Shopping for Lower Sales Tax Rates*

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Abstract

Using comprehensive high-frequency state and local sales tax data, we show that shopping behavior responds strongly to changes in sales tax rates. Even though sales taxes are not observed in posted prices and have a wide range of rates and exemptions, consumers adjust in many dimensions. They stock up on storable goods before taxes rise and increase online and cross-border shopping in both the short and long run. The difference between short- and long-run spending responses has important implications for the efficacy of using sales taxes for counter-cyclical policy and for the design of an optimal tax framework. Interestingly, households adjust spending similarly for both taxable and tax-exempt goods. We embed an inventory problem into a continuous-time consumption-savings model and demonstrate that this seemingly irrational behavior is optimal in the presence of shopping trip fixed costs. The model successfully matches estimated short-run and long-run tax elasticities with an implied after-tax hourly reservation wage of $9-13. We provide additional evidence in favor of this new shopping-complementarity mechanism.

JEL Classification: D12, E21, H31

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1 Introduction

Sales taxes in the United States are the largest source of revenue for state and local governments and are one of the most substantial taxes faced by households. As such, quantifying the timing, mechanisms, and magnitudes of households' response to changes in sales tax rates is of significant importance to areas of research like public finance, household finance, and even macroeconomics.

We approach this question with disaggregated and relatively high-frequency data on both sales tax rates and consumer spending, developing a comprehensive view of how households respond to sales tax changes in terms of levels of spending and also where that spending is done. We demonstrate that households strongly respond to sales tax changes through a variety of channels, both in anticipation of a change and following its implementation.

In addition, we take advantage of the fact that these sales tax changes are anticipated to better understand households' inventory management. For the many households who do not hold substantial financial assets, taking advantage of anticipated price differences by stocking up on storable and durable goods is one method to achieve returns on investment. We find both theoretical and empirical evidence for households engaging in this practice of inventory management, something that has been poorly documented in past research (one notable exception being Griffith et al. 2009 who examine this channel).

One principle motivation for this research is the fact that, in the past years, there has been a range of conflicting evidence about how households respond to changes in sales tax rates. Several papers, most notably Chetty et al. 2009, have shown substantial deviations from full household optimization in the face of complex or at least partly hidden tax changes, as sales taxes are in the United States (see also Finkelstein 2009, Cabral and Hoxby 2013).[1]

However, others demonstrate substantial responses to changes in consumption taxes in several countries (Crossley et al. 2014, Cashin and Unayama 2016, Büttner and Madzharova 2017, D'Acunto et al. 2018). While value-added taxes (VATs) are almost universally included in posted prices, sales taxes in the US are generally not included in prices, potentially decreasing the salience of sales taxes in the US. Importantly, inattention to sales tax rates could reduce the effectiveness of sales tax changes (and similar small or temporary tax policies) as a macroeconomic policy (Gabaix 2016), while increasing the efficiency of the revenue-raising aspects of the tax through a reduction in consumption distortion (Farhi and Gabaix 2017).

In the United States, other work has noted that households respond to sales taxes in some ways such as crossing borders or changing online spending (e.g., Agrawal 2015, Davis et al. 2016, Goolsbee 2000, Einav et al. 2014, and Baugh et al. 2015).[2]

[1] There are also important studies that analyze these issues in laboratory experiments; see e.g., Chen et al. (2014) and Feldman and Ruffle (2015).

[2] Others, notably Agarwal et al. (2017), find significant responsiveness to sales tax holidays (STH). However, STH differ from the sales tax changes in important ways. The average sales tax change lasts about 6 years, while the average STH lasts only 5 days. Moreover, sales tax changes uniformly affect taxable goods, while STH target a narrow range of products. These characteristics drive differences in both the channels available for households

Overall, this paper makes three main contributions to the literature. First, we undertake the most comprehensive analysis of consumer responses to sales tax rate changes in the US, reconciling some of the potentially conflicting empirical findings from previous work. Second, we explicitly analyze the response of spending on *tax-exempt* goods to sales tax changes, finding substantial elasticities. Third, we develop a novel quantitative model to evaluate whether the observed spending and shopping responses we observe are consistent with rational household behavior.

Our first contribution is to leverage detailed household-level spending data and 50 state and more than 2,000 distinct local sales tax changes to *quantify* the elasticity of both taxable and tax-exempt spending with respect to sales tax changes.

We focus mostly on relative high-frequency responses around the dates of tax implementation rather than around the dates the taxes are first passed so as to minimize bias from wealth and income effects.[3] While there are a large number of tax changes in total, the changes are highly persistent at a local level, with about 5 years between sales tax changes in a zip code. Moreover, through the use of newspaper archives and Google search data, we present evidence that households are aware of these tax changes, both before and after the implementation date.

We demonstrate that households respond in both the short and long run, but through different channels. In the short run, spending responses are dominated by intertemporal substitution, while long-run responses are driven by shifts in spending towards online purchases and lower tax jurisdictions. The long-run responses indicate a persistent awareness of the changes in relative prices induced by sales tax changes. As such, our results can reconcile previous work that shows insignificant spending effects of sales taxes at an annual level with other research demonstrating persistent impacts of sales taxes for online or cross-border spending.[4]

The large short-term spending elasticities are driven by stockpiling goods. The average consumer *anticipates* an upcoming tax increase and brings spending forward to periods with lower tax rates, a form of intertemporal tax arbitrage that is more pronounced for more storable and durable goods. In the long run, intertemporal substitution of spending is no longer an option for households.[5]

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to avoid taxes and differences in consumer attentiveness. For instance, we find strong evidence of intertemporal substitution of spending and spillover on exempt goods, while Agarwal et al. (2017) report that spending on goods covered by STH does not decline before or after the holidays, and few spillover effect on unaffected goods.

[3]The responses around such pre-announced sales tax changes reflect mostly (compensated) substitution effects if consumers are rational and taxes are salient. Wealth and income effects occur when consumers learn of the upcoming tax changes, well in advance of the implementation.

[4]The significant long-run responses in cross-border and online shopping demonstrate that the small average long-run spending response is due to the fact that (i) intertemporal substitution of retail spending is limited and most consumers are reluctant (or unable, given the very different sets of goods) to substitute between exempt and taxable goods, (ii) most consumers cannot easily visit lower tax jurisdictions, and (iii) many products cannot easily be purchased online (at least during our sample). This observation is important since it shows that the low average long-run response is not due to consumers forgetting about sales tax rates (e.g., Agarwal et al. 2013).

[5]We note that these estimates represent an average response. Some households may fail to recognize that taxes have changed and other households may "overreact". In this sense, the salience of the tax change must certainly have an impact on the overall response. In Appendix C, we discuss results consistent with this interpretation. We also test for heterogeneous effects, finding some evidence that higher-income households tend to have somewhat

While we have data for a large array of sales tax changes, these changes are not randomly assigned, but are often passed in response to changes in local tax revenue or are driven by changes in political leadership. However, the tax changes generally take months between inception, passage, and implementation. Because of this lag and the frequency of our data, it is unlikely that the timing of sales taxes is precisely correlated with an economic shock.[6]

In addition, we note both a significant *positive* spending response in the months before a sales tax increase which is mirrored by a *decline* after the increase in rates. This sharp spending reversal is unlikely to be caused by a monotonic trend in local economic conditions. Our results are also robust to more direct controls like indicators of local economic conditions, recessions, or even state-time fixed effects. Consistent with this identification assumption, controlling for local economic conditions does not change the estimated responses.

