The Effect of the Sales Tax on Retail Prices and Employment: Evidence from Exemptions on Clothing

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Abstract

Using frequent state and local policy revisions of apparel tax exemptions in Connecticut, New York and Vermont, I study how the sales tax affects the retail market for apparel. First, I present new evidence on the effect of the sales tax on pre-tax prices, the pass-through rate. Unlike the previous literature on this topic, I employ detailed item-level data on prices, use large good-specific changes in the tax rate and explicitly control for policy endogeneity related to business cycles. Using triple-difference IV estimation, I find that the pass-through rate is generally small and negative. This implies that consumers fully bear the burden of the sales tax with some exceptions. The burden partially shifts onto suppliers for certain apparel groups—non-seasonal goods, girls apparel, and footwear—with arguably higher elasticities of demand. The almost full shifting onto consumers is surprising given the well-documented fact that the demand for apparel at local stores is quite elastic. The lack of response suggests even more elastic supply and also that equilibrium output and, hence, inputs should decrease in response to a tax increase. I use the Quarterly Census of Employment and Wages along with apparel exemptions and estimate that county employment in the retail apparel sector decreases by 0.40% following a one percentage point increase in the sales tax. This effect indicates that a 4% sales tax exemption in New York State leads to about 2,150 new jobs, which is approximately the average county employment in this sector. To my knowledge, this is the first evidence of a strong connection between sales tax and employment. Finally, using the Consumer Expenditure Survey data, I find that a 5% sales tax rate generates a 17¢ average deadweight loss for every tax dollar collected.

Keywords: Sales Tax, Tax Incidence, Labor Expenditures.

1 Introduction

Good-specific exemptions are a common part of sales tax policy. Optimal tax theory suggests that the higher the potential distortions from taxing a good, the lower the tax rate levied on it ought to be. Two particular distortions draw the attention of policymakers: higher prices for consumers and lower number of jobs. Few economic papers precisely estimate the good-specific ad valorem tax effect on prices (Carbonnier, 2007; Doyle and Samphantharak, 2008), and none on employment. In this paper, I fill in this gap in the literature for apparel, a good on which consumers spend around 3% of their incomes, by estimating the effect of the apparel sales tax rate on incidence and employment and computing deadweight loss.

Estimating the effect of a good-specific sales tax using general rate changes is challenging because of two intrinsic features. First, the changes are small. The response of market participants to such subtle tax changes is even smaller, making it difficult to obtain precise estimates. This argument gains even more relevance given the lack of sales tax salience for consumers, who observe the tax at the register rather than in listed price (Chetty et al., 2009) and the costs of price adjustments for retailers.1 Second, changes in the general sales tax rate typically alter the relative prices for a broad set of goods and even real disposable household income at the same time, which may bias estimates of its effects due to general equilibrium effects. Using recent revisions of the sales tax exemptions solely on apparel implemented by state and local governments in Connecticut, New York and Vermont, I overcome both of these issues. A tax exemption makes items priced below a certain threshold tax-free, the most common threshold being $110. Thus, any exemption revision generates a sizable and, thus, salient tax change equal to a state or local sales tax rate, at least for some items. In my data, the maximum changes in the sales tax rate equal 6.5% in Connecticut, 7% in Vermont.

Lack of salience is unlikely to contaminate my estimation, which is based on large changes in permanent tax rate — tax exemptions. Recall that Chetty et al. (2009) provide three criteria for the salience of a tax: (i) high tax rates, (ii) large elasticity of demand and (iii) high prices for a given item. Indeed, relative to grocery items, apparel purchases readily meet the last two criteria. In case of the tax rate, the comparison is also in favor of apparel: though the tax rates are similar in magnitude, the changes in apparel industry are large and occur at higher frequency.
and 8.625% in New York. The alterations to exemptions affect only the apparel market, rendering general equilibrium effects negligible. In addition, the exemption changes happen quite frequently.

The fundamental identification problem with estimating the effect of sales tax on prices or employment is spurious correlation between a state’s economic conditions and its tax policy changes. Negative shocks to a state economy may simultaneously lower the outcome variable and increase the budget deficit which, in turn, forces legislators to impose higher tax rates. I solve this problem differently for prices and employment.

In the first case, I take advantage of the fact that legislators exempt items priced below a certain threshold but not above. This allows me to use the items priced above it as a control group for price trends in the state.\footnote{This is in addition to the other control group, which is prices in the other states} My results are robust to different threshold levels that are instituted in different states, and I argue later on that the non-exempt items offer a useful control group. I also show that pricing around the threshold is not responsive to changes in the threshold value, and I use an IV strategy to deal with the spurious correlation between prices and tax rates.

When estimating the effect of the sales tax on employment, I do not have an in-state control group as I do in the case of sales tax incidence estimation. To argue that spurious correlation between the sales tax and employment does not drive my results, I perform a robustness check where I use employment in retail stores selling goods for entertainment instead of clothing and do not find a negative effect of the sales tax changes.

To this solid foundation for identification of sales tax effects, I add very detailed, item-level, confidential data from the Consumer Price Index on apparel prices. This use of price data yields the first key result of my paper — the estimate of apparel-specific sales tax effect on pre-tax prices, i.e. the \textit{pass-through rate}.\footnote{Under the assumption of perfect competition, this pass-through rate coincides with tax incidence on producers} Using a triple difference IV empirical strategy, I find that the pass-through rate is tightly estimated to be close to zero for most types of
apparel, implying that consumers fully bear the burden of the tax. This estimate is similar to the estimates for other goods (DeCicca et al., 2013; Harding et al., 2012; Kenkel, 2005), but different from previous estimates for the apparel industry (Besley and Rosen, 1998). For some apparel items, the pass-through rate is small but not zero, suggesting more elastic demand. Specifically, retailers pay 21% of the sales tax on non-seasonal goods, whereas they pay 38% on girls apparel and 24% on footwear.

The zero pass-through rate is common for many other goods but surprising for apparel, with its well-documented high elasticity of demand (Einav et al., 2014; Hu and Tang, 2014). It suggests an even more elastic supply and, hence, a substantial decrease in quantity produced. This makes it interesting to explore how the sales tax rate affects the equilibrium usage of inputs. After merging the sales tax exemptions with data from the Quarterly Census of Employment and Wages, I find that a one percentage point increase in the sales tax rate implies a 0.4% decrease in the number of employees hired by local apparel retailers and a 0.6% decrease in expenditures on employees, suggesting that wages do not decline much. I do not find any effect on the number of stores, which represents a type of capital. In contrast, the previous literature explores the effects of a general sales tax rate on total locality employment (Thompson and Rohlin, 2013) and does not find a robust link between the two.

This result helps explain the usual practice of state enterprise zones that include lower sales tax rates as a business incentive. It also suggests that the transition between different tax rate regimes may be costly. Indeed, a New York state 4% sales tax exemption on clothing results in more than 2,150 new jobs, which is close to the average county employment in the apparel retail sector. Given that the average unemployment duration is 27 months in the sales industry according to the Census, the constant changes of exemptions in this state may lead to substantial costs.

The large effect of sales tax on the apparel retail employment implies that a sales tax substantially reduces the equilibrium quantity of sales in the market and, hence, social

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4 Throughout my paper, I assume perfect competition because none of my results contradicts it. (Sen, 2008) shows evidence that apparel industry indeed is pretty competitive.
welfare. I use the Consumer Expenditure Survey to arrive at my third key result, about
deadweight loss. Data on apparel purchases has two limitations: it does not provide detailed
geographical information about the consumer or information on whether a certain transaction
occurs online or offline. I employ the estimates from Einav et al. (2014) as a proxy for changes
in the Internet purchases. Using Goulder and Williams (2003), I find that a 5% sales tax
rate generates a 17¢ loss for every tax dollar collected.

The rest of the paper proceeds as follows. In Section 2, I provide a detailed literature
review on the empirical research relevant to my question. Section 3 gives an overview of
tax incidence theory. I also use this section to formulate empirical hypotheses I will later
test. In Section 4, I thoroughly describe the data. Section 5 contains the explanation of my
empirical strategy. In Section 6, I present my main results, followed by robustness checks of
my pass-through estimation in Section 7. In Section 8, I calculate deadweight loss.

2 Evidence on the Effects of Good-Specific Taxation

This section explains how my paper adds to the empirical literature on the effects of good-
specific taxation on prices and employment. I start by describing the literature on the effect
of taxes on consumer prices, i.e. tax incidence, which has a one-to-one correspondence with
the effect of taxes on retail prices, i.e. the pass-through rate. Throughout my discussion, I
stick to the terms pass-through rate on retailers vs. tax incidence on consumers because it (i)
clearly denotes whether I refer to consumer or producer prices and (ii) is correct regardless of
the assumption about competition. Then, I provide an overview of the few research papers
that explore the effect of the sales tax on employment, which I augment with a discussion
on the apparel expenditure literature.5

A few empirical papers study tax incidence on prices. I classify them into three cate-
gories. The papers from the first category specialize in precisely estimating the tax incidence

5I do not review the papers that study the effect of taxes on sales and purchased quantity of non-apparel
markets because this literature is not directly related to my paper. Its recent focus is on tax avoidance issues
(Beatty et al., 2009; Merriman, 2010)
parameter for a given market. They usually find that consumers fully pay the tax, which is
the case in the gasoline market with a sales tax (Doyle and Samphantharak, 2008), in the
clothing market with a sales tax (Poterba, 1996), and the alcohol market with an excise tax
(Kenkel, 2005). There are two noticeable exceptions to this rule. First, retailers pay half of
the VAT on haircuts in Finland (Kosonen, 2015). Second, Besley and Rosen (1998) shows
that the sales tax overshifts on consumers for some grocery items and the type of apparel
they consider (underwear). I extend the analysis of Poterba (1996) and Besley and Rosen
(1998) by using more granular data and a cleaner identification strategy. Particularly, I am
the first in public economics field to use the CPI confidential micro data.\footnote{The
most prominent examples of using this data in other fields are Cortes (2008) and Matsa
(2011)}

My estimates also add to the recently emerging literature which studies the effect of
the sales tax on total expenditures (Agarwal et al., 2013), online expenditures (Einav et al.,
2014) and catalog expenditures (Hu and Tang, 2014) in the apparel market. I consider prices
at traditional retailers, so the first paper is the most relevant to my research. The authors
find that consumers are very responsive to taxes: a 1% change in the sales tax rate leads
to a 2-6% drop in total expenditures.\footnote{The authors use sales tax holidays on apparel as a
source of variation in the tax rate. When estimating deadweight loss below, I find my estimate
to be similar to the lower bound of their result, which is not surprising given that I employ
permanent tax rate changes in my analysis} My finding of zero pass-through on pre-tax prices
suggests that one can easily convert their estimates into the demand elasticity.

Moreover, their result adds to my argument that a lack of salience is not a concern for
my estimation. In their seminal paper, Chetty et al. (2009) provide three criteria for the
salience of a tax: (i) high tax rates, (ii) large elasticity of demand and (iii) high prices for
a given item. Indeed, relative to grocery items, apparel purchases readily meet the last two
criteria. For the first criteria, the comparison is also in favor of apparel: though the tax
rates are similar in magnitude, the tax rate changes in the apparel industry are large and
occur at higher frequency.

The papers on tax incidence in the two other categories, which I define respectively as
demand and supply papers, go one step further and explore which characteristics of the
two sides of the market affect the tax incidence parameter. The demand papers explore the differences between consumers. Harding et al. (2012) presents evidence that consumer geographical location matters: smokers who live closer to the state border face substantially lower pass-through of an excise tax on cigarettes compared to those in the state interior. In addition, DeCicca et al. (2013) argues that search costs explain the varying tax incidence across consumers; the authors find that heavier smokers, who have higher benefits from investing time in looking for lower prices, experience lower tax incidence. I contribute to the demand papers literature by estimating sales tax incidence for various apparel groups. First, I find that the sales tax only partially shifts onto consumers who purchase girls clothing and footwear, the demand for which is arguably more elastic. Second, I am the first to consider whether the sales tax pass-through differs across seasonal and non-seasonal goods. Traditional tax incidence literature generally ignores seasonality of goods despite their surprising price behavior during peak demand (Chevalier et al., 2003).

The supply papers consider how industry characteristics affect tax pass-through rate through the elasticity of supply. Marion and Muehlegger (2011) considers the diesel fuel industry, where the elasticity of supply decreases as the refineries and inventories approach full capacity. They use variation across states in this measure for their research. Carbonnier (2007) compares the elasticity of supply between two industries: cars vs. service. The latter industry is substantially more concentrated and, thus, its supply should be less elastic. Consistent with theory, both papers find that the more inelastic is supply, the higher is the pass-through rate on producers. My paper is closer to these two supply papers. Theoretically, my pass-through result is only consistent with very elastic supply, which I show indirectly. Both academic papers (Şen, 2008) and case studies provide evidence that it is indeed the case. Interestingly, despite the inelastic supply of hybrid vehicles in the US, Sallee (2011) finds full shifting of the tax on consumers. The other empirical finding in the supply

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9In this case, a tax credit is a subsidy. The discrepancy of Marion and Muehlegger (2011) and Sallee (2011) together with recent evidence of consumer’s differential response to small tax and subsidy (Homonoff,
literature is that the pass-through rate depends on the stage where the state collects tax (Kopczuk et al., 2013).

Elastic supply implies that firms easily adjust their output and, hence, inputs. Confirming this mechanism, I find that apparel sales taxes decrease employment in the retail industry. To the best of my knowledge, this is the first paper that establishes a link between labor employed to produce a good and a tax rate on the good. It adds to a thin literature that explores the effect of the general sales tax rate on employment. While Fox (1986) and Harden and Hoyt (2003) do not find evidence for it, Thompson and Rohlin (2013) and Rohlin et al. (2014) show that the effect is present for border counties under certain conditions.

3 Theoretical Background

In this section, I briefly describe the theory behind my two main empirical questions: the effect of the sales tax on prices and employment. For the price effect, I show how demand and supply elasticities affect a pass-through rate of the sales tax on producer prices under the assumption of perfect competition. Through the section, I also discuss what changes if I relax this assumption.\textsuperscript{10} For the employment effect, I present graphical evidence that firm expenditure across all inputs should increase in the event of a sales tax rate drop.

Under the assumption of perfect competition, the pass-through rate on producers is:

$$\rho = -\frac{\epsilon_D}{\epsilon_S + \epsilon_D},$$

(1)

where $\epsilon_D \geq 0$ is the absolute value of demand elasticity and $\epsilon_S \geq 0$ — supply elasticity. The constraints on the elasticities transmit into the constraints on the pass-through rate itself: $\rho \in [-1, 0]$. As I show in Appendix A, under the assumption of imperfect competition, the pass-through rate can take any value. At this moment, I am ready to state that:

\textsuperscript{2013} suggests that one should be cautious of using them interchangeably. This is the main reason I do not describe economic literature on subsidy incidence in this review.

\textsuperscript{10} See Appendix A for the derivation of the pass-through rate on consumers and producers under the assumption of imperfect competition.
**Proposition 1.** Producer prices can either increase or decrease in response to a rise in the sales tax. Under the assumption of perfect competition, the pass-through equals the tax incidence and belongs to the interval [-1,0].

In my empirical analysis, the pass-through of a sales tax on producer prices always belongs to the interval [-1,0]. Thus, I stick to the assumption of perfect competition. Under this assumption, the concept of a pass-through rate of sales tax on either consumers or producers is synonymous to the tax incidence. Weyl and Fabinger (2013) shows that under imperfect competition, they are synonyms only for consumers. For producers, the magnitude of the pass-through rate is a lower bound on the tax incidence magnitude. This is true for deadweight loss as well. Thus, I consider my estimates of the pass-through rate and deadweight loss as conservative.

