as a function of $\Delta\tau$ by size. The discrepancy in predicted price changes comes from differences in other state variables such as relative prices and wholesale prices, which don't look tremendously different on average across package sizes.

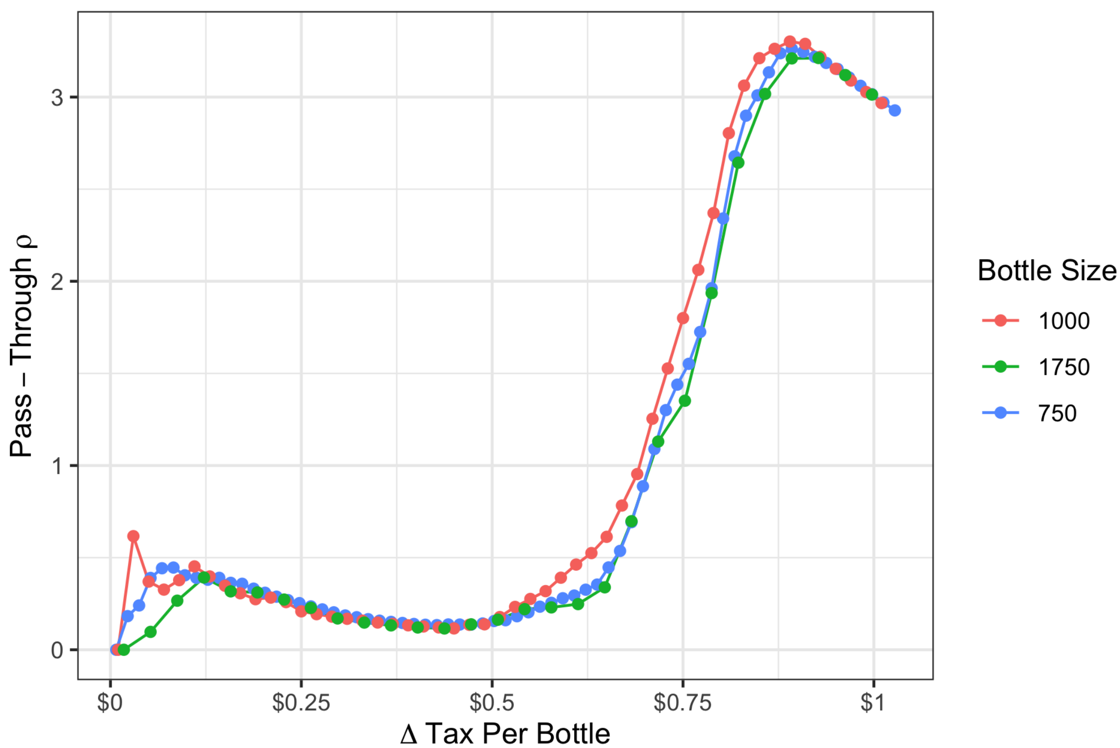


Figure F9: Counterfactual Welfare by Product Size
Implied Pass-Through Rate by Bottle Size
Vertical Lines at Observed Tax Changes.

## G. Unabbreviated Tables

Table 5 reports only the key coefficients of interest from the estimated ordered logit models. The table below reports coefficients for all variables included in the regressions:

Table G7: Ordered Logit Estimates $\Delta p \in \{-1, 0, +1, +2, +3\}$

| | Cubic | Quartic | Quintic | Spline(1) |
|---|---|---|---|---|
| Tax Change | 498.114* | 523.324* | 523.353* | 1.841* |
| | (28.189) | (28.034) | (27.995) | (0.535) |
| Tax Change$^2$ | -104.691* | -130.026* | -129.352* | -6.094 |
| | (27.446) | (28.134) | (28.172) | (3.227) |
| Tax Change$^3$ | -46.388* | -28.202 | -33.103 | 29.941* |
| | (16.433) | (17.116) | (18.926) | (8.990) |
| Tax Change$^4$ | | -39.447* | -32.614 | 3.220* |
| | | (13.420) | (17.393) | (0.238) |
| Tax Change$^5$ | | | -7.496 | |
| | | | (14.520) | |
| Wholesale price change = 0 | −0.444* | −0.435* | −0.437* | −0.434* |
| | (0.162) | (0.163) | (0.163) | (0.162) |
| Wholesale Price Change | 96.227* | 96.032* | 96.172* | 96.570* |
| | (18.534) | (17.940) | (17.899) | (17.904) |
| Wholesale Price Change$^2$ | −55.762* | −44.598 | −43.672 | −44.772 |
| | (20.628) | (20.013) | (20.176) | (20.019) |
| Wholesale Price Change$^3$ | −29.598 | −22.685 | −22.226 | −23.457 |
| | (18.614) | (18.300) | (18.533) | (18.348) |
| Total Product Sales | −0.022 | 0.042 | 0.045 | 0.043 |
| | (0.061) | (0.056) | (0.055) | (0.056) |
| Total Store Sales | 0.214* | 0.232* | 0.233* | 0.230* |
| | (0.041) | (0.040) | (0.039) | (0.040) |
| log Lag Price | −0.185 | −0.145 | −0.141 | −0.144 |
| | (0.106) | (0.114) | (0.116) | (0.115) |
| High Price | −0.224 | −0.242 | −0.249 | −0.277 |
| | (0.103) | (0.108) | (0.109) | (0.108) |
| Low Price | 0.426* | 0.406* | 0.404* | 0.454* |
| | (0.124) | (0.129) | (0.128) | (0.129) |
| Relative Price | −268.986* | −186.646* | −169.923* | −306.066* |
| | (7.735) | (7.843) | (7.903) | (8.010) |
| Relative Price$^2$ | 216.632* | 322.345* | 339.913* | 46.209 |
| | (30.202) | (30.587) | (30.451) | (30.859) |
| Relative Price$^3$ | 251.597* | 488.293* | 503.261* | 107.108* |
| | (4.622) | (4.802) | (5.056) | (4.628) |
| IL | 2.040* | 2.022* | 2.024* | 2.045* |
| | (0.594) | (0.606) | (0.609) | (0.607) |
| LA | 0.554 | 0.528 | 0.591 | 0.564 |
| | (0.430) | (0.439) | (0.462) | (0.439) |
| Total Prod Sales $\times IL$ | −0.212 | −0.268* | −0.271* | −0.268* |
| | (0.101) | (0.097) | (0.096) | (0.097) |
| Total Prod Sales $\times LA$ | 0.023 | −0.026 | −0.038 | −0.030 |
| | (0.084) | (0.079) | (0.079) | (0.079) |
| Total Store Sales $\times IL$ | −0.280* | −0.312* | −0.313* | −0.310* |
| | (0.088) | (0.085) | (0.085) | (0.085) |
| Total Store Sales $\times LA$ | −0.292* | −0.318* | −0.321* | −0.317* |
| | (0.055) | (0.053) | (0.053) | (0.053) |
| $\log(p_{j,t-1}) \times IL$ | −0.686* | −0.690* | −0.692* | −0.693* |
| | (0.210) | (0.215) | (0.216) | (0.215) |
| $\log(p_{j,t-1}) \times LA$ | −0.178 | −0.193 | −0.213 | −0.199 |
| | (0.153) | (0.158) | (0.164) | (0.158) |
| High Price $\times IL$ | 0.155 | 0.179 | 0.188 | 0.194 |
| | (0.167) | (0.170) | (0.171) | (0.170) |
| High Price $\times LA$ | −0.469* | −0.467* | −0.451* | −0.434* |
| | (0.143) | (0.147) | (0.149) | (0.147) |
| Low Price $\times IL$ | −0.356 | −0.364 | −0.363 | −0.393 |
| | (0.256) | (0.259) | (0.259) | (0.259) |
| Low Price $\times LA$ | −0.053 | −0.051 | −0.038 | −0.090 |
| | (0.167) | (0.171) | (0.169) | (0.171) |
| Relative $p \times IL$ | −395.320* | −510.813* | −529.305* | −365.164* |
| | (5.383) | (5.408) | (5.376) | (5.585) |
| Relative $p \times LA$ | −79.486* | −171.796* | −184.782* | −40.280* |
| | (3.449) | (3.558) | (3.613) | (3.518) |
| Relative $p^2 \times IL$ | −142.681* | −232.909* | −248.312* | 31.935 |
| | (16.919) | (16.961) | (16.829) | (17.279) |
| Relative $p^2 \times LA$ | −87.814* | −192.691* | −216.566* | 86.955* |
| | (11.160) | (11.491) | (11.542) | (11.351) |
| Relative $p^3 \times IL$ | −275.796* | −509.431* | −516.951* | −130.587* |
| | (4.036) | (4.063) | (4.127) | (4.095) |
| Relative $p^3 \times LA$ | −106.389* | −340.357* | −357.318* | 45.175* |
| | (1.630) | (1.826) | (1.993) | (1.577) |
| Observations | 2,371,792 | 2,371,792 | 2,371,792 | 2,371,792 |
| State-UPCs | 3,567 | 3,567 | 3,567 | 3,567 |