For our second contribution, we document that tax-exempt goods exhibit much the same pattern of response to sales tax changes as taxable goods.[7] We note that there are numerous potential explanations for this behavior. Consumers may be confused about which products are exempt, products may be *consumption* complements, and products might by *shopping* complements. In this paper, we provide evidence that the observed response of tax-exempt spending is largely driven by shopping complementarity, not consumption complementarity or confusion.

For instance, we find that only consumers with high shopping fixed costs stock up on both taxable and exempt goods. Consumers with low fixed costs on the other hand only stock up on taxable goods. We also find that online and mail order purchases only increase for taxable goods, because there are no or only few fixed costs to be shared for such purchases (e.g., common search costs). [8]

Lastly, the extent to which exempt spending responds also depends on the degree to which households can bundle their exempt and non-exempt spending. Households that shop at stores that sell solely exempt or solely taxable goods tend to have lower exempt spending responses.

Our final contribution is to address whether the magnitudes of the shopping and spending responses that we observe are rational through the use of a new quantitative model featuring rational, forward-looking consumers with full attention.

In the context of the model, households choose an optimal consumption plan and support this plan by managing inventories of storable taxable and a tax-exempt goods. Optimal inventories trade off holding costs (e.g., depreciation, opportunity costs) against the two main benefits from

larger responses (consistent with a role of liquidity in enabling the stockpiling of goods), but few household characteristics predict large differential responses.

[6]See Nakamura and Steinsson (2017, 2018) and the literature cited therein for a discussion of similar identification approaches in macroeconomics with high-frequency data.

[7]A greater fraction of products are tax-exempt in the United States relative to other countries with broader VATs. Moreover, this proportion varies across states, which each set their own rules for the goods that are tax-exempt. Overall, about 50% of spending observed in the Nielsen scanner data is exempt from state and local sales taxes.

[8]Tax payers are in principle required to pay a "use tax" to their home state when completing their annual taxes. However, compliance with the use tax is extremely low.

holding inventories of storable consumer goods identified by Keynes (1936, chp. 13).[9] First, consumers can shift purchases to periods with low taxes and prices while keeping consumption smooth. Keynes calls this the *speculative* motive. Second, consumers can reduce shopping fixed costs by holding larger inventories (e.g., fewer store visits per month), which he calls the *transaction* motive. Consistent with the transaction motive, consumers decrease the number of store visits in the month after a sales tax increase.

In this framework, the similar response of taxable and tax exempt goods is perfectly consistent with optimal inventory management. While shopping for taxable goods when tax rates are still low, consumers can reduce the need for future trips by also stocking up on tax-exempt goods. We call this property of demand *shopping complementarity*, because it holds even when the goods are consumption substitutes.

The model is successful in matching the estimated short- and long-run tax elasticities using only a few structural parameters. This is of interest because the effect of counter-cyclical policies depends on the response of aggregate demand in the short-run (e.g., Mian and Sufi 2012). Efficiency cost, static tax incidence, and optimal tax formulas on the other hand depend on long-run *consumption* elasticities.

The model yields several additional insights. It highlights the stark differences between the elasticities of intertemporal substitution of spending (EIS-S) and consumption (EIS-C) when goods are storable, a point forcefully made by Ogaki and Reinhart (1998).[10] It also demonstrates that tax and price elasticities of spending can be very different, even with rational consumers and full tax salience.[11] This is driven by the fact that changes in posted prices often differ from changes in sales taxes in terms of the amount of anticipation and the degree of permanence of the change. Hence, accounting for consumer expectations of tax and price changes is crucial when interpreting demand elasticities.[12]

We have reason to believe that our empirical results are generalizable to a wider set of both goods and households, despite them being derived from a subset of household spending on a selected sample of consumers. We replicate our primary specifications utilizing Nielsen's *store-level* sales data, thus removing any unrepresentativeness inherent to Nielsen households. Furthermore, in an extension to this paper (Baker et al. 2018) we analyze how households adjust car purchases around sales tax changes. We find a similar pattern of substitution, with even larger elasticities

[9] Keynes identifies a third motive – precautionary demand – in settings with unanticipated price or consumption shocks. See Hendel and Nevo (2006a) for a modern treatment of this idea using scanner data.

[10] A recent literature in industrial organization (IO) also focuses on demand dynamics. In a series of papers, Hendel and Nevo (2006a,b, 2013) show that accounting for consumer inventories is crucial when analyzing demand responses to temporary price reductions, i.e., "sales". Much like in Hendel and Nevo (2006a, 2013), households in our model accumulate inventories because they expect prices to be higher in the future. However, our model also captures the spending response for tax-exempt goods and the extensive-margin shopping trip response we observe in the data.

[11] Coglianese et al. (2017) make a similar point in the context of excise taxes on gasoline.

[12] An important consequence is that we cannot easily compare our results to demand elasticities typically estimated in the IO literature. The tax-induced price changes in this paper are anticipated and affect a broad range of goods simultaneously, while demand elasticity estimates for individual goods typically use unanticipated, idiosyncratic price changes.

for car sales, consistent with our predictions for more durable goods.

Our results do not seem to be overly sensitive to the type of tax change that is passed. We find that households respond qualitatively similarly for both increases and decreases, small and large changes, and state and local changes.

Finally, we note that while inventory and working capital management has received a lot of attention in corporate finance, there are few studies in household finance that analyze similar issues on the consumer side, with most research focusing on households in developing countries (see e.g. Samphantharak and Townsend 2010). The evidence presented in this paper suggests that inventory management might also be an important investment opportunity for households in developed countries.

The rest of the paper is organized as follows. Section 2 describes the data utilized in the paper. Section 3 presents the research design. Section 4 estimates the response of household spending and shopping frequency to a pre-announced sales tax increase. Section 5 presents the model of shopping behavior. Section 6 provides additional evidence of shopping complementarities. Section 7 discusses long-run effects on cross-border and online shopping. Section 8 concludes.

2 Data

Our empirical analysis uses three main types of data: detailed high-frequency household retail spending scanner data and store-level sales data (both at the product-by-store level), monthly sales tax rates by 5-digit ZIP code, and data that complement our spending-based analysis by providing direct evidence of the tax implementation lag and household foresight.