In my empirical analysis, I estimate tax incidence for different groups of apparel separately because the elasticities of demand and supply are likely to vary across these groups. So, I establish the comparative statics of the pass-through rate on producer prices with respect to the demand and supply elasticities. Formula (1) suggests that:

**Proposition 2.** The pass-through of sales tax on producer prices increases in the elasticity of demand and decreases in the elasticity of supply.

In addition to changing the prices, the sales tax may also decrease the equilibrium quantity. This forces firms to employ fewer inputs. The magnitude of this decrease depends on the demand and supply elasticities. In Figure 1 I show that the output responses increase in the elasticity of demand: \( Q_i - Q_{\tau} < Q_e - Q_{\tau} \). In Figure 2, I depict the corresponding input responses in the elasticity of demand: \( L(Q_i) - L(Q_{\tau}) < L(Q_e) - L(Q_{\tau}) \). The same result is true for the supply elasticity, which allows me to state:

**Proposition 3.** The imposition of a sales tax may lead to a decrease in the equilibrium output, and, hence, inputs employed by suppliers. The higher the elasticities of demand and supply, the larger the decrease.

Note that the deadweight loss of a sales tax also increases with respect to both elasticities.
Figure 1: Comparison of deadweight losses when pass-through rate is zero

Notes: Deadweight loss generated by a sales tax is substantially larger when demand is elastic (blue line) rather than inelastic (green line). In the former case, the deadweight loss is all the shaded area, whereas in the latter — the green shaded area.

Thus, a large effect on the inputs used by firms signals substantial losses due to the tax.
Figure 2: Comparison of changes in employment when pass-through rate is zero

Notes: Decrease in derived demand for employment generated by a sales tax is substantially larger when demand is elastic (blue line) rather than inelastic (green line). In the former case, the change equals $L(Q_e) - L(Q_\tau)$, whereas in the latter — $L(Q_i) - L(Q_\tau)$.

4 Data

The tax data effectively dictates the geographical and time coverage of my sample. All substantial changes in the legislation start in 2000 and occur in Connecticut, New York and Vermont, my treatment states; the other states in the Northeast Census Region and, in case of pass-through rate estimation, states in the Midwest Census region serve as a broad control group. So, my sample comprises these states from the years 1997 (three years before any tax exemption policy changes) through 2012 (the last available year in the rest of the data sets). For all Northeast states, I construct data on local and state tax exemptions and tax rates.

For my analysis, I merge the tax data set with three external data sets:

1. confidential price information from the rich Consumer Price Index (CPI) micro data set, made available by the Bureau of Labor Statistics (BLS), to estimate the pass-through rate

11The changes in the general tax rate in Midwest States are small to affect my estimates. I do not refer to them as to treatment states.
2. the Quarterly Census of Employment and Wages, to estimate the effect of the sales tax rate on local employment

3. the Consumer Expenditure Survey, to estimate the demand elasticity in order to calculate deadweight loss

Below, I detail the construction and/or collection of these data for the sales tax and then for the first two data sets. The description of the third data set is in Appendix B.

### 4.1 Sales Tax Rate

In this subsection, I describe in detail how the sales tax rate varies for different price categories in the treatment states and compare it with the variation in the control states. For the Northeast, I collect the data on state and local sales tax exemptions and the general sales tax rate from previous and current versions of state government websites. I find that the only discrepancy between my data and the CPI data occurs due to alternations in the exemptions. Given that there are no apparel-specific exemptions in the Midwest, I use the tax rates from Consumer Price Index micro data for this region.

A sales tax exemption makes items for a certain price-category tax-free. In the past two decades, four states have changed their sales tax exemption rules on apparel, defined as clothing plus footwear: Connecticut (twice), New York (six times), Rhode Island (once) and Vermont (twice). I, however, ignore the exemption in Rhode Island because it affects only a small share of apparel items that cost more than $250.\(^\text{12}\) The other exemptions generate tax rate decreases or increases ranging from 5 to 9 percentage points, and, thus, can substantially influence the behavior of market participants. Note that a given tax exemption affects only a certain, treated, group of items in a treatment state, allowing all the other items in the state to serve as a control. In this subsection, I describe in detail how the sales tax rate vary

\(^{12}\)Also, the revision in the Rhode Island exemption happens at the very end of my sample: in October of 2012. Such items generally include night dresses, fancy suits, etc.
for different price categories in the treatment states and compare it with the variation in the control states.

In Columns (1-2) of Table 1, I provide New York cumulative tax rates (that is, in both the state and in particular counties and municipalities) for items priced below and above $110, the most common threshold value in this state, and in Figure 3 I demonstrate the path of New York state and New York City sales taxes and exemptions. The three drops of the rate for cheaper items are due to three introductions (2000, 2006, 2012) and two repeals (2003, 2010) of state tax exemptions. The phase-in of the last introduction occurred in two steps: in April 2011, the threshold rose from $0 to $55 and then doubled in April 2012. When the exemption is in place, the tax rate is not necessarily zero because New York state legislation allows its cities (but not towns or villages) and counties to establish as well as exempt their own sales tax rates. The magnitude of the local and state taxes are around 4% each. In addition, there is a small Metropolitan Commuter Transportation Mobility tax (0.375%) levied by eight counties.\textsuperscript{13} 22 of the 62 counties and 6 of the 61 cities in the state of New York have tried exemptions at least once. New York City is a leader in this policy: its exemptions are more generous even than the state’s (see Figure 3). The items priced above the exemption threshold face a general sales tax rate, which slightly rises throughout my sample. Its behavior and magnitude is very similar to that in Midwest states, which also generally allow their localities to administer sales tax rates.

In Connecticut (Columns 3-5 of Table 1) and Vermont (Columns 6-7), legislators have changed the exemption policy twice. Starting from the $75 threshold in 1997, the Connecticut legislators first decreased the threshold to $50 in 2003 and then completely repealed the exemption in 2011. Alternatively, Vermont started exempting apparel items priced above $110 in 2001, followed by an extension for all items in 2007. Connecticut does not allow localities to administer a sales tax — and in Vermont only four municipalities charge a 1% additional to state tax before 2007, when the new exemption rules eliminates any tax on

\textsuperscript{13}I use all state and local changes in the tax rate for my estimation
Table 1: Population Weighted Average Cumulative Sales Tax Rates in Northeast and Midwest States for Apparel by Price Categories

<table>
<thead>
<tr>
<th>Average Sales Tax Rates in</th>
<th>Treatment States</th>
<th>Control States</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NY</td>
<td>CT</td>
</tr>
<tr>
<td>Year</td>
<td>≤ $110</td>
<td>$110 &gt; $110</td>
</tr>
<tr>
<td>1998</td>
<td>7.91</td>
<td>7.91</td>
</tr>
<tr>
<td>2001</td>
<td>1.74</td>
<td>7.93</td>
</tr>
<tr>
<td>2004</td>
<td>8.40</td>
<td>8.40</td>
</tr>
<tr>
<td>2007</td>
<td>2.34</td>
<td>8.27</td>
</tr>
<tr>
<td>2010</td>
<td>6.60</td>
<td>8.47</td>
</tr>
<tr>
<td>2012</td>
<td>2.44</td>
<td>8.47</td>
</tr>
</tbody>
</table>

The Northeast control states (MN, MA, NH, NJ, PA, RI) have constant rates

Notes: The data on the state and local tax rates is from state government websites, whereas the population numbers for states and municipalities are from 2010 Census. I use December tax rates for each year in the table. For treatment states and Illinois, I compute the average of cumulative tax rates weighted by population of municipalities. For the “Other Midwest” states, I use state and average municipal tax rate weighted by state population. “Other Midwest” states are Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, West Virginia, Wisconsin.

clothing.

The tax rates in the control states stay almost constant throughout my sample. New Hampshire does not impose any sales tax, whereas Pennsylvania and New Jersey fully exempt clothing from taxation. Maine’s cumulative/state tax rate is equal to 5%. In Massachusetts, a 2008 state sales tax increase from 5% to 6.25% affects only a small share of items priced above $175. The same argument applies to Rhode Island’s exemption repealed in October 2012 that makes items priced above $250 taxable. In Illinois (Column 7), there is a tiny increase in the sales tax rate from 7.5% to 7.6% in the last two decades, whereas the rest of the Midwest states experience an almost a 9% increase from 5.32% to 5.77%.
Figure 3: Cumulative Sales Tax Rate in New York City

Notes: Green line represents the tax rate for items priced above $110, whereas black — below $100. “city” or “state” denotes city or state tax exemption change.

4.2 CPI Micro Data

For estimating the pass-through rate on pre-tax prices, I use the confidential Consumer Price Index (CPI) micro data, to which the Bureau of Labor and Statistics has graciously granted me access. This nationally and regionally representative data is a panel with around 36,000 apparel price observations every year. After randomly selecting a specific item at a specific store for the sample, the surveyors follow it until the item becomes permanently unavailable at the store. They also collect detailed information on item characteristics, such as seasonality, apparel category and local tax rate. Previous research in public economics has not used these data. The most prominent examples of its usage in other fields of economics are papers by Cortes (2008) and Matsa (2011)

Below, I explain how I use the CPI data for my analysis. First, I flesh out the specifics of the CPI data collection process that affects my choice of variables and empirical strategy. Second, I provide general summary statistics for my price regressions. I describe how the

14Bureau of Labor and Statistics Chapter 17 provides a detailed description of the whole CPI collection process
BLS categorizes missing observations and provide summary statistics for each category in Appendix C.

4.2.1 BLS Data Collection Process

The CPI microdata is designed to compute price indexes and inflation rates. Ideally, it is a balanced panel, which consists of \( n \) quotes, or units of observations. Any quote \( q^i \) is a vector of prices on a good \( i \in 1, ..., n \) from month \( t = 1 \) to month \( t = T \): \( q^i = (p^i_1, p^i_2, ..., p^i_T) \).

For instance, a good could be a red, large-size, 100% cotton, men’s t-shirt displayed at the Gap store with the following address: 543 Madison Avenue, Poughkeepsie, NY.\(^{15}\) Then, the price level \( PL_t \) at any time, \( t \), is a weighted average of all the quote prices collected at \( t \):

\[
\frac{1}{n} \sum_{i} w_i \cdot p^i_t. \quad (16)
\]

In practice, most apparel goods are not on the market for a long time period. At some point, the Gap may close this particular store or decide to permanently cancel this good from the store shelves for a number of reasons: red becoming unfashionable, cotton turning into an expensive commodity, and so forth. Once, the BLS surveyor learns about the cancellation, she substitutes another good for the t-shirt. The new good may be very similar to the old t-shirt, or maybe a different shirt. However, the prices for the new good still enter in the old quote. Such goods, which provide the prices for the same quote, the CPI methodology calls quote versions. For brevity, I refer to a quote version as an item. More formally, an item is a good \( m_i \), a vector of prices which enters quote \( i \) from \( t = h \geq 1 \) to \( t = k \leq T \):

\[
q_{m_i} = (p^i_h, p^{i}_{h+1}, ..., p^i_k).
\]

Figure 4 provides an example of a quote evolution over time, with one substitution in May and another in December.

In my data, a unit of observation is an item with one exception. When replacing one quote version for another in a sample, the surveyor first looks for a close substitute for the missing item; otherwise, she randomly selects another item from the same apparel category.

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\(^{15}\)This is a hypothetical example, which is not taken from the actual data.

\(^{16}\)The weights depend on the relative share of the good in consumer expenditures. They do not matter for my analysis.
In the t-shirt example, a close substitute may be a t-shirt containing 97% cotton. If the data shows that the surveyor manages to replace a canceled item with a similar one, I consider these two items as a single unit of observation or as one item in my data.\textsuperscript{17} In Figure 4, Version 1 and Version 2 are close substitutes which explains why their prices are equal in March and April, but Version 3 is not a close substitute and has a lower price. My choice of the unit of observation results in an unbalanced panel.\textsuperscript{18}

To make good substitutions of versions, the BLS surveyors collect detailed descriptions for every item, including its color, size, material and country of origin. In my analysis, I do not use the majority of these characteristics because it is not possible to construct a consistent data set for them over the years. However, I employ the information on item categories and groups. In the CPI micro data, there are 6 apparel groups (Men, Boys, Women, Girls, Footwear and Babies) and 29 categories or Entry Item Levels (ELI). A category usually consists of three or four types of apparel. For example, ELI “AA011” includes men sweaters, men t-shirts and men vests.

In addition to item categories and groups, I use several other variables from the CPI data. First, I observe the exact date when a surveyor collects a price observation, which allows me to control for sales tax holidays, a popular cross-state policy that exempts the sales tax on apparel for a small period of time (1-10 days). Second, the data provide information on the months when an item is on season. The procedure for defining a season range for a given item has two steps. First, BLS employees located at headquarters decide whether an item’s category, or ELI, is seasonal. If so, they assign a six-month season to all items in that category. When the surveyor initiates an item in the sample, she asks a store representative when the season for the item starts and ends. Finally, the “Sale” determines the cases when

\textsuperscript{17}In most cases, these two goods are essentially the same good which the collector may re-describe due to unrelated reasons. The CPI data has a special variable determining the similarity of two items.

\textsuperscript{18}Alternatively, I could choose a quote as the unit of observation and employ price-quality adjustments that the BLS uses to compare prices across two consecutive quotes which are not close substitutes. I believe that this may result in biased estimates. Based on hedonic regressions, the quality adjustment methodology varies over time and maybe analyst-dependent. If analysts are inclined to make adjustments in a certain way (for instance, to keep inflation constant), this may affect my estimates in an unpredictable manner.
Figure 4: CPI Quote Evolution Over Time

Notes: The black arrows show the observations used for computing CPI. A yellow circle represents temporary missing observation (stockout), whereas red - permanent missing observation (cancellation). The number in each circle shows the price of the item. Versions represent different items entering one quote a given item is on sale.

4.2.2 Summary Statistics

My sample consists of item-month observations. It spans from 1997 to 2012 with the exception of March 1997 and December 2012, when the data is unavailable for analysis at the BLS cluster due to technical issues. For each unit of observation, time series are either monthly or bimonthly, which depends on the location of price collection. Only in three metropolitan areas (New York City, Chicago and Los Angeles) do the surveyors report prices on the same units every month. This fact suggests that prices in Chicago could be a good control in New York. Keeping this in mind, I add to my sample Illinois and all other states from Midwest States. The inclusion has two other benefits. First, it increases the number of control observations and states in my sample which is useful given that the CPI data does not have prices from several Northeast states. Second, it smooths the average prices across odd and even months in control states, which is important for my instrument construction procedure.

There are several sample adjustments that I make. I consider only observations on prices from traditional retailers because quotes from catalog and online stores have a small
representation (2-3%) in the BLS data. I drop from my sample all the items that ever cost more than $1000 because their behavior may differ from the rest of the items.

Table 2 shows summary statistics for all the variables involved in my estimation of tax incidence. Columns (1-2) show means and standard deviations for the two treatment states, NY and CT, whereas Columns (3-5) provide the same information for the control geographical areas: other Northeast states, Illinois and other Midwest states. Average prices are more than a quarter higher in NY and CT relative to the other states. I attribute this to the fact that more stores in these areas sell luxury brands. About 15% of prices are above $110, the most common threshold value in NY, implying that the in-state control group is large.

I control for other variables that reflect price or tax variation or item characteristics. Sales tax holidays are popular in both treatment states. The distribution of seasonal items and groups is almost the same across the states. 30.4% of all quotes are non-seasonal goods. About 11% each are Fall and Spring Seasonal Goods, where I define fall season to last exactly from August to January and spring season exactly from February to July. The most represented groups of apparel in my sample are adult clothing (women - 33%, men - 29%) and, footwear (19%).