2.1 Sales Tax Data

For data on local sales tax rates, we turn to Thomson Reuters OneSource sales tax service. This source allows us to construct a national database of ZIP code level sales tax rates at a monthly frequency from 2008 to 2015. The data contain comprehensive information on all sales taxes imposed in a given ZIP code stemming from the state, county, city, and from special tax rate districts, such as school or water districts, etc. Moreover, there is information on the combined sales tax in a ZIP code, which may differ from the sum of all of the aforementioned sales tax rates due to statutory maximum sales taxes imposed at a state level (e.g., state sales tax is 4% and the state imposes a maximum total local sales tax rate of 5%) or the fact that a lower-level tax jurisdiction such as a city overrides the sales tax rate of a higher-level jurisdiction, such as state sales tax rate. Our final sample includes over 40,000 ZIP codes from 48 states and Washington DC, excluding Alaska and Hawaii which are not covered by Nielsen's scanner data.

[Figure 1 about here]

2.1.1 Size and Frequency of Tax Changes

Figure 1 shows the variability in both levels and changes of state and local tax changes, of which we have approximately 50 and 2,000, respectively.[13] Local changes are driven overwhelmingly by changes in city and county level taxes, while other sales taxes covering metro areas, water districts, school districts, or other geographic groupings play a much smaller role. Despite this large number of tax changes, the average zip code goes about 5 years between tax changes. This is because there are many sales tax jurisdictions in the US. For instance, there are about 3,000 counties, 20,000 cities (incorporated places) and over 40,000 ZIP codes which we observe for 8 years in this data.

Sales tax changes in our sample period are highly asymmetrical. 80% of total observed changes in sales tax rates are positive, with average total sales taxes increasing from about 6.9% in 2008 to 7.2% in 2014. Restricting to changes in state sales taxes, we find that about 75% of changes are positive, with state sales taxes increasing from 5.4% to 5.7% on average over the decade to 2014.

While sales taxes are not uniformly distributed over months in a year, we do not find that they are excessively clustered in any particular month. January sales tax changes make up less than 20% of total sales tax changes. The first month of each quarter is overrepresented, with January, April, July, and October all exhibiting higher than average numbers of sales tax changes.

2.1.2 Additional State Tax Changes

State sales taxes generally make up the majority of total sales taxes in a given ZIP code. We therefore augment our sample with hand-collected state level changes in sales tax rates from 2004-2008 to match the sample period of the retail scanner data described below. The average state-level sales tax change (in absolute value) is 0.61 percentage points and the 25th and 75th percentiles of state level changes are 0.25 percentage points and 1 percentage point. Local sales tax rate changes are similar both on average (mean 0.54 percentage points, median 0.5 percentage points) and in their dispersion (standard deviation of 0.37 percentage points vs. 0.38 percentage points for state level tax changes).

2.2 Retail Spending Data

Household-level retail spending data is obtained from the Nielsen Consumer Panel (NCP, formerly the Homescan Consumer Panel) and store-level retail sales are obtained from the Nielsen Retail Scanner Panel (NRP).

[13] Several other papers (e.g., Cashin and Unayama 2016, D'Acunto et al. 2018) study responses to large singular changes in VATs. The large number of sales tax changes across localities allows us a great deal of power in assessing household responses and allows us to control for business cycle or time-related effects, add state-period fixed effects, and study differences in responses across tax changes of varying size.

2.2.1 The Nielsen Consumer Panel

The NCP consists of a long-run panel of American households in 52 metropolitan areas from 2004 to 2014. The NCP aimed at measuring household demographic characteristics, household income, and spending on retail goods. Using bar-code scanners and diary entries, participants are asked to report all spending on household goods following each shopping trip. Monetary prizes and other drawings are utilized to incentivize higher levels of engagement.

The NCP is constructed to be a representative sample of the US population and demographic information about participants is obtained each year. Nielsen maintains high quality data with regular reminders to participants that prompt them to report fully, and will remove non-compliant households from their panel.[14] Broda and Weinstein (2010) provide a more detailed description of the NCP. Einav et al. (2010) perform a thorough analysis of the NCP, finding generally accurate coverage of household purchases though having some detectable errors in the imputed prices Nielsen uses for a subset of goods. Overall, they deem the NCP to be of comparable quality to many other commonly-used self-reported consumer datasets.

Overall, there are more than 150,000 households in our sample with average tenures of about 4 years. For the purposes of this paper, we choose to exclude households that change ZIP codes at any point in their time. This exclusion is done because we generally cannot tell the exact month of a move within a year, so any change in sales taxes that accompany such a move may generate a spurious relationship with observed retail spending. Following these exclusions, over 135,000 households remain, yielding over 6 million household-month observations.

Given the nature of the data collection, the NCP primarily covers trips to grocery, pharmacy, and mass merchandise stores. The types of goods purchased span groceries and drug products, small electronics and appliances, small home furnishings and garden equipment, kitchenware, and some soft goods.

To categorize individual products (Nielsen's 'Product Groups') into taxable or tax-exempt goods, we first categorize products into one of the following broad categories: groceries, clothing, prepared food, medication, beer, liquor, wine, cigarettes, and non-exempt goods. We choose these categories to cover the range of categories that are treated differently on a state-by-state basis when it comes to determining whether a product is exempt from the sales tax. We then assign the 119 Product Groups to these 9 broader exemption categories. For instance, "Crackers", "Dough Products", "Fresh Meat", and "Fresh Produce" would be Product Groups categorized as 'grocery' purchases. Groceries, in turn, are often exempt from any state or local sales tax. "Prepared Food Ready to Serve" is assigned to the 'prepared food' category, while "Soft Goods" are treated as 'clothing'. The tax treatment of clothing or prepared food differs by state. Finally, a wide range of goods such as "Automotive" products, "Hardware and Tools", and "Toys and Sporting Goods" are categorized as 'taxable' since goods of that type are taxable in any state in the United States.

[14] Approximately 80% of households are retained from year to year.

The ability to measure spending at a good- and merchant-specific level, rather than at a merchant- or geographically-aggregated level (as in Cashin and Unayama 2016 or Agarwal et al. 2017) is crucial to our ability to fully understand households' response to changes in sales taxes. Without this good- and merchant-specific view, we would be unable to measure how spending shifts between exempt and taxable goods, and further substitution across merchants (e.g., to online or cross-border sales) would likewise be hidden. That is, good-specific data is required to conclude whether households are truly aware of sales taxes and respond in rational ways across the many potential dimensions of adjustment.

Overall, the NCP tracks a sizable amount of a household's spending on material goods. On average, we observe over \$350 of spending per month for each household. About half of this spending is on goods exempt from sales taxes while half is subject to sales taxes. Across states with sales taxes, only approximately 25-35% of total consumer spending is subject to sales taxes. This is largely due to the fact that almost all services are untaxed in most states, and households now spend over 50% of their total expenditures on services.

2.2.2 Addressing Non-Representativeness using Store-Level Data

One concern with the NCP is sample selection since consumers who opt-in to the panel might not be representative based on unobservable characteristics, in particular how much attention they pay to sales taxes. To assess this issue, we also use store-level sales data from the Nielsen Retail Scanner Panel (NRP), which contains price and quantity information of each UPC carried by a covered retailer and spans the years 2006-2014. Nielsen provides the location of the stores at the three-digit ZIP code level (e.g., 602 instead of 60208), and we use a population-weighted average sales tax rate using the cross-walk provided by Thomson Reuters.