4.3 Employment Data

To estimate the effect of the sales tax on employment, I use data from the Quarterly Census of Employment and Wages (QCEW). The data provide total number of employees on monthly basis as well as total payroll, average wages, and total number of establishments on quarterly basis for different industries at the county level. I merge it with county-level self-constructed tax rate data and the U.S. Census population data. In this subsection, I present summary

---

19 Data on the Internet stores enters the CPI micro data in 2003
20 The CPI data does not cover price quotes in Vermont, but I use Vermont as a treatment state when working with the other data sets
21 Indeed, there are three times more observations of items priced from $500 to $1,000 in NY and CT relative to IL, which has the highest average price among the control areas.
Table 2: Summary Statistics for Apparel Items, Price Regressions

<table>
<thead>
<tr>
<th></th>
<th>NY</th>
<th>CT</th>
<th>Other NE</th>
<th>IL</th>
<th>Other MW</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price, $</td>
<td>86.4</td>
<td>88.8</td>
<td>58.7</td>
<td>67.2</td>
<td>56.0</td>
<td>65.1</td>
</tr>
<tr>
<td></td>
<td>(156)</td>
<td>(174)</td>
<td>(94)</td>
<td>(112)</td>
<td>(89)</td>
<td>(113)</td>
</tr>
<tr>
<td>Tax Rate</td>
<td>0.048</td>
<td>0.021</td>
<td>0.008</td>
<td>0.075</td>
<td>0.049</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.029)</td>
<td>(0.020)</td>
<td>(0.022)</td>
<td>(0.028)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Instrument for Tax Rate</td>
<td>0.044</td>
<td>0.020</td>
<td>0.008</td>
<td>0.075</td>
<td>0.049</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.029)</td>
<td>(0.020)</td>
<td>(0.022)</td>
<td>(0.028)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Item is on Sale, %</td>
<td>35.2</td>
<td>44.1</td>
<td>41.6</td>
<td>38.1</td>
<td>40.6</td>
<td>39.6</td>
</tr>
<tr>
<td></td>
<td>(47.7)</td>
<td>(49.7)</td>
<td>(49.3)</td>
<td>(48.6)</td>
<td>(49.1)</td>
<td>(48.9)</td>
</tr>
<tr>
<td>Sales Tax Holiday, %</td>
<td>1.16</td>
<td>1.96</td>
<td>0.005</td>
<td>0.150</td>
<td>0.030</td>
<td>0.309</td>
</tr>
<tr>
<td></td>
<td>(10.72)</td>
<td>(13.87)</td>
<td>(0.712)</td>
<td>(3.86)</td>
<td>(1.72)</td>
<td>(5.55)</td>
</tr>
<tr>
<td>Monthly Quotes</td>
<td>0.828</td>
<td>0.556</td>
<td>0.289</td>
<td>0.756</td>
<td>0.050</td>
<td>0.387</td>
</tr>
<tr>
<td></td>
<td>(0.377)</td>
<td>(0.497)</td>
<td>(0.453)</td>
<td>(0.429)</td>
<td>(0.219)</td>
<td>(0.487)</td>
</tr>
<tr>
<td>Nonseasonal Goods</td>
<td>0.307</td>
<td>0.267</td>
<td>0.296</td>
<td>0.309</td>
<td>0.310</td>
<td>0.304</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td>(0.442)</td>
<td>(0.456)</td>
<td>(0.462)</td>
<td>(0.462)</td>
<td>(0.460)</td>
</tr>
<tr>
<td>Fall Seasonal Goods</td>
<td>0.132</td>
<td>0.095</td>
<td>0.118</td>
<td>0.111</td>
<td>0.111</td>
<td>0.117</td>
</tr>
<tr>
<td></td>
<td>(0.339)</td>
<td>(0.294)</td>
<td>(0.323)</td>
<td>(0.314)</td>
<td>(0.315)</td>
<td>(0.321)</td>
</tr>
<tr>
<td>Spring Seasonal Goods</td>
<td>0.131</td>
<td>0.099</td>
<td>0.113</td>
<td>0.099</td>
<td>0.109</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>(0.337)</td>
<td>(0.299)</td>
<td>(0.317)</td>
<td>(0.299)</td>
<td>(0.312)</td>
<td>(0.316)</td>
</tr>
<tr>
<td>Men’s Clothing</td>
<td>0.313</td>
<td>0.320</td>
<td>0.278</td>
<td>0.283</td>
<td>0.290</td>
<td>0.291</td>
</tr>
<tr>
<td></td>
<td>(0.464)</td>
<td>(0.466)</td>
<td>(0.448)</td>
<td>(0.450)</td>
<td>(0.454)</td>
<td>(0.454)</td>
</tr>
<tr>
<td>Women’s Clothing</td>
<td>0.315</td>
<td>0.321</td>
<td>0.360</td>
<td>0.329</td>
<td>0.325</td>
<td>0.334</td>
</tr>
<tr>
<td></td>
<td>(0.465)</td>
<td>(0.467)</td>
<td>(0.480)</td>
<td>(0.470)</td>
<td>(0.468)</td>
<td>(0.472)</td>
</tr>
<tr>
<td>Footwear</td>
<td>0.185</td>
<td>0.149</td>
<td>0.181</td>
<td>0.196</td>
<td>0.200</td>
<td>0.189</td>
</tr>
<tr>
<td></td>
<td>(0.389)</td>
<td>(0.356)</td>
<td>(0.385)</td>
<td>(0.397)</td>
<td>(0.400)</td>
<td>(0.392)</td>
</tr>
<tr>
<td>No. of Obs.</td>
<td>94,793</td>
<td>16,411</td>
<td>157,742</td>
<td>76,866</td>
<td>171,242</td>
<td>517,054</td>
</tr>
</tbody>
</table>

Notes: The data comes from Consumer Price Index micro data with one exception. I fix the inaccurate reporting of the sales tax rate after exemption alterations in the CPI data by self-collecting data on exemptions. It covers a time period from January 1997 to December 2012. There are five geographic areas that I compare: New York, Connecticut, Other NorthEast Census Region states, Illinois and Other Midwest Census Region states. Price is exclusive of a sales tax. Sales tax holiday equals to one if on the day of price collection a state holds sales tax holidays on apparel. I explain in “Empirical Strategy” section how I construct an instrument for the sales tax. All the variables, except for price, tax rate and instrument for tax rates, are dummies.
statistics for the variables obtained from QCEW and the Census.

Bureau of Labor and Statistics (BLS) collects the data on wages and employment for all the industries in most of the counties. For a subset of small counties, BLS does not publish the data due to non-disclosure restrictions. Generally, the set of these counties is fixed for long time periods (5-10 years) and is unlikely to bias my estimates. For my analysis, I obtain the data for two industries: “448-Clothing and clothing accessories stores” and “451-Sporting goods, hobby, book and music stores”, thus excluding department and big box stores that sell apparel and entertainment goods. The first industry describes the employment of the apparel retailers and is of my primary interest. The second industry is for robustness checks of my results.

---

\[22\] I do not find any relationship between the tax rate and counties entering/exiting the sample.
Table 3: Summary Statistics for Retail Establishments, Employment Regressions

<table>
<thead>
<tr>
<th>CT</th>
<th>ME</th>
<th>MA</th>
<th>NH</th>
<th>NJ</th>
<th>NY</th>
<th>PA</th>
<th>VT</th>
<th>RI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apparel and Entertainment Retailers: Data at County-Monthly Level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of Employees</td>
<td>2,272</td>
<td>381</td>
<td>2,387</td>
<td>712</td>
<td>2,648</td>
<td>2,187</td>
<td>1,031</td>
<td>1,037</td>
</tr>
<tr>
<td>(Apparel Retailers)</td>
<td>(2,260)</td>
<td>(596)</td>
<td>(2,140)</td>
<td>(794)</td>
<td>(2,076)</td>
<td>(6,047)</td>
<td>(1,893)</td>
<td>(1,082)</td>
</tr>
<tr>
<td>Missing, %</td>
<td>1.7</td>
<td>18.9</td>
<td>5.6</td>
<td>0.5</td>
<td>3.0</td>
<td>9.4</td>
<td>14.8</td>
<td>10.1</td>
</tr>
<tr>
<td>No. of Employees</td>
<td>1,116</td>
<td>267</td>
<td>1,227</td>
<td>492</td>
<td>1,087</td>
<td>793</td>
<td>463</td>
<td>393</td>
</tr>
<tr>
<td>(Entertainment Retailers)</td>
<td>(1,076)</td>
<td>(478)</td>
<td>(1,235)</td>
<td>(516)</td>
<td>(929)</td>
<td>(1,436)</td>
<td>(720)</td>
<td>(287)</td>
</tr>
<tr>
<td>Missing, %</td>
<td>15.5</td>
<td>23.8</td>
<td>19.9</td>
<td>14.5</td>
<td>17.7</td>
<td>27.0</td>
<td>26.7</td>
<td>15.1</td>
</tr>
<tr>
<td>Population</td>
<td>436,038</td>
<td>81,542</td>
<td>459,349</td>
<td>127,895</td>
<td>409,429</td>
<td>313,722</td>
<td>188,805</td>
<td>210,829</td>
</tr>
<tr>
<td>No. of Obs.</td>
<td>1,544</td>
<td>3,088</td>
<td>2,702</td>
<td>1,930</td>
<td>4,053</td>
<td>11,773</td>
<td>12,738</td>
<td>965</td>
</tr>
</tbody>
</table>

Apparel Retailers: Data at County-Quarterly Level

| Establishments | 214 | 44 | 229 | 72 | 243 | 209 | 102 | 103 | 32 |
| Payroll, $1,000 $ | 10,353 | 1,532 | 11,447 | 2,801 | 13,299 | 13,785 | 4,196 | 4,210 | 1,045 |
| (11,576) | (2,537) | (12,114) | (3,164) | (11,984) | (59,705) | (8,570) | (4,593) | (1,489) |
| Taxed Payroll, $1,000 $ | 4,266 | 641 | 4,374 | 974 | 6,563 | 3,249 | 1,291 | 1,978 | 399 |
| (6,491) | (1,364) | (6,553) | (1,648) | (8,349) | (15,529) | (3,457) | (3,164) | (829) |
| Weekly Wages, $ | 334 | 297 | 355 | 324 | 358 | 284 | 288 | 332 | 323 |
| (76) | (65) | (94) | (98) | (112) | (98) | (67) | (82) | (84) |
| No. of Obs. | 615 | 998 | 1,042 | 777 | 1,592 | 4,263 | 4,348 | 352 | 801 |

Notes: The data comes from Quarterly Census of Employment and Wages except for population which is from the U.S. Census. It covers the period from January 1997 to December 2012. “Payroll” represents total expenditures on labor by retailers in a county, whereas “Taxed Payroll” - total expenditures on labor subject to Unemployment Insurance tax. Missing observations are due to non-disclosure requirements. There is a bigger proportion for them for “Entertainment Retailers” (“451-Sporting goods, hobby, book and music stores”) because it is a smaller industry. The data on the number of employees and population is at monthly level, the letter variable obtained by extrapolation. The rest of the variables are at quarterly level.
Table 3 presents summary statistics for the variables involved in my empirical analysis. The data on the number of employees is available at a monthly level. Average employment by county varies substantially across the Northeast states. It is proportional to county population, which determines the percent of missing observations. For instance, two states with the lowest average county population (Maine and Rhode Island) have the highest proportion of missing observations for the employment in apparel stores. Average employment in entertainment stores is about half as large but varies similarly across states. This, perhaps, explains a greater number of missing observations, ranging from 19% to 35%.

The other variables for the apparel industry are at quarterly level. They include the number of stores, overall expenditures on employees (payroll), overall expenditures on employees subject to Unemployment Insurance tax and average weekly wages. The average number of stores in a county varies from 32 to 243. The average payroll ranges from $1 million to $14 million. The taxable amount is generally 2.5 lower. Finally, average weekly wages do not vary as much as the other variables, the smallest being in New York ($284) and the largest in New Jersey ($358). Given that Census does not adjust for the hours spent at work, one should not conclude that the discrepancy in weekly wages signals any discrepancy in per-hour rates across states. Nevertheless, the average for weekly wages in my sample is very close to what a full-time employee on the minimum wage would earn.

5 Empirical Strategy

In this section, I explain my empirical strategy for estimating the effects of the sales tax on retail prices and employment. I begin by illustrating the difference-in-difference (DD) methodology for estimating the effect on employment using temporal and spatial variation; in this case, the changes in the sales tax occur at the county level, so I can include state-time trends. When estimating the pass-through rate of the sales tax on pre-tax prices, I extend my methodology to triple difference using item-level variation within localities because the
exemptions change the tax rates only for the items priced below certain thresholds. The latter feature of the exemptions implies that the sales tax rate is dependent on the outcome variable and, hence, endogenous. To deal with this issue, I construct an instrumental variable, making my empirical strategy — IV triple difference. To the best of my knowledge, this is the first paper in the tax incidence literature that uses such strategy to control for the main concern of estimating tax effects: the endogeneity of tax policy with respect to business cycles.\footnote{When estimating the effect on employment, I address this issue by performing a robustness check.} Another feature that distinguishes my empirical analysis is the usage of local tax rate changes, which helps me explicitly account for any issues related to localities responding in a certain way to state tax rate changes (Agrawal, 2014).

5.1 The effect on Employment and Expenditures

To estimate the effect of sales taxes on employment, I use a standard difference-in-difference methodology. My dependent variable is the logarithm of the number of employees $\log(1 + Emp_{cm})$ in apparel retailers, where $c$ and $m$ denote county and month.\footnote{I use log-transformation because the sales tax rate affects the relative rather than absolute employment in a same way across counties} I regress it on the sales tax rate $\tau_{cm}$:

$$
\log(1 + Emp_{cm}) = \alpha + \beta_1 \times \tau_{cm} + Controls_{cm} + \nu_c + \mu_m + \epsilon_{cm}.
$$

County fixed effects control for constant characteristics affecting retail employment in the county, such as the number of interstate roads passing through. The month fixed effects control for any common shocks that simultaneously affect the states in the Northeast apparel markets, for instance, Christmas sales. I also use population as a control variable because it helps predict the overall number of retail employees in any county.

The DD methodology provides unbiased estimates under the assumption of no systematic difference in trends between treatment and control groups. To show that this assumption is likely to hold in my case, I explicitly control for trends using state specific fourth-order
time polynomial, which is possible because of my focus on county-level data. In addition, I perform a robustness check using the number of employees in the entertainment retail industry (books, hobby, music and games) as a dependent variable while keeping the changes in the sales tax rate for the apparel retail industry. Given that permanent tax exemptions occurs only in the latter industry, I expect the coefficient estimates to equal zero in the robustness exercise.

The empirical specification for estimating the effect of the sales tax on household expenditures is very similar to (2) with slight adjustments. First, the unit of observation is a household $h$, resulting in household rather than county fixed effects $\nu_h$. I observe each household at most four times. Second, the tax rate varies at the state level but not the local level because I only observe the household’s state of residence: $\tau_{cm}$ becomes $\tau_{sm}$.

5.2 Pass-through rate

To estimate the pass-through rate of the sales tax on pre-tax prices, I substantially extend the methodology discussed above, which is possible because the CPI data allows me to observe the items priced above and below the exemption threshold in treated localities and states. Thus, I have an in-state (in-locality) control group, which makes my empirical methodology for estimating the pass-through rate essentially triple difference. The unit of observation is now an item denoted by $i$.\(^{25}\) I extend the definition of my time index. My data continues to be at a monthly level. However, the variation in tax rate is at finer level due to sales tax holidays, occurring on certain days of a month in some states. Luckily, the CPI data reports the exact day of price collection. So, I am able to control for sales tax holidays that happen disproportionately more in treatment states. Another control variable is item seasonality, $\text{Seasonality}_{im}$. I describe it later. Finally, I include item $\nu_i$ and month $\mu_m$ fixed effects.

\(^{25}\)Reminder: an item is a certain good (“Levi’s” gray, 100% cotton, M-size, men t-shirt) located in a given store (1235 5th Avenue, New York City)
Thus, my main specification for estimating the pass-through rate becomes:

\[
\log(p_{im}) = \alpha + \beta_1 \times \tau_{im} + \beta_2 \times SalesTaxHolidays_{im} + \text{Seasonality}_{im} \nu_i + \mu_m + \epsilon_{im}. \tag{3}
\]

I omit location fixed effects because item fixed effects controls for this particular characteristic as well as for other constant characteristics: color, size, composition, etc.\textsuperscript{26} There is, however, one potential limitation that the inclusion of item fixed effects imposes on my estimates. It mainly identifies changes in prices for the items that are in the market both before and after the policy change. Yet, in apparel industry, many items are seasonal. Usually, the stores keep them on the shelves for one or two seasons. If, after a change in tax exemption policy, the store manager prefers to wait until item replacement for a price adjustment, perhaps because of menu costs, my estimates of long-run effects are biased towards zero. In my empirical estimates, I show that this bias is not substantial by considering seasonal and nonseasonal items separately at some point of my analysis.

I use monthly fixed effects to control for any common shocks that simultaneously affect both the Northeast and Midwest apparel markets. An example of such a shock could be very cold weather during a particular season or federal government trade regulation changes. In certain cases, I also include state-month-year fixed effects to account for state-specific shocks in prices. The seasonality variables control for substantial changes in prices throughout a seasonal item’s lifetime. My data allows me to see the first and last months the item is supposedly in season.\textsuperscript{27} I find that the number of months till the end of the season captures

\textsuperscript{26}An alternative approach is to substitute item FE with quote FE. Remember from “Data Section”, that a quote consists of consecutive items, which are not necessarily similar. To account for the differences between two items belonging to the same quote, BLS analysts provide a price adjustment measure, a value that explains all non-inflationary discrepancies in the prices of the two items. The BLS analysts often estimate the adjustment using hedonic regression models and personal judgment. This methodology is not consistent over years and across analysts, which may lead to either imprecise or biased estimates.

\textsuperscript{27}The BLS office in Washington decides the months when a certain item is on/off season. This measure has a flaw in that it is not geographically specific. However, given that the weather conditions are presumably the same in the states I consider, it should not affect my estimates.
sizable price changes. I use a set of eleven dummies to control for seasonal changes:

\[
\text{Seasonality}_{im} = \sum_{0}^{10} \psi_{\text{season end}(m) - m} \mathbb{1}(\text{in season}(m)) + \psi_{11} \mathbb{1}(\text{nonseasonal good}),
\]

and I add another dummy for non-seasonal goods.

The changes in tax exemptions cause the tax rate for items in some price categories to change, leaving it unchanged for other items. Thus, these unaffected items serve as a within-locality control group in my estimation, which makes my empirical strategy triple differences. Their presence helps me address the concern that state tax policy may be a response to state or local business cycles. For example, state legislators may decrease the tax rates during recessions when prices also fall. Such policy behavior would bias my pass-through rate estimate downwards without the control of unaffected items. To sum up, my empirical strategy provides unbiased estimates of the pass-through rate conditional on no systematic differences in price trends for items priced above or below the threshold. Additional identification comes from the tax-independent seasonal drop in prices (the drop natural to apparel items due to the approach of the season’s end). The average magnitude of the drop for an item in season for six months is around 40%. Thus, when the threshold is in place and does not change, the items priced above the threshold, but not substantially above, experience a tax regime change, whereas the rest of the items serve as the control group.

### 5.2.1 Instrumental Variables

On one hand, the presence of exemption thresholds allows for item-specific tax rate changes, which helps in addressing the endogeneity of the tax policy. On the other hand, the thresholds create an incentive for stores to decrease pre-tax prices that are slightly above the exemption threshold to generate a substantial drop in the after-tax prices. Suppose, a store in Connecticut sells jeans for $50 in March 2010 and the tax rate depends on the price in
the following way:

\[
\tau_{i, March 2010}(\text{price}_{i, March 2010}) = \begin{cases} 
0, & \text{when price}_{i, March 2010} < $50 \\
6.35\%, & \text{otherwise.}
\end{cases}
\]

(5)

With a cumulative state and local tax rate \(\tau_{lt}\) of 6.35\%, the after-tax price is $53.17. If the store drops the price by 1%, the tax rate becomes 0 and the after-tax price $49.90.

To overcome this endogeneity concern, I use an instrumental variable approach similar to the literature that estimates the income tax elasticity with respect to the marginal tax rate (Gruber and Saez, 2002). The instrument is the would-be tax applied to the predicted price of an item in the absence of the policy. To obtain this predicted price, I regress price \(\log(p_{im})\) on fixed effects for the 24 item categories, 4 regions (New York, Connecticut, other Northeast states, Midwest states), month-year dummies and seasonality dummies,

\[
\log(p_{im}) = \alpha + \gamma_{\text{item category}} + \gamma_{\text{region}} + \mu_m + \text{seasonality}_{im} + \epsilon_{im},
\]

(6)

restricting my sample to observations not affected by exemption policy. Thus, I exclude observations after year 2000 in both treatment states: New York and Connecticut.\(^{28}\)

Plugging coefficient estimates into (6), I predict the logarithm of prices for the items in the two states after 2000. I then plug in these predicted logarithms into tax rate functions similar to (5) to get tax rates in the two states after 2000 that serve as instrumental variables. The intuition for this instrument is the following: the average prices on different apparel categories should be correlated among the control states, New York, and Connecticut; however, the average prices in the control states are not responsive to changes in New York and Connecticut state policies. In results not presented here, I use this average price directly as an instrument. None of the results presented below change in a substantial way.

The instrument averages are pretty close to those of actual sales tax rates. This is

\(^{28}\)Vermont does not enter in the CPI data sample
not surprising, given that the instrument should be different from the actual tax rate only around the exemption threshold in the treatment states. In all the results presented below, the coefficient before the instrument in the first stage is strongly significant. Its magnitude does not fall below 0.8 and $F$–static always exceeds 20.

6 Results

I present graphical evidence and the main regression results from my empirical analysis. First, I show that there is no change in apparel retail prices in response to the exemptions that alter the tax rate, implying that it is the consumers who bear the full incidence of a sales tax rate. Given that consumer expenditures are quite responsive to the sales tax, as I demonstrate in the end of this section, a lack of response by retailers in the price dimension implies an increase in the quantity supplied by retailers. This, in turn, should raise the amount of inputs employed. In this section, I consider two inputs: labor (the number of employees) and one type of capital (the number of stores). While the sales tax does not affect the capital, the retail employment increases by 0.33% in response to a one percentage point sales tax drop. In absolute terms, this number implies that a 4% New York state sales tax exemption makes apparel retailers in this state hire an additional 2,150 employees.

6.1 Sales Tax and Prices

6.1.1 Tax Incidence Around Exemption Threshold

Before presenting my regression results, I provide graphical evidence that stores do not change pre-tax prices in response to the tax rate, even in the extreme situation of a discontinuous drop in the tax rate when prices drop by a small amount. In Figure 5, I plot the distributions of prices for apparel items in New York around the most common exemption threshold value ($110). On the left, I include only the observations from the months without the exemption, and on the right — with the $110 exemption. One would expect a higher
Figure 5: Comparison of price distribution around the $110 exemption threshold in New York with (right) and without (left) the tax exemption. Items priced between $90 and $130 are included in the sample. There are 5,250 observations. McCrary (2008) test shows that the drops in the price density around $110 equal 0.74 with exemption and 0.77 without exemption.
density of price distribution just below the threshold value (bunching) when the exemption is in place because a 1¢ drop in retail price from $110 to $109.99 saves a typical New York consumer almost $9.

Surprisingly, the densities behave almost identically around the threshold point. Using the McCrary (2008) test, I find that bunching is slightly higher without exemption than with it. There could be several explanations for this behavior, one of which is the lack of tax exemption saliency (Chetty et al., 2009). This explanation, however, is not consistent with a large response of the equilibrium quantity to the sales tax. Another explanation is that a lot of apparel retailers operate nationwide. If consumers do not buy a certain item in New York, the store can ship it to another state to sell. This evidence suggests that it is reasonable to expect consumers to bear the full incidence of sales tax on apparel.

### 6.1.2 Estimation of Pass-through Rate

Table 4 shows the results of my triple difference IV estimation of pass-through rate on apparel pre-tax prices, controlling for sales tax holidays and seasonality. Main changes in the sales tax rate come from the revisions of the tax exemptions in three Northeast states. Given that these revisions affect the prices only for some items in any locality or state, my estimates are robust to the endogeneity of tax policy in response to business cycles, conditional on the assumption that the price trends for items above and below the exemption thresholds ($50-$110) are the same.

In Column (1), I present the estimates for my main specification. I include all items priced below $1,000 and consider both Northeast and Midwest states. The coefficient equals −0.06, which implies that producers pay only 6% of a sales tax. One cannot reject the hypothesis that the consumers bear the full incidence of the tax because the coefficient is not statistically significant. Given that the point estimate of the pass-through rate is quite small, one would like to know whether it has a narrow 95-percent confidence interval that does not include economically important values. Based on the numbers in Column (1), the upper bound on
the magnitude of the pass-through rate equals \(-0.0632 - 1.96 \times 0.051 = -0.17\). As I show in the end of this section, the deadweight loss value is almost the same whether I use the point estimate or this upper bound value of the pass-through rate.

In Column (2), I show that this result changes sign but still has a wide confidence interval when excluding the Midwest states; in this case, the main control states for New York and Connecticut become Massachusetts, New Jersey and Pennsylvania.\(^{29}\)

In the first two columns, the “Sales Tax Holiday” dummy is statistically and economically insignificant. The point estimate suggests that prices decline between 0.2\% to 0.9\% during sales tax holidays, and that the pass-through rate on producers is positive in sign and ranges from \(0.2/0.05 = 4\%\) to \(0.9/0.05 = 18\%\) assuming that sales tax holidays drop the tax rate by 5\%. The dummy is effective in controlling for tax holidays. Indeed, Column (3) shows that dropping the months when sales tax holidays occur does not change the sales tax rate coefficient.

In Columns (4,5), I show that the estimates are similar using either of the two treatment states, where identification comes from state and local exemption alterations in New York or only state exemption alterations in Connecticut. I find that in Connecticut, in Column (5), the effect of sales tax on prices is significant, and its magnitude equals 15\%, suggesting that retail stores bear a small share of a sales tax. However, this estimate is not statistically or economically different from the estimate in Column (1). It may reflect the fact that the average pre-tax price level on apparel is the highest in Connecticut (at $89) relative to all other states in my sample, implying that consumers may invest more in avoiding the sales tax.

I confirm the robustness of zero pass-through rate of a sales tax on producer prices in section 7. In addition, I show that the sales tax does not alter the retailers quality, measured by the number of stockouts, and product variety, measured by cancellations. In the next subsection, I consider the effect of sales tax on employment.

\(^{29}\)There are no observations for Vermont in the Consumer Price Index data
Table 4: Panel Data Estimates of the Effect of Sales Tax on Apparel Prices

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Whole Sample</th>
<th>W. /o Midwest States</th>
<th>W. /o Sales Tax Holiday Months</th>
<th>Treatment States</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Sales Tax Rate, %</td>
<td>−0.0632</td>
<td>0.0538</td>
<td>−0.0782</td>
<td>−0.0566</td>
</tr>
<tr>
<td></td>
<td>(0.0515)</td>
<td>(0.0418)</td>
<td>(0.0625)</td>
<td>(0.0478)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>−0.272</td>
<td>−0.893</td>
<td>0.670</td>
<td>−1.86</td>
</tr>
<tr>
<td></td>
<td>(0.904)</td>
<td>(0.829)</td>
<td></td>
<td>(0.529)</td>
</tr>
</tbody>
</table>

Item and month FE included in all specifications

<table>
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<th>No. of Obs.</th>
<th>508,788</th>
<th>267,042</th>
<th>333,334</th>
<th>491,632</th>
<th>418,954</th>
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<tbody>
<tr>
<td>$R^2$</td>
<td>0.056</td>
<td>0.054</td>
<td>0.046</td>
<td>0.056</td>
<td>0.059</td>
</tr>
<tr>
<td>No. of Items</td>
<td>61,331</td>
<td>31,127</td>
<td>51,731</td>
<td>59,471</td>
<td>52,322</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors clustered at the state level are in parentheses. Apparel price quotes, tax rate and control variables come from Consumer Price Index micro data; tax exemption data is self-collected from official State government websites. The sample covers January 1997 to December 2012 and all states from the Northeast and Midwest Census Regions. “Sales Tax Holiday” dummy equals one if a store’s state holds a sales tax holiday on the price collection date. The table presents the coefficient on this dummy multiplied by 100. Given the non-linear sales tax schedule in treatment states, I instrument for the sales tax rate. The first-stage F-statistic is substantially above 20 in all the regressions. Each regression includes item and month-year fixed effects and controls for seasonality. In all regressions, I exclude items ever priced above $1,000.
6.2 Sales Taxes and Employment

Given (i) zero pass-through of sales taxes to retail prices and (ii) evidence from the other papers (Einav et al., 2014; Hu and Tang, 2014) that consumers reduce their pre-tax expenditures at traditional retailers when tax rates increase, stores should respond to changes in the sales tax policy in the quantity dimension. Higher sales tax rates should lead to lower equilibrium quantity, and, in turn, lower usage of inputs.

In this subsection, I estimate how the sales tax affects retailer use of two main inputs: labor and a specific type of capital, measured by the number of establishments. I find that a 1 percentage point increase in the sales tax rate leads to a 0.4% drop in the number of retail employees and a 0.6% decrease in the overall payroll, suggesting lower wages for the remaining employees. However, there is no evidence of any significant reduction in the number of establishments.

6.2.1 Employment

Before presenting my regression analysis, in Figure 6 I provide graphical evidence for my main result that employment does indeed decrease in response to hikes in the sales tax. For this, I compare the normalized number of employees hired by apparel retailers in New York and three other Northeastern states: Massachusetts, New Jersey and Pennsylvania. I consider the time period from January 1997 to January 2009.

There are four reasons for choosing these months and states. First, the alterations in the sales tax exemption policy in New York occurs three times: two introductions and one repeal. In each case, the alterations affect a substantial part of the apparel market — items priced below $110 — making these policies symmetric. Third, the changes happen every three years and so are uniformly spread across time. Finally, at least in the first two changes, New York state exemptions affect all counties simultaneously. The last thing to note about the sample for Figure 6 is that I include in it only counties that stay in every month for the entire period. The dropped counties usually have the smallest population in their state, and
therefore, are unlikely to influence this graph.\textsuperscript{30}

In Figure 6, I show how normalized number of employees varies in New York versus MA-NJ-PA. For normalization, I subtract the overall number of employees at entertainment retail stores (which sell music, books, games and goods for hobbies) from that at apparel retail stores. This subtraction allows me to eliminate the positive trend component in New York employment. In addition, I divide the resulting series for both geographical areas by their values in March 2000 for the ease of comparison. The normalized employment is lower in New York relative to the other three states when the sales tax is in place: before the first introduction of the tax exemption (left vertical line) and in between the repeal (middle line) and second introduction (right line). When apparel is tax exempt, the employment levels are almost the same in the treatment and control areas.