3 Methodology

Our primary empirical methodology is to utilize a dynamic difference-in-differences specification with relatively high-frequency spending data at the household/store-month level. The economic interpretation of our empirical results depends crucially on whether the tax changes were anticipated. If tax changes are anticipated, then spending changes and shopping behavior around the tax changes documented in later sections reflect substitution effects, while income and wealth effects take place at the time households learn about an upcoming tax change.

Using newspaper article ratios and manually collected information on dates at which state sales tax legislation passed, we document that the news media covers upcoming sales tax rate changes well in advance and that there is a lag of several month between passage and implementation of a tax change. Hence, households have easy access to relevant sale tax information well in advance of the tax changes. More importantly, using Google Search data we show that some households *actively* acquire information about sales tax rates in advance of the tax rate changes. Both results are consistent with our findings in Section 4 that households adjust their spending patterns around sales tax changes.

3.1 Information About Future Tax Changes

This section provides direct evidence of the long lag between the date when a tax change is legislated and the date when the tax change is finally implemented (i.e., the implementation lag) and of fiscal foresight on the part of individuals.

3.1.1 Fiscal Lag between Passage and Implementation of State Tax Changes

For the more than 50 state tax changes, we manually identify the date at which the tax law was legislated on. As the most conservative estimates, we utilize the date of final passage (eg. date of signing by a governor) rather than any intermediate step (eg. passage by state legislature or even a committee).

We find that the median distance from this final state approval to the date of implementation is just over 3 months, with a mean distance of about 9 months. The shortest time from final approval until implementation was one week (following a government shutdown and emergency budget deal in New Jersey in 2006) and the longest was a tax change passed over 4 years in advance of its implementation.

We see these time periods as conservative estimates of when households could become aware of the upcoming tax changes. In most cases, it was fairly clear in advance of these last dates that the tax would be passed. For instance, the bill might be passed by the lower house of the legislature with both the upper house and the governor committing to pass or sign it when it arrives on their desks. The process from a bill's proposal to its final signature or vote would often take a period of 2 weeks to 3 months.

3.1.2 Evidence from Newspaper Article Counts

Unfortunately, *local* sales tax changes are too numerous to manually identify the date a law passes. For another measure of advance notice of tax changes, we turn to newspaper data. Much information about a future tax change becomes available well before a law passes the legislative process (see e.g., Kueng 2018). Such laws are typically discussed in the media well before they voted on by the politicians or by the voters in case of ballot initiatives.

To deal with these issues, we employ data from the Access World News Newsbank database to measure news coverage of sales taxes at both a state and local level. We query a set of over 3,000 national, state, and local US newspapers at a monthly frequency from 2008 to 2015. Our query obtains the number of articles for each city-month or state-month that mention the term 'sales tax' or 'sales taxes'. We exclude classified ads and restrict our search to newspapers rather than newswires or magazines. Raw counts of articles may give a misleading measure of news coverage of sales taxes given changes in the number and size of newspapers at any given time. To better gauge relative news coverage, we normalize each monthly value by the total number of newspaper articles written in that month and location.

We conduct searches at two levels of geographic aggregation. The first is at a state level (including Washington DC as its own state). The second is at a city level, where we attribute newspapers to cities based on Access World News' categorization. Given that both our sales tax and retail spending data are at a ZIP code level, we match states and cities to ZIP codes using the city-state-ZIP matches in the Thomson Reuters sales tax data. This method yields a good match, with only 77 out of 1,468 cities with newspapers being unable to be matched to ZIP codes in our sample.

[Figure 2 about here]

Figure 2(a) shows an alternative metric of fiscal foresight in the months surrounding state sales tax rate changes relative to the previous analysis of manually collected legislative dates. It displays the evolution of the ratio of news articles that mention sales taxes in the 10 months before and 10 months after a change in sales tax rates. Specifically, it displays the coefficients from regressing the log-level of the newspaper article ratio on leads and lags of monthly state sales tax changes, controlling for state and time fixed effects. The dashed lines represent 95% confidence intervals using standard errors clustered at the state level.

We find a gradual increase in articles, with the article ratio being significantly higher than the baseline level starting approximately 6 months prior to the change. In the month before the change occurs, the peak ratio is about 75% higher than the baseline. Since this figure is scaled by the size of the change, larger sales tax changes tend to get more news coverage relative to smaller changes. Following the change, news about sales taxes quickly recedes to the baseline level, with the ratio being indistinguishable from zero just 1-2 months following the change.

3.1.3 Evidence from Google Searches

To obtain direct measures of foresight by individuals, we use Google search data obtained from Google Trends from 2004 to 2015 to study the search behavior of consumers around sales tax rate changes. Google Trends is a Google application that gives a time series of the relative amount of local search activity for specific search terms on Google.com. The values of Google Trends represent the number of searches on Google.com for the specified search term relative to the total number of searches on Google.com derived from a sample of all Google search data. Google Trends is normalized such that the highest value for the entire time period and term is set equal to 100. Its range of values is always between 0 and 100, where higher values correspond to higher ratios of total searches on Google.com for a given search term.

A potential concern, discussed in detail by Stephens-Davidowitz (2013), is that Google Trends imposes thresholds for reporting search data below which it imputes a zero value. For instance, too few searches were done for the search term 'econometrics' in July 2006 in Texas. Therefore, Google Trends displays a 0 rather than a low number, producing large swings in the time series data. For the term 'sales tax', there are a large number of zeroes between 2008 and 2010 in smaller states. We treat these values as missing data rather than true zeroes, due to the censoring that Google employs. In the years after 2010, there are only a few zeroes per year. Our results are robust to excluding all data from the years prior to 2011 or excluding smaller states altogether from the estimation.

While Figure 2(a) shows that households have in principle ready *access* to the latest information about upcoming sales tax changes, it remains to show that households actively acquire this information. Figure 2(b) shows that households indeed increase the search for information about sales taxes in anticipation of a sales tax change. The figure plots the coefficients of the same specification as before, replacing the newspaper article ratio with the Google Search index. As with the newspaper-based measure, search peaks in the month before a change takes place, rising to over 130% of the baseline level of search. Google searches about sales taxes do not respond as far in advance of the change occurring but have significantly elevated levels for a longer period than does the news-based measure. This may reflect a subset of households only realizing sales taxes may have changed over a longer period.

3.2 Estimating Spending and Shopping Response to Sale Tax Changes

For most of our examination of the impact of changes in sales tax rates, we look at monthly changes in spending and shopping behavior at a household or store level. By construction, the control groups are those households/stores who did not experience a change in the sales tax rate that they face in the same period. The same household that is in the control group during one period might face a tax change in another period and thus will be in the treatment group. However, given the relative rarity of tax changes in a particular jurisdiction, a particular household will be in the treatment group for only one or two months across the sample.

All regressions include both period and household/store-level fixed effects, thus controlling for seasonal effects, macroeconomic effects, and allowing for household/store-level trends over time.