\section*{6.2.2 Estimation of the Effect of Sales Taxes on Employment}

Table 5 shows the results of my difference-in-difference estimation of the effect of the sales tax rate on employment. Column (1) presents the results for a regression without time trends: a one percentage point increase in the sales tax rate results in a 0.42\% decrease in the number of employees. The coefficient is not statistically significant, the standard error being almost equal to the coefficient.

To decrease the standard error, in Columns (2-6) I use state time trends, which are polynomials of the 4\textsuperscript{th} order interacted with state dummies. These trends control for various state economic conditions that may affect apparel employment, such as changes in minimum-wage laws or the unionization of the industry. Indeed, in Columns (2-6) standard errors decrease by roughly a fourth compared to Column (1) after controlling for state trends. In Column (2), I find that the point estimate is almost the same but now strongly significant. I consider its value (\(-0.40\)) as my key estimate. It implies that a New York state 4\% sales tax exemption on clothing increases the number of employees by \(4 \times 0.4\% = 3.35\%\), which

\textsuperscript{30}For my regression analysis, I show that my estimates stay significant for both samples with and without these counties.
Figure 6: Comparison of normalized employment in New York and Massachusetts-New Jersey-Pennsylvania area. Green lines denote exemption introductions, brown – repeals. Normalized employment is the difference between the number of employees in apparel and entertainment stores, divided by its values in March 2000.
explains about 10% of time variation of the New York apparel retail employment in my sample. In absolute numbers, tax exemption gives New York state $0.033 \times 2,188 \times 62 = 2,143$ new jobs, where 2,188 is the average number of employees in a county and 62 is the number of counties.

For some small counties in my sample, the Census omits the data due to nondisclosure concerns, particularly at the beginning of my sample. The omission may bias my results towards zero if the counties that experience a higher drop in employment are more likely to have missing observations. This is plausible in my case given that lower employment in a county generally results in higher nondisclosure.\textsuperscript{31} To show how the nondisclosure affects my results, I perform the regression on two restricted samples. In Column (3), I exclude all the counties that have any missing observations, and the coefficient becomes one and a half times larger: $-0.67$. This restriction, however, is on the dependent variable and, thus, may not be effective. In Column (4), I use a restriction on the independent variable, considering only the counties with population higher than 50,000 at any moment in time. The coefficient, as expected, decreases compared to that in Column (3) but stays bigger than in Column (2): $-0.49$, confirming the concerns of a downward bias.

To make sure that there are no unaccounted factors driving my results, I do two other checks. First, I explicitly control for any changes in retail industry in a given state by using the data on employment in the Entertainment Industry as a control. The coefficient stays strongly significant and equals $-0.57$. Second, as a placebo test, in Column (6) I regress employment in the entertainment industry on the sales tax rate for clothing items. If there is some general trend in employment that is correlated with the tax rate variable, I expect the coefficient to be similar to Columns (1-5). As we can see, the coefficient in Column (6) is positive, assuaging any concerns. An interesting caveat is that the coefficient is also significant, suggesting that the employees fired in the apparel retail sector may flee into the entertainment retail sector.

\textsuperscript{31}I do not find any effect of the sales tax rate on the probability of nondisclosure.
Table 5: The Effect of Sales Tax on Retail Employment in Apparel Industry

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Apparel</td>
<td>Apparel</td>
<td>Counties w.</td>
<td>Counties w.</td>
<td>Counties w.</td>
<td>Counties w.</td>
</tr>
<tr>
<td>No Trend</td>
<td>−0.415</td>
<td>−0.395***</td>
<td>−0.666***</td>
<td>−0.489***</td>
<td>−0.569***</td>
<td>0.342***</td>
</tr>
<tr>
<td>(0.264)</td>
<td>(0.083)</td>
<td>(0.071)</td>
<td>(0.076)</td>
<td>(0.144)</td>
<td>(0.089)</td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td></td>
<td></td>
<td>Large counties</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td></td>
<td></td>
<td>Control</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tax Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.189**</td>
</tr>
<tr>
<td>(Ent.-ment)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.057)</td>
</tr>
<tr>
<td>Entertainment</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Trends</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>County and month FE included in all specifications</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. of Obs.</td>
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<td>34,558</td>
<td>26,788</td>
<td>29,501</td>
<td>29,887</td>
<td>29,887</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.130</td>
<td>0.154</td>
<td>0.203</td>
<td>0.179</td>
<td>0.185</td>
<td>0.162</td>
</tr>
<tr>
<td>No. of Counties</td>
<td>206</td>
<td>206</td>
<td>153</td>
<td>163</td>
<td>201</td>
<td>201</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors clustered at the state level in parentheses. “Ent.-ment” (short for entertainment) stores sell books, computer games, music and items for hobby. Data on employment comes from the Quarterly Census of Employment and Wages, on population – from the Census. “State Trend” is a control variable, which is an interaction of a fourth order polynomial with a state dummy. The number of counties is smaller in Columns (3) and (4) because I consider only the counties that are present in the sample for all the months and counties that have population above 50,000 respectively. In Columns (5-6), I use data on the entertainment employment as a robustness check.

‡ $p<0.01$, ** $p<0.05$, * $p<0.1$
### Table 6: The Effect of Sales Tax on Employee Remuneration and Establishments in the Apparel Retail Industry

<table>
<thead>
<tr>
<th>Dependent Var.</th>
<th>(1) Wage</th>
<th>(2) Payroll</th>
<th>(3) Taxed Payroll</th>
<th>(4) Establishments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax Rate</td>
<td>−0.289***</td>
<td>−0.630**</td>
<td>−0.873*</td>
<td>−0.122</td>
</tr>
<tr>
<td></td>
<td>(0.0714)</td>
<td>(0.247)</td>
<td>(0.395)</td>
<td>(0.285)</td>
</tr>
</tbody>
</table>

County, month FE, and state trends included in all regressions

<table>
<thead>
<tr>
<th></th>
<th>(1) Wage</th>
<th>(2) Payroll</th>
<th>(3) Taxed Payroll</th>
<th>(4) Establishments</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Obs.</td>
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<td>13,784</td>
<td>9,889</td>
<td>13,784</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.499</td>
<td>0.223</td>
<td>0.664</td>
<td>0.282</td>
</tr>
<tr>
<td>No. of Counties</td>
<td>206</td>
<td>206</td>
<td>206</td>
<td>206</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors clustered at state level in parentheses. All the dependent variables refer to the apparel industry. “Taxed Payroll” are the taxed expenditures on labor borne by the apparel retailers. In all the regressions I include the logarithm of population as well as state trends, which is an interaction of a fourth order polynomial with a state dummy, as controls.

In addition to changing the number of employees, apparel retailers can use other instruments of adjusting labor expenditures. Given that apparel retailers hire a number of part-time employees and use a sales-based remuneration system, they can either reduce the number of working hours or the per-hour wage. While the data does not allow me to distinguish between these two channels, I can estimate their cumulative effect using variables for weekly wages and overall payroll. In Table 6, I use them as outcome variables. Column (1) shows that the average weekly wage decreases by 0.29% following a one percentage point sales tax increase. Payroll changes consist of the number of employees (estimates in Columns (1-5) in Table 5) and the wages of remaining employees. Columns (2) is in fact quite close to the overall combined effect: −0.63.

Finally, I check whether the sales tax rate also affects the equilibrium amount of capital, measured by the number of establishments. The coefficient on tax rate in Column (4) of Table (6) is of the right sign but is not significantly different from zero. Indeed, it is hard to expect that the sales tax rate, which varies every three years on average, would influence the capital decisions which are usually long-term.
6.3 Sales Tax and Total Expenditures on Apparel

I present the empirical results for the effect of sales tax on total household expenditures on apparel. Using the Consumer Expenditure Survey (CE) data for the same geographical and time span as above, I find that consumers are quite responsive to apparel prices, with the elasticity of demand ranging from $-4.9$ to $-1.1$. Data limitations, which allow me to use tax rate variation only at the state level, might influence the precision of my estimates. Though one should treat them critically, I prefer to keep them here in order to estimate the elasticity of supply and perform deadweight loss analysis later.

I use the CE interview component. Given that the respondents report their monthly apparel spending for the past three months at any interview, I only consider the data for the first month prior to the interview. It does not substantially affect my estimation power but allows me to avoid any bias associated with incorrect reporting of purchases that increases with time away from the interview (Bradburn, 2010).

I use the difference-in-difference empirical strategy explained in subsection 5.1. This strategy has three particular features. First, the regressions are at the household-month level. Second, I use either a dummy variable, which equals 1 when expenditures for a household in a given month are non-zero, or a continuous variable for expenditures. Given that the expenditures can be nonnegative, I apply the inverse hyperbolic sine transformation to the dependent variable. It has the same interpretation as a log-dependent variable but permits zero values.

Finally, consistent with the previous subsection, I define my main explanatory variable to equal the tax rate for the lowest price category exempted from the sales tax. This implies that exemptions with different thresholds ($50, 55, 75, 110$) have the same treatment. I show that this assumption does not substantially affect my estimates in two ways. First, I restrict my sample to include only tax exemptions with the threshold equal to $110; second, I create an adjusted tax rate, which equals the average tax rate for the items priced below

\[ \text{32} \text{For example, a sales tax increase may lead to a higher saliency of a sales tax rate} \]
Table 7 shows the estimates of the effect of sales tax on household apparel expenditures. In Column (1), controlling for state trends, I find that the coefficient of interest equals $-2.3$: a 1% percentage point increase in sales tax leads to a 2.3% decrease in tax inclusive household expenditures on apparel. Given that the expenditures are tax inclusive, the coefficient on the sales tax is an estimate for the sum of the demand elasticity plus one. In Column (1), I show that the coefficient is significantly different from 1, and, hence, I readily reject the null hypothesis that the demand elasticity is zero. In Column (2), I use a dummy for whether a household purchases any apparel in a given month or not. I find that a 1 percentage point increase in sales tax decreases the probability that a household shops in a given month by 0.3%. This implies that the sales tax affects consumer shopping behavior on the extensive margin too.

In Columns (1-2), my main explanatory variable is the tax rate on exempted items. To see whether ignoring the exemptions thresholds affect my results, I do the following two exercises. First, in Columns (3-4), I consider an alternative measure of the sales tax rate. I compute the average tax rate for the items priced below $110 \( \tau_{\text{adjusted}} = \tau \times \Pr(\text{price} < \text{threshold}) \), where the probability is from a normal distribution with mean and standard deviation based on the summary statistics for prices in Table 2. Surprisingly, the results stay almost the same as in Columns (1-2). Second, in Columns (5-6), I restrict my sample to exemptions where the threshold equals $110. This excludes Connecticut and all observations after April 2011, when New York exempts items priced below $55. The coefficients in both regressions slightly decrease and stay significant. For the continuous dependent variable, the coefficient on the tax rate now equals $-2.0$, implying that a 1 percentage point increase in the sales tax rate decreases the tax inclusive expenditures by 2%. The implied demand elasticity from the coefficient equals $-3.0$, the 95% confidence interval being $[-3.9; -1.1]$. In the computation of elasticities and deadweight loss in section 8, I use these both the point estimate and the

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This formula is an approximation because it ignores the presence of the apparel items purchased at the Internet/catalog retailers, which do not charge sales tax. In section 8, I provide a precise formula.
Table 7: The Effect of Sales Tax on Clothing Expenditures

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td></td>
<td>Whole Sample</td>
<td>$110 Thresholds</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Ex.-tures</td>
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<td>Ex.-tures</td>
<td>Dumberry</td>
<td>Ex.-tures</td>
<td>Dumberry</td>
<td>Ex.-tures</td>
</tr>
<tr>
<td>Tax Rate</td>
<td>$-2.26^{++} \ (0.876)$</td>
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<td>$-2.01^{++} \ (0.955)$</td>
<td>$-0.33^{**} \ (0.121)$</td>
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<td></td>
</tr>
<tr>
<td>Adj. Tax Rate</td>
<td>$-2.27^{+++} \ (0.897)$</td>
<td>$-0.35^{**} \ (0.119)$</td>
<td></td>
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<td></td>
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</table>

Household, month FE, and state trends included in all regressions

<table>
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<tr>
<th></th>
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<th>(2)</th>
<th>(3)</th>
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<th>(5)</th>
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<td>78,824</td>
<td>61,864</td>
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<tr>
<td>$R^2$</td>
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<td>0.033</td>
<td>0.045</td>
<td>0.033</td>
<td>0.047</td>
<td>0.034</td>
</tr>
<tr>
<td>No. of HH</td>
<td>26,043</td>
<td>26,043</td>
<td>26,043</td>
<td>26,043</td>
<td>20,143</td>
<td>20,143</td>
</tr>
</tbody>
</table>

Notes: Robust standard error clustered at the state level in parentheses. Data on household monthly purchases in between January 1997 and January 2013 comes from the Consumer Expenditure Survey. I consider only the data for the first month prior to the interview. The coefficient before all the tax rate variables in odd Columns (1,3,5), is significantly different from one, with $P$–value less than 0.05 in all the cases. In these columns, I apply an inverse hyperbolic sine transformation (IHST) for the outcome variable, the interpretation being similar to log-transformation specifications. In even Columns (2,4,6), the outcome variable is a dummy equal to 1 if a household buys any apparel in a given month. In Columns (3-4), I use an average tax rate for items priced below $110 as my main explanatory variable. All the specifications in the table include state, month fixed effects and individual state time trends of $4^{th}$ order. Alternatively, in Columns (5-6), I restrict the sample to include only exemptions with thresholds equal to or above $110, dropping all observations after April 2011 and observations for Connecticut households.

The result for the dummy variable in Column (5) is almost identical to that in Column (1).

7 Robustness Checks

I augment my estimation of the pass-through rate started in the previous section. First, I confirm the robustness of my zero pass-through rate result in a variety of ways. Along the way, I show that the tax incidence differ on various subsamples. I find that the tax rate is not fully passed through to consumer prices of non-seasonal goods (tax incidence...
is 79%), girls apparel (62%) and footwear (76%). Second, I check whether the probability of items missing from store shelves changes in response to a sales tax rate, which can bias my pass-through rate estimates. I divide the missing observations into temporarily missing (stockouts) and permanently missing (cancellations) and present evidence that there is no effect of the sales tax rate on either of them. Simultaneously, the latter statement implies that both store quality (measured by the rate of stockouts) and store variety (measured by the rate of cancellations) stay constant in response to the sales tax rate.