We estimate the response of various outcomes to changes in total and state sales taxes, respectively, by running regressions of the following form:

$$\Delta y_{ht} = \beta \Delta \ln(1 + \tau_{jt}) + \gamma_h + \theta_t + \lambda' z_{ht} + \varepsilon_{ht}. \tag{1}$$

Δy_{ht} is the change in the outcome of interest in month t by household or store h. We consider several outcome variables, including the log of pre-tax expenditures on taxable goods (i.e., expenditures evaluated at posted pre-tax prices), log expenditures on tax-exempt goods, log online and mail-order purchases, the fraction of spending done in a neighboring tax jurisdiction, and measures of shopping frequency. $\Delta \ln(1+\tau_{jt})$ is the log-change of the gross of sales tax rate (since sales taxes are ad valorem) in that month in the corresponding tax jurisdiction j, a zip code or a state (our results are little changed when utilizing the percentage change in sales taxes rather than the logged gross change in prices). γ_h are household/store fixed effects and θ_t are period fixed effects (year and month indicators). z_{ht} are additional time-varying household, store, or jurisdiction co-variates. Standard errors are clustered at the level of the source of the tax changes (i.e., at the level of the tax jurisdiction j), either state- or ZIP-level.

4 Response of Spending and Shopping Behavior

4.1 Taxable Spending

[Table 1 about here]

Table 1 shows how consumer spending by Nielsen panelists on retail goods subject to sales taxes changes following a change in the sales tax rate. We restrict the main analysis to tax increases both because the vast majority of tax changes in our sample period are tax increases and because the model below featuring storable and durable goods implies an asymmetric response to sales tax changes. Stocking up before a sales tax increase is easier and more likely synchronized across households in the month before the tax increase compared to letting inventories of storable and durable goods deplete in anticipation of a sales tax decrease.

4.1.1 The Spending Tax Elasticity

Panel A documents the main results of the analysis. Column 1 shows that following an increase in the combined total sales tax rate of one percentage point (e.g., from 3% to 4%), taxable household retail spending decreases by 2%. This change in spending is measured in the month of the tax change relative to the month prior.[15]

Column 2 restricts the analysis to state-level tax changes, which allows us to extend the analysis back to 2004, the start of the Nielsen Consumer Panel. The sales tax elasticity of taxable expenditures is almost identical to the one estimated using total sales tax changes in column 1, although it is estimated with less precision due to the fewer tax changes (despite the longer sample period).

4.1.2 Tax Increases vs. Decreases

Column 3 shows that we obtain comparable results when analyzing only tax decreases. The tax elasticity is slightly smaller for tax decreases (1.7) compared to tax increases (2.0) but this small difference is not statistically significant.

4.2 Robustness of Spending Results

The two main concerns with the analysis presented in Table 1 are that the elasticities might be affected by changes in local economic conditions that might have led to the sales tax change,

[15] The vast majority of sales tax changes go into effect on the first of the month, so the entire month is under the new sales tax rate. Our estimates are robust to excluding or weighting sales tax changes that occur on a different day of the month (the 15$^{\text{th}}$ is the second most common day).

and that Nielsen consumers are not representative for the general population.

[Table 2 about here]

4.2.1 Controlling for Economic Conditions

Table 2, Panel A tests the robustness of these results. Column 1 adds local and state unemployment rates to control for local business cycle conditions. It also controls non-parametrically for time-varying household characteristics like income and family composition. We see little change in the coefficient of interest following the addition of these controls. Similarly, dropping the months from January 2008 to June 2009 that were part of the Great Recession according to the NBER recession dating committee also sees little change in the estimates, as seen in Column 2. Column 3 only uses within-state variation in sales taxes, including highly granular state-period fixed effects. Again, we find that the magnitudes of our estimates remain virtually unchanged.

Consumers can respond to an anticipated sales tax increase using four main margins of adjustment: moving purchases of storable and durable goods forward to the months before a sales tax increase (and potentially also consumption), shifting spending online and not paying use taxes, shopping in a neighboring tax jurisdiction with a lower sales tax rate, and substitution consumption from taxable to exempt goods. Columns 4 and 5 sequentially shut down the second and third margin (which are the focus of Section 7), thereby restricting the response to intertemporal substitution, while Section 4.3 below analyzes the extent to which households substitute consumption from taxable to exempt goods in the long run.

Column 4 restricts the sample to households that did not do any online and mail order purchases in that year, and Column 5 further restricts the sample to households that also do not purchase products in an alternative three-digit ZIP code outside of their own home ZIP code. As one might expect, the point estimates are larger in absolute value for such households that can only respond by engaging in intertemporal substitution, but we cannot reject that the response is the same as in the full sample. The small difference in the response reflects the fact that cross-border and online shopping only constitute a minority of purchases for most consumers in the NCP.

4.2.2 Representativeness of Nielsen Data

As mentioned above, one concern with the NCP is that consumers that select into the panel might not be representative based on unobservable characteristics, in particular how much attention they pay to sales taxes. In Panel B we address this issue directly by using store-level data from the Nielsen Retail Scanner Panel (NRP) instead of the household-level NCP data, thus removing any unrepresentativeness inherent to Nielsen households. We find slightly larger responses than in the NCP data (column 1 vs. 6), although we again cannot reject the hypothesis that the two estimates are the same because of the larger standard errors of the store-level estimates. However, we would expect larger responses in the store-level data because, while households can take steps to maintain their levels of spending by shifting to untaxed or less-taxed jurisdictions, stores have fewer margins to adjust their exposure to a sales tax increase in the short run.

Columns 7 and 8 show that these short-run responses are robust to controlling for state and local unemployment rate and adding state-period fixed effects, thereby identifying the response from local tax rate changes.

4.3 Intertemporal Substitution

Any consumer who is aware of an upcoming sales tax increase can at least temporarily avoid paying a higher tax by moving spending forward, even if he does not have the opportunity to shop online or to shop in a neighboring tax jurisdiction with a lower sales tax rate. Hence, intertemporal substitution is the most general adjustment mechanism and this section explores the extent to which consumers take advantage of it.

Intertemporal substitution is also the only margin of adjustment that requires consumers to be forward-looking. Tax incentives for the other two margins of adjustment, cross-border shopping and substitution to online purchases, only change when tax rates change. Estimates of these margins therefore do not test forward-looking behavior.

4.3.1 Shopping Behavior and Intertemporal Substitution

Consumers can move both consumption or spending forward to periods with low tax rates. If goods are storable or durable, these two forms of intertemporal substitution are not the same since consumers can purchase storable goods in advance of the sales tax increase without changing their consumption behavior.[16] If intertemporal substitution of consumption is low, increases in inventory purchases should decrease the shopping frequency as a larger inventory can support the same consumption rate over a longer period. Hence, comparing the tax elasticity of shopping trips with the tax elasticity of spending provides useful information about the elasticity of intertemporal consumption substitution, a point which the model in Section 5 establishes more formally.

Panel B of Table 1 shows that the number of distinct store visits responds negatively to increases in sales tax rates. The number of trips falls by a similar amount as overall spending, suggesting that the trips adjustment margin is a dominant one. This finding is robust to controlling for household characteristics and for business cycle conditions. Moreover, this extensive margin elasticity is estimated more precisely than the spending elasticity, with standard errors that are 30% smaller.

[16] Again, this analysis focuses on substitution effects that happened after any income and wealth effects have taken place, which typically happens when consumers learn about the upcoming tax increase.

4.3.2 Fiscal Foresight and Intertemporal Substitution Dynamics

Since sales taxes are almost always announced significantly in advance, we might expect that changes in household behavior precede the effective date of the sales tax change *if* households are forward-looking and are aware of upcoming sales tax changes. To test this prediction, we estimate a dynamic version of equation (1), regressing *levels* of taxable and tax-exempt spending on leads and lags of the sales tax rate changes. For example, a positive coefficient in period $t = -2$ indicates an increase in sales tax two periods in the future tends to drive higher than average *levels* of spending in a given period.

[Figure 3 about here]

Figure 3 plots the patterns of spending in the months surrounding a change in sales taxes that is scaled to reflect a 1 percentage point tax increase. We find elevated levels of spending in the period preceding a sales tax increase that quickly reverse once the change takes effect. For a sales tax increase of 1 percentage point, we see a dramatic fall in spending in the month of the change (period 0) relative to the previous months (period -1), equivalent to a decline in spending of about 2.5%, similar to the more static responses reported in Table 1.

As seen in Figure 3, and across a range of specifications, we find that the average deviation from the household's shopping trend quickly converges to zero relative to the pre-tax-change period. That is, the short-term response of household spending is significantly different than, and greater than, any long-term response. Interestingly, exempt goods see a similar build-up prior to the tax increase and undergo a similar fall in the months afterwards. We study the response of tax-exempt goods to a change in sales tax rates in more detail in Section 4.6 below.

[Table 3 about here]

Table 3, Panel A shows that adding a lead in regression specification (1), which is in first differences, leads to similar results as the dynamic specification in levels shown in Figure 3. Spending increases in the month before a 1 percentage point tax increase by about 1.8%, followed by a 2% decreases in the month of the tax increase, thereby reverting to the same level of spending as before within one month of the tax reform (although measured based on pre-tax prices).

4.4 Storability, Durability, and Intertemporal Substitution

Given the revealed desire to shift spending forwards in time, we would expect to see this substitution manifest itself to a larger degree for more durable or storable goods. Tt would not be feasible to purchase a several-month supply of baked goods or fresh produce.

4.4.1 Measuring Storability

To examine whether this pattern holds true empirically, we must first categorize all products in the Nielsen Consumer Panel data by their durability and storability. We do so in two ways.

First, we use average purchasing patterns in the data to inform us about the storability of each product. To do so, we categorize each product group with a continuous measure of how frequently products in a given group were purchased. For instance, carbonated beverages, purchased every other week by an average household, would have a value of approximately $\frac{1}{2}$ (2 average purchases per month), while women's fragrances may have a value greater than 12 (purchased less than once a year). This 'shopping cycle', which is the purchase frequency of a typical product in product group g, is calculated first at a household level and then averaged across all households in the sample,

$$\text{Storability}_g = \ln\left(\frac{1}{N_H}\sum_{h=1}^{H}\frac{1}{T_h}\sum_{s=1}^{S_h}\mathbb{1}\{\text{Trip}_{sg}\}\right)^{-1}.$$

$\mathbb{1}\{\text{Trip}_{sg}\}$ denotes whether shopping trip $s \in S_h$ is one in which household h made a purchase from product group g. T_h measures the total number of months household h is in the sample and N_H represents the total number of households in the overall sample.

This first measure of storability and durability has the advantage that it is good-specific and continuous. However, it does not capture certain cases well.[17] We therefore supplement our analysis with a binary measure of durability by manually categorizing the 119 product groups contained in the Nielsen data into durable or storable groups following Cashin (2017).

Table 3, Panel C shows the product groups of taxable items sorted from highest to lowest number of times a product is purchased in this group per month (or from lowest to highest shopping cycle). The measures of storability and durability correspond fairly well, with durable goods as defined by Cashin (2017) on average having significantly lower purchases per month (0.3) than goods that are not classified as durable (0.8). However, the correlation coefficient is only 0.5, reflecting the fact that many non-durable products are fairly storable.[18]

4.4.2 The Impact of Storability on the Magnitude of the Spending Response

Panel B explores heterogeneity in the spending response by storability and durability of the purchased products. We interact the change in sales tax rates with our measures of product durability and storability. To do this, we conduct our analysis of heterogeneous behavior across categories of goods at a state-month level by regressing log-changes in pre-tax expenditures on taxable goods in (1) on state sales tax changes interacted with the one of the two measures of product storability and durability, either the continuous average inverse purchase frequency or the discrete hand-classified durability indicator. Collapsing the data to the state-month level minimizes problems that arise from individual households having large numbers of zeroes for their monthly spending on particular fine categories, but also reduces the number of observations

[17] For instance, many consumers might buy turkey meat only once a year, which does not reflect its storability but its seasonal demand as a traditional Thanksgiving dinner.

[18] Note that the average taxable product is purchased slightly less than once a month suggesting that monthly aggregation of purchases is a sensible choice when analyzing household-level data as in Table 1 rather than product-level data as in Table 3.

by an order of magnitude and thus the power of the analysis.

Column 3 uses the simple binary indicator for durability while Column 4 uses our preferred measure of storability, the continuous product group level data on inverted logged purchase frequency. Column 3 uses the simple indicator for durability as an interaction variable and finds a negative point estimate but it is not statistically different than zero. In Column 4, products purchased more frequently tend to be less affected by a change in sales taxes while infrequently purchased products see a larger than average response.

In Columns 3 and 4, we find that not only do more durable and more storable products have larger declines in the month of a sales tax increase, but they also see larger build-ups in the month prior to the increase. In fact, durable and storable products are the only product categories that see any increase in spending in the month before a sales tax increase.

To show the tremendous heterogeneity in responses by storability, in Column 5 we interact the sales tax changes (both current and lead) with the quartiles of the storability measure. We see an enormous range of demand elasticities. Purchases of products in the top quartile of storability increase by 15% the month before a 1 percentage point sales tax increase and then fall by 13% in the month of the tax change.

These results are consistent with recent studies of intertemporal household spending behavior. Cashin (2014) for instance also finds that this pattern was seen around changes in the sales tax rate in New Zealand. Using data regarding three substantial changes in the national sales tax (Goods and Services Tax) rate, he finds strong evidence for intertemporal substitution among both durables and non-durables. Consistent with our estimates he finds that the magnitude of the substitution from the month of the change to the month prior to the change is 3 to 5 times larger for durable or storable goods than for non-durable and non-storable goods.