7.1 Sensitivity of Zero Pass-through Rate Estimate

Table 8 shows that my estimates of pass-through rate are similar across time periods and the direction of tax changes. As a baseline, I use the sample from Column (1) of Table 4, which excludes all the items that are ever priced above $1,000. First, I divide the sample into pre-crisis (before 2008) and post-crisis (after 2008) periods. There are two rationales behind this step. First, the behavior of market participants after the Great Recession may be different, in and of itself. For instance, the American Footwear and Apparel Association reports that consumer spending on apparel shrank after the Great Recession and returned to pre-crisis levels only in 2012. Second, both NY and CT changed their tax rate at some point during the recession. NY repealed tax exemption in October 2010 and reintroduced it in April 2011. This coincided with a big change in cotton prices in late 2010 and early 2011. Column (1) shows that the point estimate during the pre-crisis period is almost the same as in the main specification (Column (1) in Table 4). After the start of the Great Recession (Column (2)), the coefficient becomes positive but still does not differ from zero. In the last two columns of Table 8, I provide estimation results for tax increases and decreases separately. From classical economic theory we know that the estimates should be the same. Yet, previous research finds that they differ, for instance in (Doyle and Samphantharak, 2008). For the tax increase, I choose the time period from 2002 to 2004, when both New York and Connecticut repeal sales

---

Table 8: Sensitivity to Time, Treatment State and Tax Change Direction

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-Crisis</td>
<td>After-Crisis</td>
<td>Tax↓</td>
<td>Tax↑</td>
</tr>
<tr>
<td>Sales Tax Rate, %</td>
<td>−0.070*</td>
<td>0.060</td>
<td>−0.042</td>
<td>0.118</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.167)</td>
<td>(0.040)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>−0.245</td>
<td>−0.180</td>
<td>−0.611</td>
<td>0.563</td>
</tr>
<tr>
<td></td>
<td>(0.659)</td>
<td>(2.30)</td>
<td>(1.40)</td>
<td>(0.497)</td>
</tr>
</tbody>
</table>

Item and month FE included in all specifications

<table>
<thead>
<tr>
<th></th>
<th>379,801</th>
<th>127,408</th>
<th>195,115</th>
<th>92,948</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Obs.</td>
<td>**</td>
<td></td>
<td></td>
<td>**</td>
</tr>
<tr>
<td>R²</td>
<td>0.058</td>
<td>0.054</td>
<td>0.058</td>
<td>0.058</td>
</tr>
<tr>
<td>No. of Items</td>
<td>46,022</td>
<td>19,208</td>
<td>28,964</td>
<td>14,303</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors clustered at the state level are in parentheses. The “Sales Tax Holiday” dummy equals one if a store’s state holds a sales tax holiday on the price collection date. The table presents the coefficient on this dummy multiplied by 100. The first-state F-statistic for sales tax rate instrument is substantially above 20 in all the regressions. Each regression includes item and month-year fixed effects and controls for seasonality. Column (1) excludes all observations from Connecticut, whereas Column (2) – from New York. Column (3) considers time period before January 2008, whereas Column (4) after December 2008. Column (5) restricts the sample to include time periods when the tax decreases (1999-2001; 2005-2007), whereas Column (6) – when the tax increases (2002-2004). In all regressions, I exclude items ever priced above $1,000.
tax exemptions, whereas for the tax drop, I consider two time periods when NY introduces a tax exemption (1999-2001 and 2005-2007). The coefficient is still insignificant, implying that the sales tax is fully passed through to consumer prices regardless of the direction of change in the tax rate.

<table>
<thead>
<tr>
<th>Dependent Var.</th>
<th>Log of Apparel Pre-tax Price</th>
<th>Item on Sale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)  (2)  (3)  (4)</td>
<td>(5)  (6)</td>
</tr>
<tr>
<td></td>
<td>NY    CT</td>
<td>Men and Women</td>
</tr>
<tr>
<td>Tax Rate</td>
<td>$-0.015$ $-0.070$ $-0.048$ $-0.145^{**}$</td>
<td>4.21 5.64</td>
</tr>
<tr>
<td></td>
<td>(0.054) (0.088) (0.086) (0.070)</td>
<td>(9.26) (6.47)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>$-0.265$ $-0.780$ $0.172$ $-0.818$</td>
<td>$-0.795$ $-1.625^{*}$</td>
</tr>
<tr>
<td></td>
<td>(0.914) (0.899) (0.539) (1.82)</td>
<td>(0.882) (0.844)</td>
</tr>
<tr>
<td>Month FE</td>
<td>X     X</td>
<td>X</td>
</tr>
</tbody>
</table>

Controls for State Trends:
- 4th order polynomial X
- State-Month FE X X X

Item fixed effect included in all specifications

| No. of Obs. | 508,788 508,788 491,632 418,954 287,929 508,788 |
| No. of Items | 61,331 61,331 59,471 52,322 39,083 61,331 |

Notes: Robust standard errors clustered at the state level in parentheses. Column (1) adds a 4th order time polynomial for treatment states. In Columns (2-4), I use a state dummy interacted with month fixed effects. Column (3) excludes observations from Connecticut, whereas Column (4) from New York. In Columns (5-6), I explore how sales tax rate affects the probability of item being on sale. “Item on Sale” equals to 100 if the item is on sales. “Sales Tax Holiday” dummy equals one if a store’s state holds a sales tax holiday on the price collection date. In the table, I present the coefficient on this dummy multiplied by 100. Each regression includes item fixed effects and controls for seasonality. The F-statistic for sales tax rate instrument is substantially higher than 20 in all the regressions. In all regressions, I exclude items ever priced above $1,000.

A key advantage of my empirical strategy is that it allows me to control for state specific time shocks. Thus, including explicit controls for the state trends or state-month interactions should not affect my estimates. The left panel of Table 9 shows that it is indeed the case. Column (1) shows the results for the whole sample when I include an interaction between
state dummies and a fourth-order time polynomial, whereas Column (2) shows them when I include an interaction between state and month dummies. Columns (3) and (4) repeat Column (2) but exclude observations from Connecticut and New York respectively. The coefficients on the tax rate in all these columns stays almost the same compared to the cases when I do not control for trends. This outcome is also true for the pass-through rate in Connecticut alone, which remains significant.

In the right panel of Table 9, I present additional evidence for the zero pass-through rate on retail prices. I show that the tax rate does not affect the likelihood of items being on sale, a common way of changing the prices in the apparel industry. My summary statistics show that sales occur in 40% of the price observations which permits the use of linear specification rather than logit or probit regressions. Column (5), which restricts the sample to observations for men’s and women’s apparel only, and Column (6), the whole sample, show that the estimate of pass-through rate is not statistically different from zero. In the second case, its magnitude implies that a 1 percentage point hike in the sales tax increases the likelihood of a sale by 5%. In addition, I find that a sales tax holiday makes a sale less probable by 1.6%. This effect is marginally significant.

In Table 10, I explore whether pass-through rate differs across apparel groups. Following the BLS, I consider six groups of apparel: Men, Boys, Women, Girls, Footwear and Babies. The point estimates for Boys, Girls and Footwear (Columns 2, 4, and 5) are substantially different from the full sample results. In all these cases, the coefficient is negative and relatively large in magnitude. In the last two cases it is also statistically significant.

These results suggest that consumers of these items have a higher elasticity of demand for apparel sold at local retail stores. This is a plausible argument for the footwear industry where e-commerce is thriving. A good signal of it is the emergence of a big online shoe retailer “Zappos.com” in the early days of the Internet, which does not have an analog in

---

35 The price variable in CPI data reflects the price changes associated with sales. I employ this regressions to estimate the extensive margin of price changes in response to the tax rate.
36 This are mutually exclusive goods. Footwear is a separate category
37 “Why shoes have dominated this generation of e-commerce”, 18 Feb 2013, by Michael Carney
### Table 10: Tax Incidence for Different Apparel Groups

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Men</td>
<td>Boys</td>
<td>Women</td>
<td>Girls</td>
<td>Shoes</td>
<td>Babies</td>
</tr>
<tr>
<td>Sales Tax Rate</td>
<td>-0.037</td>
<td>-0.159</td>
<td>0.013</td>
<td>-0.377***</td>
<td>-0.241**</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.188)</td>
<td>(0.124)</td>
<td>(0.103)</td>
<td>(0.098)</td>
<td>(0.103)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>-0.729</td>
<td>0.192</td>
<td>-0.362</td>
<td>2.50</td>
<td>1.56</td>
<td>1.52</td>
</tr>
<tr>
<td></td>
<td>(1.92)</td>
<td>(1.14)</td>
<td>(0.551)</td>
<td>(2.21)</td>
<td>(1.26)</td>
<td>(1.25)</td>
</tr>
</tbody>
</table>

**Item and month FE included in all specifications**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Obs.</td>
<td>141,911</td>
<td>25,868</td>
<td>146,016</td>
<td>34,733</td>
<td>90,166</td>
<td>31,904</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.036</td>
<td>0.060</td>
<td>0.121</td>
<td>0.092</td>
<td>0.029</td>
<td>0.078</td>
</tr>
<tr>
<td>No. of Items</td>
<td>11,780</td>
<td>2,453</td>
<td>27,306</td>
<td>5,066</td>
<td>8,482</td>
<td>3,446</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1

**Notes:** Robust standard errors clustered at the state level in parentheses. Columns (1-6) restrict the sample to apparel items of certain type: Men, Boys, Women, Girls, Footwear, Babies. “Sales Tax Holiday” dummy equals one if a store’s state holds a sales tax holiday on the price collection date. In the table, I present the coefficient on this dummy multiplied by 100. Each regression includes item and month-year fixed effects and controls for seasonality. The first-stage F-statistic for sales tax rate instrument is substantially above 20 in all the regressions. In all regressions, I exclude items ever priced above $1,000.
the clothing industry. A potential explanation for more elastic demand for girls’ and boys’
clothing is that for kids fit matters less, allowing people to search more in thrift stores or
get items from friends.\textsuperscript{38}

In Table 11, I break the sample into seasonal and non-seasonal goods, the latter consisting
mainly of cheaper items like underwear and t-shirts. Focusing on the sample to non-seasonal
goods allows me to consider the effect of the sales tax on retail prices when both sides of
the market have time to adjust to a new tax policy. 70\% of price observations in my sample
come from seasonal items, which are present in the market only for certain months of a year
and often go out of the market soon after a tax exemption change. Instead of adjusting the
price immediately, retailers may be willing to wait until item replacement. In this case, my
estimates of the pass-through rate would be biased towards zero.

For non-seasonal goods, which have an average lifespan in my sample of two and a half
years, this argument is unlikely to hold. Indeed, in Column (1), the pass-through rate for
non-seasonal goods is statistically significant and different from the point estimate for the
whole sample. In the long run, retailers share some burden of the sales tax and pay 21\% of
it for such items.

Columns (2-5) show that the pass-through rate is not significantly different from zero
for seasonal goods. In Column (2), I consider all seasonal items. Columns (3-5) focus on
two most popular seasons: fall (season lasts exactly from August to January) and spring
(exactly from February to July). In all cases, the pass-through rate, though insignificant, is
positive, which is theoretically possible only under the assumption of imperfect competition.
The sign of the pass-through rate signals another economically important difference between
seasonal and non-seasonal items, through the extent of competition. Non-seasonal goods are
usually more generic which promotes competition across retailers supplying these goods. As
I showed in Appendix A, under some plausible conditions, this should lead to a higher pass-
through rate for retailers. Thus, my conclusion is that long-run incidence lies somewhere in

\textsuperscript{38}Another explanation may be that teenagers (a) spend a bigger portion of their income on clothing and
(b) have more free time to search for a good bargain.
the middle between the estimates in Columns (1) and (2). As I show below, my deadweight loss analysis is not sensitive to changes in the tax rate within this range.

### Table 11: Tax Incidence for Seasonal and Non-seasonal Items

<table>
<thead>
<tr>
<th></th>
<th>(1) Non-Seasonal</th>
<th>(2) Seasonal</th>
<th>(3) Fall</th>
<th>(4) Spring</th>
<th>(5) Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tax Rate</td>
<td>−0.211***</td>
<td>0.003</td>
<td>0.113</td>
<td>0.145</td>
<td>0.081</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.077)</td>
<td>(0.080)</td>
<td>(0.127)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>−0.302</td>
<td>−0.254</td>
<td>0.414</td>
<td>2.17</td>
<td>−0.707</td>
</tr>
<tr>
<td></td>
<td>(0.891)</td>
<td>(1.10)</td>
<td>(1.10)</td>
<td>(1.52)</td>
<td>(1.52)</td>
</tr>
</tbody>
</table>

**Item and month FE included in all specifications**

<table>
<thead>
<tr>
<th></th>
<th>No. of Obs.</th>
<th>R²</th>
<th>No. of Items</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>184,579</td>
<td>0.010</td>
<td>13,962</td>
</tr>
<tr>
<td></td>
<td>324,193</td>
<td>0.075</td>
<td>47,410</td>
</tr>
<tr>
<td></td>
<td>101,954</td>
<td>0.091</td>
<td>15,466</td>
</tr>
<tr>
<td></td>
<td>49,894</td>
<td>0.087</td>
<td>7,651</td>
</tr>
<tr>
<td></td>
<td>52,059</td>
<td>0.102</td>
<td>7,821</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors clustered at the state level are in parentheses. The “Sales Tax Holiday” dummy equals one if a store’s state holds a sales tax holiday on the price collection date. In the table, I present the coefficient on this dummy multiplied by 100 to avoid too many zeros at the beginning. In Column (1), I restrict the sample to only non-seasonal items, whereas in Column (2) - seasonal. In Columns (3-5), I consider Fall and Spring goods. Fall season starts in August and ends in January, whereas Spring one starts in February and continues until July. F test statistic is above 20 in all the regressions. In all regressions, I exclude items ever priced above $1,000.

### 7.2 Stockouts and Cancellations

In this subsection, I test whether the tax rate affects the probability of encountering different types of missing observations. There are two reasons for this analysis. First, a change in the overall probability of missing observations may bias my estimates of the pass-through rate. Consider the case when a decrease in the sales tax leads to a disproportionally higher demand for cheaper items. Given this change in the demand, more low-priced items might be sold out. This, in turn, raises average prices, thus biasing the pass-through rate estimates downwards.

Second, the change in the rate of stockouts, items temporarily missing from the shelves,
and cancellations, items permanently missing from the shelves, is of interest in and of on
their own because they represent quality and variety dimensions of the stores respectively.
For example, the increase in the stockout rate implies low store quality as a consumer is less
likely to find the size or the color of an item she likes. Of course, this statement is completely
ture only if the variety of items, proxied by the cancellation rate, stays the same.

For my estimation, I use the same specification as for prices:

\[
\text{Log}(\text{Stockouts}_{it}) = \alpha + \beta_1 \times \tau_{it} + \beta_2 \times \text{SalesTaxHolidays}_{it} + \text{Seasonality}_{im_t} + \nu_i + \mu_m + \epsilon_{it}, \tag{7}
\]

the only main difference being the dependent variable. It is now a dummy that is nonzero
when the observations are missing, out of stock or canceled, depending on the regression.
To avoid too many zeros at the beginning in coefficient value, I multiply this dummy by
100. For cancellations, I also use fixed effects at the quote rather than item level; otherwise
the number of observations drop substantially.\(^{39}\) This change, however, does not affect my
results. When price is missing, the sales tax rate is also missing in the BLS data. In this
case I use the last observed tax rate for this item as the actual tax rate. This substitution
does not bias my results because I use an instrument that is constructed the same way as in
the price regression.

In Table 12, I present the results for non-seasonal goods. Column (1) shows that the
sales tax rate does not influence the probability of encountering a missing observation on a
unrefined sample. I find some evidence that the quality of retail stores increases (the number
of stockouts decreases, in Column (2)) and variety decreases (the number of cancellation
increases in Column (3)). After applying the sample refinements discussed in Appendix
C for stockouts and cancellations in Columns (4-5), both coefficients become small and
insignificant. The point estimate in Column (4) says that a 5% rise in sales tax results in
0.5% decrease in the amount of missing observations. While this effect is big relative to
the average rate of missing observations for nonseasonal items (5%), it is small overall. The

\(^{39}\) A quote consists of several consecutive items
Table 12: The Effect of Sales Tax Rate on Stockouts and Cancellations, Nonseasonal Goods

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>All Missing</th>
<th>Stockouts</th>
<th>Cancellations</th>
<th>Stockouts</th>
<th>Cancellations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Tax Rate</td>
<td>−0.0502</td>
<td>−0.280***</td>
<td>0.109**</td>
<td>−0.101</td>
<td>−0.00641</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.0788)</td>
<td>(0.0524)</td>
<td>(0.0774)</td>
<td>(0.0370)</td>
</tr>
<tr>
<td>Sales Tax Holiday</td>
<td>0.233</td>
<td>−0.271</td>
<td>−0.118</td>
<td>−0.553</td>
<td>−0.0178</td>
</tr>
<tr>
<td></td>
<td>(1.446)</td>
<td>(1.141)</td>
<td>(1.030)</td>
<td>(1.125)</td>
<td>(0.729)</td>
</tr>
</tbody>
</table>

*Item and month FE included in all specifications*

<table>
<thead>
<tr>
<th></th>
<th>No. of Obs.</th>
<th>No. of Items</th>
<th>No. of Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>215,197</td>
<td>23,155</td>
<td>8,560</td>
</tr>
<tr>
<td></td>
<td>175,821</td>
<td>18,765</td>
<td>8,550</td>
</tr>
<tr>
<td></td>
<td>202,284</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>126,906</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>194,277</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>No. of Obs.</th>
<th>No. of Items</th>
<th>No. of Quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>202,284</td>
<td>13,437</td>
<td>8,550</td>
</tr>
</tbody>
</table>

**Notes:** Robust standard errors clustered at state level in parentheses. Dependent variables are dummies that equal 100 if an item is missing, temporarily out of stock (stockout) or permanently out of stock (cancellation). Column (1) includes data for both stockouts and cancellations. Columns (2,4) contain only observations with stockouts, whereas Columns (3,5) – with cancellations. The number of observations in Columns (4-5) is smaller because I apply the Matsa (2011) refinement for dependent variables: in case of stockouts, I drop all the observations three months prior to their cancellations. In addition, I consider only observations in between first and last valid price observation. I only keep cancellations that occur after valid price observations in the sample. Each regression includes item and month-year fixed effects and controls for seasonality. The first stage F-statistic for the sales tax rate instrument is substantially above 20 in all the regressions. In all regressions, I exclude items ever priced above $1,000.
point estimate in Column (6) is almost zero. Thus, I conclude that for nonseasonal items (a) missing observations do not influence my pass-through rate results and (b) neither quality nor variety of apparel retailers change in response to changes in the sales tax rate.

| Table 13: The Effect of Sales Tax Rate on Stockouts and Cancellations, Seasonal Goods |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
|                                 | (1)                              | (2)                              | (3)                              | (4)                              |
|                                 | Missing                          | Stockouts                        | Cancel.                          | With Data Refinements            |
| Tax Rate                        | 0.660***                         | 0.502***                         | 0.184***                         | −0.0447                          | −0.0343                         |
|                                 | (0.0686)                         | (0.0797)                         | (0.0379)                         | (0.0780)                         | (0.0259)                         |
| Sales Tax Holiday               | 1.689**                          | 1.751*                           | −1.091*                          | 0.896                            | −0.505                          |
|                                 | (0.742)                          | (0.987)                          | (0.626)                          | (1.065)                          | (0.475)                          |

Item and month FE included in all specifications

| No. of Obs.                  | 828,846                          |
| R²                          | 0.253                            |
| No. of Items                | 99,111                           |
| No. of Quotes               | 30,024                           |

‡ p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors clustered at state level are in parentheses. Dependent variables are dummies that equal 100 if an item is missing, temporarily out of stock (stockout) or permanently out of stock (cancellation). Column (1) includes data for both stockouts and cancellations. Columns (2,4) contain only observations with stockouts, whereas Columns (3,5) – with cancellations. The number of observations in Columns (4-5) is smaller because I apply the Matsa (2011) refinement for dependent variables. For both stockouts and cancellations, I drop all out-of-season observations. In addition, for stockouts I consider only observations in between first and last valid price observation. I only keep in the sample cancellations that occur after valid price observations. Each regression includes item and month-year fixed effects and controls for seasonality. The first-stage F-statistic for the sales tax rate instrument is substantially higher than 20 in all the regressions. In all regressions, I exclude items ever priced above $1,000.

In Table 13, I repeat the regressions in Table 12 but now for seasonal items. In Columns (1-3), I consider the effect of the sales tax rate on all missing observations, stockouts and cancellations. In all three regressions, I observe significant positive effects that are high in magnitude on both stockouts (0.5%) and cancellations (0.18%). The first coefficient is counterintuitive; a higher rate of stockouts implies higher demand for the items. It is hard to expect that a sales tax increase boosts the demand for items. Indeed, after the refinement I
find no significant effect of the sales tax rate on either stockouts or cancellations in Columns (4) and (5). The point estimate for both effects essentially equals zero in both Columns (4) and (5). As in the case of nonseasonal items, I conclude that my (a) missing observations do not influence my pass-through rate results and (b) neither quality nor variety of apparel retailers change in response to the sales tax.

8 Elasticities and Deadweight Loss

Substantially decreasing the labor expenditures of traditional apparel retailers, sales tax must generate sizable distortions in apparel market. Using the methodology in Goulder and Williams (2003), which explicitly accounts for distortions in the labor market, I find that a sales tax of 5% results in a 17¢ average deadweight loss for every tax revenue dollar collected. In addition, I find that the presence of the catalog and online retailers does not substantially affect my estimates. Along the way, I also compute the demand and supply elasticities to make my results comparable with other papers.

First, I derive the formula that expresses the demand elasticity for apparel sold at traditional retailers $\epsilon_{D,l}$ as a function of Einav et al. (2014)’s parameter, $\beta_o = \frac{d\log(Exp_o)}{d\tau}$, and the two parameters estimated earlier in this paper (the pass-through rate of a sales tax on pre-tax prices, $\rho = \frac{d\log(p_l)}{d\tau}$, and the effect of the sales tax rate on total apparel expenditures, $\beta_{total} = \frac{d\log(Exp)}{d\tau}$). Index $l$ represents the fact that most purchases at brick-and-mortar retailers happen locally, whereas index $o$ represents online.

Note that one can express the effect of the sales tax rate on local expenditures as a function of the demand elasticity, $\epsilon_{D,l}$, and the pass-through rate, $\rho$:

$$\frac{d\log(Exp_l)}{d\tau} = \frac{d\log(Exp_l)}{d\log(p_l \times (1 + \tau))} \frac{d\log(p_l \times (1 + \tau))}{d\tau} = (\epsilon_{D,l} + 1)(\rho + \frac{1}{1 + \tau}). \quad (8)$$

40 The pass-through rate formula here is the first approximation of the formula in section 3 because $\log(1 + \tau) \approx \tau$
To recover the elasticity, I first totally differentiate the trivial equality for overall household expenditures on apparel,

$$Exp = Exp_o + Exp_l,$$

(9)

by tax rate $\tau$ and divide both parts of it by $Exp$ to obtain:

$$\frac{d \log(Exp)}{d\tau} = \frac{d \log(Exp_o)}{d\tau} \times \frac{Exp_o}{Exp} + \frac{d \log(Exp_l)}{d\tau} \times \frac{Exp_l}{Exp},$$

(10)

where $\alpha$ is the share of online/catalog expenditures out of the total. Then, I plug (8) into (10) and rearrange the terms to get the following representation of the elasticity of demand for apparel at traditional retailers:

$$\epsilon_{D,l} = \frac{\beta_{total} - \alpha \beta_o}{(1 - \alpha)(\rho + \frac{1}{1 + \tau})} - 1$$

(11)

This formula provides two comparative statics results important for this discussion. First, the demand elasticity increases in absolute terms in $\alpha$ and $\beta_o$. Thus, disregarding the online segment of apparel market results in a lower elasticity of demand. Given that the household generally avoids paying sales tax on online purchases in that period, this value serves as a lower bound for the elasticity of demand for the total expenditures on apparel. Second, lower pass-through rate results in a higher demand elasticity.

The derivation of expression (11), as well as of the demand elasticity itself, does not depend on the degree of competition. This is not true for the supply elasticity, which I can only recover from the pass-through rate and expression (11) based on the assumption of perfect competition:

$$\epsilon_{S,l} = \frac{\beta_{total} - \alpha \beta_o}{(1 - \alpha)\rho} - (1 + \frac{1}{(1 + \tau)\rho}).$$

(12)

The expressions (11) and (12) show that, keeping pass-through rate fixed, the ratio of two elasticities stays constant. Hence, they are inversely related.
Now, I am ready to compute both elasticities and the deadweight loss for the traditional apparel market by using the empirical values for $\beta_o$, $\beta_{total}$, $\rho$ and $\alpha$. I use the formula from Goulder and Williams (2003) for computing average deadweight loss:

$$
\text{DWL} = \frac{\frac{1}{2} \tau_{apparel} \epsilon_{D, apparel} - \tau_{Labor} \epsilon_{Labor} (\theta + 1)}{1 - \tau_{Labor} \epsilon_{Labor, Income}}
$$

(13)

where I set the tax rate on apparel, $\tau_{apparel}$, equal to 5%. I use the values for the parameters associated with labor markets suggested by Goulder and Williams (2003): tax rate for labor supply, $\tau_{Labor} = 40\%$, the compensated labor supply elasticity, $\epsilon_{Labor} = 0.25$, the income elasticity of labor supply, $\epsilon_{Labor, Income} = -0.2$, and I assume that clothing is an average substitute for leisure, $\theta = 0$. An implicit assumption of this model is perfectly competitive markets for labor and apparel. Relaxing this assumption leads to a higher estimate of the loss.

In the first three rows of Table 14, I explicitly account for the presence of the online segment of the apparel market. I compute its average over-the-years share based on the Annual Retail Trade Survey performed by Census. I use the estimate of 1.82(0.86) for the effect of the sales tax rate on online sales ($\beta_o$), from Column (1) of Table 6 in Einav et al. (2014). In the first row named “Preferred Values”, I use the point estimates of the coefficients from the main specifications: the effect of the sales tax on overall apparel expenditures, $\beta_{total}$, comes from Column (3) of Table 7, and the pass-through rate on retailers, $\rho$, from Column (1) in Table 4. With these values, I obtain a pretty elastic demand: $-3.37$. This result is consistent with Agarwal et al. (2013) who also use the Consumer Expenditure Survey and short-term source of variation in sales tax – sales tax holidays – to estimate the elasticity of clothing demand to be in between 4-6 in absolute value.

Given the close-to-zero pass-through rate, the supply curve is close to being absolutely elastic: 62. Note, that it is fully consistent with Figure 5 presented in the “Results” section. Perhaps, a plausible explanation for this result is the following. Since my natural experiment affects the sales tax in only three states, the supply function here may represent the ability
of firms to divert in or out the flow of items that are already produced from other states to the treatment ones, rather than the ability of firms to produce an additional unit of output.

The entry in the previous to the last column of Table 14 shows the annual deadweight loss $DWL = 2.1$ billion if there is a 5% sales tax rate on clothing for the whole US. The average deadweight loss in this case equals 0.17: $1$ raised in revenue results in a loss of $17\$\text{c}$. In fact, the two terms in equation (13) are almost equal, thus the marginal deadweight loss, e.g. the loss of increasing a tax rate from 5% to 6%, is one and a half times larger: $25\$\text{c}$.

I do not present the computations of the standard errors for neither elasticities nor losses because this requires the knowledge of the non-diagonal elements in $\beta_{ce}$, $\beta_e$ and $\rho$ variance-covariance matrices.\footnote{When I use some reasonable assumptions for this matrix, I find that standard errors are very small, resulting in the strong significance of all the estimates in the table below} To obtain the estimates of the elements, I would need to have simultaneous access to three separate data sets, two of which have substantial non-disclosure restrictions. Instead, I show how my computations change under alternative values of the parameters, which in certain cases go to and beyond the 95% confidence intervals for the estimates. In the second row, I show how my computations of the elasticities and losses change when I use an upper bound of the 95% confidence interval for the effect on expenditures. All the estimates decrease in their magnitudes. The demand elasticity becomes equal to $-1.4$, supply one — 34, and average deadweight loss 0.12. This estimate of the deadweight loss is conservative in the sense that to arrive at this number I make all the assumptions in favor of minimizing the deadweight loss.

In the next rows of Table 14, I present the estimates of the elasticities and losses under an alternative value for the pass-through rate of the sales tax on retail prices, $\hat{\rho}$, from Column (1) of Table 11, which considers only nonseasonal items. The supply elasticity drops by almost four times: 17. However, both deadweight loss and its ratio to revenue are very close to the “Preferred Values” case. This is not surprising given that small changes in the pass-through rate do not alter the demand elasticity estimate.

In the last row of Table 14, I check how the elasticities and deadweight loss estimates
change if I do not consider online retailers. All the estimates again are very close to the “Preferred values” case. This is due to a relatively small share (less than 6%) of online and catalog retailers in the market during the time period considered.
Table 14: Estimates of Demand Elasticity, Supply Elasticity and Deadweight Loss

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Estimated Parameters</th>
<th>Resulting Values</th>
<th>$\text{DWL}_\text{Rev.}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_{\text{total}}$</td>
<td>$\rho$</td>
<td>$\epsilon_{D,I}$</td>
</tr>
<tr>
<td>With Online Retail:</td>
<td>$d\text{Exp}_{\text{total}}/d\tau$</td>
<td>$\rho$</td>
<td>$\epsilon_{D,I}$</td>
</tr>
<tr>
<td>Share $\alpha = 0.052$; $\beta_o = d\text{Exp}_o/d\tau = 1.82$</td>
<td>$-2.01$</td>
<td>$-0.062$</td>
<td>$-3.37$</td>
</tr>
<tr>
<td>Preferred Values</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upper Bound of $\beta_{\text{total}}$</td>
<td>$-0.237$</td>
<td>$-0.062$</td>
<td>$-1.37$</td>
</tr>
<tr>
<td>Alternative $\rho$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$-2.01$</td>
<td>$-0.211$</td>
<td>$-3.81$</td>
</tr>
<tr>
<td>Without Online Retail:</td>
<td>$\alpha = 0$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preferred Values</td>
<td>$-2.01$</td>
<td>$-0.062$</td>
<td>$-3.14$</td>
</tr>
</tbody>
</table>

**Note:** This table shows which demand elasticity, supply elasticity and deadweight loss correspond to the parameters, pass-through rate $\rho$ and the effect of the sales tax on total apparel expenditures $\beta_{\text{total}}$ estimated in this paper. Preferred values for these parameters come from Column (1) of Table 4 and Column (5) of Table 7 respectively; the alternative value for the pass-through rate comes from Column (1) of Table 11. “Upper Bound” represents upper bound of the 95% confidence interval. I use the data from the Annual Retail Trade Survey to compute the share of online expenditures, $\alpha$, averaged over the sample years. The effect of the sales tax rate on online expenditures, $\beta_o$, comes from Column (1) of Table 6 in Einav et al. (2014).
9 Conclusion

In this paper, I estimate the effect of the sales tax on retail employment and prices. Using the CPI micro data and large apparel-specific tax rate changes, I find zero pass-through rate of the sales tax on pre-tax prices, implying that consumers fully bear the burden of the sales tax. Such a pass-through rate is common for a few other goods, but surprising for apparel with its highly elastic demand.

My result implies that apparel retailers have an even more elastic supply than the highly elastic demand. Thus, a sales tax increase should substantially decrease some equilibrium output, and, hence, inputs. I show that the labor expenditures of retailers decrease by 0.6% in response to a 1 percentage point increase in the sales tax, whereas the number of employees decreases by 0.4%. The magnitude of this effect in absolute numbers can be state as follows: a New York state sales tax exemption on clothing of 4% generates more than 2,150 new jobs, which is close to the average county employment in the apparel retail sector.

The substantial drop in the equilibrium output should lead to a large deadweight loss of apparel taxation. Indeed, using the Consumer Expenditure Survey data, I find that a 5% sales tax rate generates a 17c average deadweight loss for every tax dollar collected. These results are of particular interest to policymakers, given the lack of consensus among states over how (or even whether) apparel, with annual sales totaling $245 billion, should be taxed. The implications from this paper are twofold. Given the substantial deadweight losses of apparel taxation, the recent trend of tax avoidance through the Internet purchases may be welfare improving. Second, tax exemption alterations, which themselves require numerous legislative hours, also affect the labor market significantly, and are, thus, too costly to happen frequently.