Accounting for a product's storability is very important when price changes are anticipated. The reduced-form elasticity in Column 1 (and the elasticities in the other tables) represents an average tax elasticity across many different products with different tax elasticities, potentially highly related to differences in storability and durability. When extrapolating our estimates, policymakers therefore need to take into account two factors that have opposite effects on the tax elasticity of aggregate consumer spending. On the one hand, as mentioned in Section 2.2, the proportion of tax-exempt *services* is higher in the broader economy than is seen in the Nielsen data, which only covers consumer goods. In the next subsection we show that spending on tax-exempt consumer goods also responds to sales tax changes due to shared shopping trip costs. To the extent that services not covered by Nielsen (e.g. healthcare spending, rent) have relatively low shopping complementarities with taxable goods, this would reduce the tax elasticity of aggregate consumer spending relative to our estimates.

On the other hand, Nielsen also does not cover some significant taxable expenditure categories such as large durables. For example, three primary categories of taxable goods that are unobserved in our data are automobiles, large consumer electronics, and "white goods" (e.g. washing machines and refrigerators). In related work, we analyze the response of automobile purchases to sales tax changes (Baker et al. 2018), which shows that accounting for such durable products indeed increases the tax elasticity of aggregate consumer spending.

4.5 Price and Quantity Responses

While the majority of the paper discusses household responses in terms of changes in dollars of retail spending, it is possible that this may portray an incomplete view of household behavior. If retailers adjust prices or households shift spending to different types of goods, we may have a different interpretation of how the pre-tax spending response relates to actual consumption.

[Table 4 about here]

Table 4 examines two other important margins. Panel A mirrors the analysis done in Table 1 but using log-changes of quantities (items) purchased as the dependent variable rather than log-changes in spending. We find qualitatively similar effects, with declines in quantities mirroring the declines in spending following an increase in sales tax rates. This indicates that households are likely not simply substituting lower quality and lower priced goods to reduce pre-tax spending.

Panel B tests another potential confounding margin of adjustment. If retailers fully offset sales taxes, we might observe a decline in pre-tax spending with no actual decline in total (tax-inclusive) spending. Using data on both retail and wholesale prices we find that there is limited amounts of offsetting behavior on the part of firms. Retail prices decline by 0.15%-0.20% in the month following a 1 percentage point increase in sales tax rates, while wholesale prices remain unaffected.

Wholesalers tend to have much more stable prices, with fewer short-term sales than do retailers. Moreover, they less geographically concentrated and do not price to highly local conditions to the same extent that retailers do. Thus, a near-zero response from such wholesalers may be less surprising than among retailers themselves. We leave a more complete analysis of the firm response to sales tax changes, taking into account the response of demand documented in this paper, to future research.

4.6 Tax-Exempt Spending

In theory, we might expect that the effect of a sales tax increase on tax-exempt spending would be zero, or would mainly capture income or wealth effects of the tax reform. Hence, if we do not think that there are strong patterns of substitution between taxable and tax-exempt goods, tax-exempt spending could be used as a natural "control group" to estimate the effect of a tax change using a within-household difference-in-differences specification. However, there are a few reasons why we might still see an effect even for goods that are not directly affected by sales tax rate changes. Households may be unaware of the fact that some goods are exempt from sales taxes or may mis-attribute an exempt product to a non-exempt category.

In addition, sales tax changes apply to many goods at the same time and hence are different from idiosyncratic (pre-tax) price changes typically used to estimate demand. Sales tax changes can thus also affect store traffic in the same way large store sales are used by retailers for the purpose for cross-selling other goods with higher margins that are not on sale. In this section we therefore analyze the response of tax-exempt spending in order to assess the total effect of a sales tax rate increase on retail spending.

[Table 5 about here]

Table 5 reports the response of tax-exempt spending in the month of a sales tax rate increase relative to the previous month, mirroring the specifications seen in Table 1 and Table 2. Panel A finds a highly significant response of exempt spending to changes in both state and local sales taxes. This effect remains when limiting the analysis to state sales tax changes or local tax changes and when controlling for household characteristics and local business cycle conditions. Our estimates for tax-exempt goods are lower than for taxable goods, but both are significantly different than zero and are statistically indistinguishable from one another. Figure 3 shows that tax-exempt spending mimics the behavior of taxable spending not only in the month of the sales tax increase but also in the months surrounding that tax change.

5 A Model of the Shopping Response to Sales Taxes

Because we find evidence that complementarities in shopping for both taxable and exempt goods seem to drive household spending, we develop a model of household shopping to determine whether such behavior can be rationalized both qualitatively and quantitatively.[19]

In the model, rational forward-looking consumers know about an upcoming sales tax increase at date t_τ and choose consumption continuously. This setting corresponds to our main empirical research design which focuses on the high-frequency spending response around a sales tax increase, but after the upcoming sales tax change has been announced. Hence, these are compensated changes after the direct wealth effect of the higher future tax rate has already been incorporated into the steady-state consumption *levels*. Moreover, because these tax changes occur relatively infrequently within a tax jurisdiction, we use a perfect-foresight model.

5.1 The Model

Consumers face transaction fixed costs of shopping (e.g., time spent shopping, search costs, etc.) and therefore choose discrete-time transaction dates t_n in order to maximize lifetime utility

$$\int_{t=0}^{\infty} e^{-\rho t} u\big(C(t)\big) dt$$

with instantaneous utility $u\big(C(t)\big) = \frac{C^{1-1/\sigma}}{1-1/\sigma}$. $C(t) = \big(\sum_i b_i^{1/\eta} c_i(t)^{1-1/\eta}\big)^{\frac{\eta}{\eta-1}}$ is the composite good consisting of taxable good $c_\tau(t)$ and a tax-exempt good $c_e(t)$, where η is the intra-temporal elasticity of substitution between consumption of taxable and exempt goods. The household receives

[19] To save space, we provide the more detailed derivation of the model in Appendix B.

a constant flow of earned income y and can invest either in a risk-free asset a with continuously compounding return r or in inventories s_i of storable consumer goods which depreciate at rate δ.[20] For notational simplicity and without much loss of generality, assume that the starting date of the analysis, date $t = 0$, is a transaction date. The intertemporal budget constraint is

$$a_0 + \int_{t=0}^{\infty} e^{-rt} y \; dt = \sum_{n=0}^{\infty} e^{-rt_n} K_{t_n}$$

with initial financial assets a_0 and transversality condition $\lim_{n\to\infty} e^{-rt_n} a_{t_n} = 0$.[21] K_{t_n} are the total shopping trip costs that occur at transaction date t_n and include the fixed costs per trip κ and total consumption expenditures $P_{t_n} S_{t_n}$,

$$K_{t_n}\big(C_{t_n}, \Delta t_n\big) = \kappa + P_{t_n} S_{t_n}\big(C_{t_n}, \Delta t_n\big). \tag{2}$$

C_{t_n} denotes instantaneous consumption of the composite good at the beginning of the endogenously chosen period of length $\Delta t_n = t^-_{n+1} - t_n$, where t^-_{n+1} is the limit from below of the next transaction date t_{n+1}.