Tatiana A Homonoff. Can small incentives have large effects? The impact of taxes versus bonuses on disposable bag use. 2013.


Appendices

A The Pass-Through Rate Under Imperfect Competition

Using the framework of Weyl and Fabinger (2013), I derive the pass-through rate of an ad valorem tax under the general case of imperfect competition between single-product firms.\footnote{For the analysis of tax incidence under competition between multiproduct firms, see Hamilton (2009).} This framework has the advantage of nesting all commonly used models of complete information with imperfect competition. Originally, the authors employ it to obtain the general formula for the pass-through rate and tax incidence of excise taxes.

Under imperfect competition, when all the firms are identical, a profit-maximizing quantity $q$ (or after-tax price $p$) is such that the price mark-up satisfies:

$$p(q) - \theta(q)ms(q) = mc(q)(1 + \tau), \quad (14)$$

where $\theta$ is a market structure parameter, which is equal to 0 in case of perfect competition, $\frac{1}{n}$ in case of Cournot with $n$ firms and 1 in case of monopoly.\footnote{This is the conduct parameter introduced by Genesove and Mullin (1998) variation on Bresnahan (1989). However, in this case it can also depend on the output as in the differentiated products Nash-in-prices model.} $ms = -p'(q)q$ represents the marginal surplus for an individual firm, whereas $mc$ – the marginal cost of the firm. Note that $p$ is the price paid by consumers; thus, the sales tax rate $\tau$ multiplies the marginal cost.

Taking logs of both sides of equation 14 and differentiating them by $\frac{d}{d\log(1+\tau)}$ results in the following:

$$\rho_c - \theta'(q)q'(p)\rho ms(q) - \theta ms'(q)q'(p)\rho = \frac{mc'(q)}{mc}q'(p)p\rho + 1, \quad (15)$$

where $\rho_c = \frac{d\log p}{d\log(1+\tau)}$ represents the pass-through rate of a sales tax on consumer prices, or, alternatively, the tax incidence on consumers. Solving for it leads to:
where $\epsilon_D = -\frac{d \log q(p)}{d \log p}$ is the absolute value of demand elasticity, $\epsilon_\theta = \frac{d \log q(\theta)}{d \log \theta}$ — the inverse elasticity of the market structure parameter, $\frac{1}{\epsilon_{ms}} = \frac{d \log m_s(q)}{d \log q}$ — the inverse elasticity of marginal surplus, and, finally, $\frac{1}{\epsilon_S} = \frac{d \log m_c(q)}{d \log q}$ — the inverse elasticity of supply of an individual firm. The formula for sales tax incidence on consumers differs from that for excise tax incidence derived in Weyl and Fabinger (2013) only by the presence of the second term in the numerator.\(^{44}\)

Using expression (16), I can show that the pass-through rate of a sales tax on producer prices, $\rho = \rho_c - 1$, can be of either sign or exactly zero, depending on the values of $\epsilon_D$, $\epsilon_{ms}$ and $\theta$. First, under the assumption of perfect competition ($\theta = 0$), the pass-through is non-positive and its magnitude is less than or equal to one in absolute terms:

$$\rho = \frac{1}{1 + \frac{\epsilon_D}{\epsilon_S}} - 1 = -\frac{\epsilon_D}{\epsilon_S + \epsilon_D} \in [-1, 0].$$  \hspace{1cm} (17)

Second, the pass-through rate can be equal to zero. Consider the case of monopolistic competition, when consumers have iso-elastic demand, firms have constant marginal costs and the number of products is large (like in Fullerton and Metcalf (2002)). The firm entrance does not affect conduct parameter: thus, $\epsilon_\theta = \infty$. Iso-elastic demand and large number of products imply the equality of the demand elasticity and the inverse elasticity of marginal surplus: $\epsilon_D = -\epsilon_{ms} = \frac{1}{1-\gamma}$, where $\gamma$ is a measure of substitutability. In addition, firms have constant marginal costs, which leads to $\epsilon_S = \infty$. Plugging all the values of the parameters in (16) yields zero pass-through rate:

\(^{44}\)Given how I define $\epsilon_D$, this term is always negative. This observation allows me to extend the result in Anderson et al. (2001) that a more-than-full pass of a sales tax on consumers necessarily implies a more-than-full pass of an excise tax, regardless of the cost curve form and under a broader set of symmetric imperfect competition models.
\[ \rho = \frac{1 - \frac{\epsilon_D}{\theta}}{1 + \frac{\epsilon_D}{\epsilon_m}} - 1 = 0. \]  \hfill (18)

Finally, for a generalized CES-logit model with constant elasticity of demand \( \alpha > 1 \) and constant marginal costs, Anderson et al. (2001) show that the pass-through rate is positive. In this case,

\[ -\frac{\epsilon_D}{\epsilon_\theta} - \frac{\epsilon_D}{\epsilon_m} > 1. \]  \hfill (19)

These examples confirm that the pass-through rate can be of any sign and value.

**B  Expenditure Data**

To estimate the effect of the sales tax on consumer apparel expenditures, I use the interview component data from the Consumer Expenditure Survey (CE). I augment the CE data with self-constructed data on sales tax rates at state level, the finest geographical level at which the data is publicly available. I restrict my sample to the Northeast states where all the tax exemptions occur. My data set spans from January 1997 to December 2012. It is a rotating panel of households. I observe apparel expenditures of every household at most four times.

In this section, I describe the features of the survey relevant to my research. Then, I explain how I aggregate the tax rate variable to a state level, the finest geographical area in the data. Finally, I provide summary statistics.

The respondents of Consumer Expenditure Survey report their apparel purchases every quarter for a one year period. The surveyor asks them to provide the following information about every item purchased in the three complete calendar months preceding the interview: month of purchase, tax-exclusive price, broad apparel group (men’s shirt vs. women footwear) and whether the item is a gift. (Bradburn, 2010) shows that such data collection leads to the underreporting of expenditures: every month away from the interview on average makes consumers forget about 15% of their purchases. Given that sales tax may alter
the reporting of expenditures, I consider the data only for the first month preceding the interview in my estimation. Before publishing the data, BLS makes two price adjustments. First, it computes after-tax prices, where the sales tax corresponds to the consumer’s place of residence. Second, it imputes and changes some prices in accordance with its internal policy. In the second case, BLS explicitly indicates it. In my analysis I use the adjusted prices, though my results do not change after dropping them.

After observing the household purchasing behavior for one year, BLS employees replace it with another randomly selected one. To preserve continuity in the averages, 25% of households in the sample change every quarter, rather than all of them at a certain moment. Theoretically, given my sample restrictions, I should have 4 observations for each household. In practice, I have on average 3 observations due to non-response issues. The main feature and advantage of using the data from the CE interview component is the possibility of observing apparel purchases for a number of households before and after the change in sales tax rates. This makes it outstanding relative to other data sources.\[45\]

The main limitation of my data is the tabulation of household location to a state level which prevents me from using the local tax rate data. Fortunately for me, only one state (New York) in my sample allows localities to impose sales tax rates on clothing. I assume that the cumulative rate in this state is equal to that in New York City because Big Apple contains half of NYS population and BLS oversamples this area. Another assumption that I rely on is that the sales tax rate is equivalent to the one applied to goods priced below the exemption threshold. In most cases, the threshold value is quite high ($110 in NY and VT) and covers 80%-85% of price distribution, exceptions being $50 and $75 thresholds in CT from the beginning of the sample to 2011 and NY from April 2011 to April 2012. Excluding these cases from my data does not substantially alter my results.

In Table 15, I compare summary statistics for apparel expenditures and sales tax rates

\[45\]For instance, the Diary component of the Consumer Expenditure Survey reports household expenditures only for two consecutive weeks. This period is too short to provide data about enough households before and after the policy changes
Table 15: Summary Statistics For Households, Expenditure Regressions

<table>
<thead>
<tr>
<th></th>
<th>Treatment</th>
<th>Control</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CT</td>
<td>NY</td>
<td>VT</td>
</tr>
<tr>
<td>Clothing Expenditures, $</td>
<td>120</td>
<td>104</td>
<td>105</td>
</tr>
<tr>
<td></td>
<td>(287)</td>
<td>(300)</td>
<td>(242)</td>
</tr>
<tr>
<td>Any Expenditures</td>
<td>0.499</td>
<td>0.396</td>
<td>0.495</td>
</tr>
<tr>
<td>Footwear Expenditures, $</td>
<td>21.6</td>
<td>17.0</td>
<td>17.3</td>
</tr>
<tr>
<td></td>
<td>(66.3)</td>
<td>(73.4)</td>
<td>(46.6)</td>
</tr>
<tr>
<td>Any Expenditures</td>
<td>0.226</td>
<td>0.156</td>
<td>0.223</td>
</tr>
<tr>
<td>Tax Rate, %</td>
<td>0.59</td>
<td>2.83</td>
<td>1.38</td>
</tr>
<tr>
<td></td>
<td>(1.84)</td>
<td>(3.80)</td>
<td>(2.23)</td>
</tr>
<tr>
<td>No. of Obs.</td>
<td>5,622</td>
<td>24,170</td>
<td>1,249</td>
</tr>
</tbody>
</table>

Notes: Standard deviations are in parentheses. The data are from the Interview Component of the Consumer Expenditure Survey and covers states from the Northeast Census Region and months from January 1997 to December 2012. The statistics from Column (3) informs us that a household in New York State on average spends $104 per month, the probability of any expenditures on apparel being 40%. Columns (1-3) present information for each treatment state individually (Connecticut, New York and Vermont); Columns (4) and (5) are for the control states divided according to their geographical and population sizes (Maine, New Hampshire and Rhode Island vs. Massachusetts, New Jersey and Pennsylvania). Column (6) presents the information for the whole sample. The tax rate variable is in percentage points and represents the cumulative state and local tax rate that consumers face. Given that geographical location data is available only at state level, the New York State sales tax rate equals the New York City one.
across five geographical areas. The first three areas correspond to the treatment states: Connecticut, New York and Vermont. The other two areas consist of the control states divided according to their population and geographical size: MN-NH-RI and MA-NJ-PA. Table 15 shows that a family in the Northeast on average spends monthly $92 on clothing and $16 on footwear. There are two areas that slightly deviate from this pattern; CT households spend more on both goods ($120), and the three New England Control States spent less on clothing ($66). This difference in behavior is negligible relative to the standard deviation, which is 2-3 times bigger than the mean expenditures. Households roughly shop for clothing once in two months and once in five months for footwear. The sales tax rate vary substantially within the treatment states: the standard deviation for the tax rate is bigger than the mean for all of them. The standard deviation for the tax rate within control states is almost zero, the high value in Column (4) representing substantial across-state variation (unlike other control states, Maine has non-zero tax).

C Item Disappearance

In addition to item being permanently unavailable (cancellation), there are two other reasons for a price observation to be missing. First, a store may temporary exhaust its supply of the item, which, following Matsa (2011), I call a stockout. In Figure 4, there are two stockouts in April and November. Second, item may be missing from the shelves because it is out of season. In Table 16, I present summary statistics for the different types of missing observations. I divide the sample into seasonal and nonseasonal goods because they are very different: average lifespan for the former is 1.5 years, whereas for the latter 3 years. In the raw CPI micro data, there are 59% of missing observation for seasonal goods and 20% for non-seasonal, the former being strikingly large. These numbers are due to the practices of CPI methodology to collect all plausible information about underlying processes of item disappearance.
The practice, generating the biggest portion of missing observations, is the collection of data for seasonal items when they are off-season. The BLS surveyors do it to make sure that the item is seasonally but not permanently unavailable. In the latter case, they substitute the item with another one. The more imminent the new season, the better the representative is aware of whether the item will be present on the shelves. Indeed, dropping all the off-seasonal observations leads to a decrease in the fraction of missing observations down to “only” 26%, which is comparable with non-seasonal items.

The second practice is collecting the data for two different quote versions simultaneously. In Figure 4, this happens when “Version 2” replaces “Version 1” in April. Note that two observations for the same quote and month are present in the data, one being a missing observation. If the dependent variable is a cancellation, I drop the April observation for “Version 2”. Alternatively, if it is a stockout, I drop the observation for “Version 1”. This is an example of a more general pattern of cleaning the data. When the dependent variable is a stockout, I exclude from my sample all the cancellations. This leads to 9.5% of stockouts for nonseasonal goods and 23% for seasonal goods in my sample. Alternatively, when using cancellations as the outcome variable, I drop all the stockouts. This results in 6.9% of cancellations for nonseasonal goods and 13% for seasonal goods. Bigger numbers for seasonal goods reflect the fact that the seasonal frames in CPI data may not coincide with the actual ones.

In practice, the classification of items in stockouts and cancellation is also not ideal. As Bils (2004) emphasizes, misclassification usually occurs right when the item becomes seasonally or permanently unavailable. For instance, suppose an item sells out one month before the season ends. Ideally, if the season indeed ends the following month, it should be tabulated as a stockout. However, the store representative may think of this item as being out-of-season because the season for this item according to representative is over. Moreover, the manager may be uncertain about the item returning to the shelves next season at this

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46 Another reason for collecting this data is, perhaps, for a better assignment of seasonal frames for the current and future items. See the explanation of determining item seasonality in CPI data below
Table 16: Summary Statistics for Apparel Items, Missing Observations Regressions

<table>
<thead>
<tr>
<th></th>
<th>Nonseasonal Items</th>
<th>Seasonal Items</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Refined</td>
<td>(2) Refined</td>
</tr>
<tr>
<td>All Missing Observations, %</td>
<td>20.0 -</td>
<td>59.0 -</td>
</tr>
<tr>
<td></td>
<td>(40.0) -</td>
<td>(49.2) -</td>
</tr>
<tr>
<td>No of Obs.</td>
<td>216,242 -</td>
<td>833,660 -</td>
</tr>
<tr>
<td>Stockouts, %</td>
<td>9.48 5.41</td>
<td>23.4 8.62</td>
</tr>
<tr>
<td>No of Obs.</td>
<td>178,546 128,914</td>
<td>454,210 204,951</td>
</tr>
<tr>
<td>Cancellations, %</td>
<td>6.90 3.07</td>
<td>13.0 4.66</td>
</tr>
<tr>
<td>No of Obs.</td>
<td>202,455 194,445</td>
<td>764,976 400,065</td>
</tr>
</tbody>
</table>

Notes: Data for missing observations is from January 1997 to December 2012. There are three main cases for the items in my data to be missing: temporarily missing (stockout), permanently missing (cancellation) and out of season. Columns (1-2) and Columns (3-4) show the summary statistics for nonseasonal and seasonal items respectively. In Columns (2,4), I show summary statistics for the samples after refinements similar to Matsa (2011). See the text for the details on the refinements. The first three rows of Columns (2,4) have no values because they the refinements are done separately for stockouts and cancellations.
moment. If it is not, then the item is actually a cancellation. Even for the non-seasonal goods, an uncertainty of whether the item comes back may lead to the mistabulation of stockouts and cancellations.

Based on the suggestions in Bils (2004) and Matsa (2011), I refine my data in the following way. For the stockout regressions, I drop all the observations in the three months preceding the permanent unavailability of an item. I do not apply this rule to the seasonal items because in apparel market a lot of these items stay in the market for only one season. So, this refinement leads to a substantial drop in the sample size. In addition, for any item, I consider only the observations that are in between the first and the last valid price observations. In addition, I drop those first and the last observations because they are always equal to 1. These refinements lead to a 5.4% of stockouts for nonseasonal items and 8.6% of seasonal items. For cancellation regressions, I apply a single refinement criterium: a cancellation must appear right after a valid price quote. This results in 3% of cancellations for nonseasonal items and 4.7% for seasonal ones.