S_{t_n} is the necessary beginning-of-period inventory of the composite good to support consumption until the next transaction date. Inventory $s_i(t)$ of good i solves the differential equation $\dot{s}_i(t) = -\delta s_i(t) - c_i(t)$ at any point during the shopping interval. Because there is no uncertainty, there is no precautionary inventory demand and households optimally exhaust inventories fully right before the next shopping trip, $s_i(t^-_{n+1}) = 0$. This terminal condition determines the necessary initial inventory at the beginning of the shopping cycle. The expenditure-minimizing cost of a unit of the composite consumption good purchased at date t_n is $P_{t_n} = \big(\sum_i b_i p_{i,t_n}^{1-\eta}\big)^{1/(1-\eta)}$ and Hicksian demand is $c_{i,t_n} = b_i(\frac{p_{i,t_n}}{P_{t_n}})^{-\eta} C_{t_n}$. Total expenditures at the beginning of the shopping interval can be expressed in terms of inventory of the composite good, $P_{t_n} S_{t_n} = \sum_i p_{i,t_n} s_{i,t_n}$, with $s_{i,t_n} = b_i(\frac{p_{i,t_n}}{P_{t_n}})^{-\eta} S_{t_n}$. To simplify notation, we define $f(\Delta t_n; \alpha) = \int_{t=0}^{\Delta t_n} e^{\alpha t} dt = \frac{e^{\alpha \Delta t_n} - 1}{\alpha}$ such that the quantity purchased at date t_n given price index P_{t_n} is $S_{t_n} = C_{t_n} \cdot f(\Delta t_n; \phi)$, where $\phi = \delta - \sigma(\delta + \rho)$ is the effective discount rate of utility over the transaction interval Δt_n, which accounts for the pure time preference, the user cost of inventory, and the consumer's willingness to shift consumption intertemporally within a period between two shopping transactions.

[20] Given that we model goods as decaying exponentially, the assumption that depreciation across goods is equal is unlikely to substantially alter our results. Exponential decay implies that the amount of stocking up in advance of a tax increase is determined by a weighted average durability, not by the most perishable good. Adding good-specific depreciation to the model would allow the household to substitute along the margin of product choice – consuming fewer perishable goods around the time of the tax increase. In practice, consuming highly perishable goods does necessitate frequent trips to the store. But, in reality, a household may either forgo highly perishable goods temporarily or purchase such goods separately at a store with lower trip costs – both of which are still consistent with a relatively strong shopping complementarity. Indeed, though there is only one store location in the model, the practical possibility of a corner store with low trip cost but higher prices or limited products seems consistent with the insignificant spending response for highly perishable items in the data.

[21] We write continuous time variables as $x(t)$ and discrete time variables as x_{t_n}, where $x_{t_n} = x(t_n)$ is the value of x at the beginning of the endogenously chosen transaction interval.

5.1.1 Optimality Conditions

We formulate this problem as a dynamic program by discretizing the consumption plan to match the shopping intervals, building on an early model by Howitt (1977). For this purpose, we define the indirect utility function of consumption between shopping transactions as

$$U(C_{t_n}, \Delta t_n) = \max_{\{C(t)\}} \left\{ \int_{x=0}^{\Delta t_n} e^{-\rho x} u\big(C(t_n + x)\big) dx : \quad \int_{x=0}^{\Delta t_n} e^{\delta x} C(t_n + x) dx = S_{t_n} \right\} \tag{3}$$
$$= u(C_{t_n}) \cdot f(\Delta t_n; \phi).$$

Defining total wealth $w_{t_n} = a_{t_n} + y/r$, the problem can be written as a dynamic program,

$$V(w_{t_n}) = \max_{C_{t_n}, \Delta t_n} \Big\{ U(C_{t_n}, \Delta t_n) + e^{-\rho \Delta t_n} V(w_{t_{n+1}}) : \quad w_{t_{n+1}} = e^{r \Delta t_n}(w_{t_n} - K_{t_n}) \Big\}. \tag{4}$$

The envelope theorem requires that an additional dollar received at the beginning of each transaction period has the same present utility value,

$$V'_{t_n} e^{-r\Delta t_n} = e^{-\rho \Delta t_n} V'_{t_{n+1}}. \tag{5}$$

Optimal consumption and beginning-of-period inventory of the composite good are characterized by the first-order condition

$$\partial_C U'_{t_n} = \partial_C K'_{t_n} \cdot V'_{t_n}. \tag{6}$$

$\partial_C K'_{t_n} = P_{t_n} f(\Delta t_n; \phi)$ is the effective price of consumption taking into account the inventory costs. Combining equations (5) and (6) we obtain the familiar Euler equation for the growth rates of unobserved beginning-of-period consumption,

$$\frac{C_{t_{n+1}}}{C_{t_n}} = e^{\sigma(r-\rho)\Delta t_n} \left(\frac{P_{t_{n+1}}}{P_{t_n}} \right)^{-\sigma},$$

and of observable beginning-of-period inventory of the composite good,

$$\frac{S_{t_{n+1}}}{S_{t_n}} = \frac{C_{t_{n+1}}}{C_{t_n}} \cdot \frac{f(\Delta t_{n+1}; \phi)}{f(\Delta t_n; \phi)}. \tag{7}$$

The less familiar necessary condition determining the optimal transaction interval is

$$\partial_{\Delta t} U'_{t_n} - \partial_{\Delta t} K'_{t_n} \cdot V'_{t_n} = e^{-\rho \Delta t_n} \Big[\rho V_{t_{n+1}} - r w_{t_{n+1}} \cdot V'_{t_{n+1}} \Big]. \tag{8}$$

The left-hand side captures the net marginal utility at date t_n of increasing the time until the next shopping transaction at date t_{n+1}, which equals the present value of the additional consumption utility net of the additional cost to support the extension of the transaction interval. The terms in square brackets on the right-hand side capture the net marginal cost from starting the next period later, which equals the cost from delaying the continuation value net of the additional interest earned.

5.1.2 Steady State

From equation (5) we see that the stationary state, which starts at the first transaction date t_{ss} after the tax increase, requires $r = \rho$ unless the value function is linear. The optimal inventory and transaction intervals in the stationary state are jointly determined by combining equations (4) to (6),

$$(1-\sigma)\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}} = e^{\phi\Delta t_{ss}}\frac{f(\Delta t_{ss};r)}{f(\Delta t_{ss};\phi)} - 1, \tag{9}$$

and by the budget constraint in the stationary state $w_{t_{ss}} = (1-e^{-r\Delta t_{ss}})^{-1}(P_{t_{ss}}S_{t_{ss}}+\kappa)$. In the stationary state, the consumer trades off the additional user cost by marginally extending the shopping trip interval against the marginal benefit of pushing the fixed costs further into the future. To gain intuition, we can related this condition to the familiar square-root formula from static inventory models *if* we assume that the consumer is unwilling to substitute consumption intertemporally ($\sigma = 0$) and if we take a second-order approximation of (9) around $\Delta t_{ss} = 0$,

$$\Delta t_{ss} \approx \sqrt{\frac{\kappa}{\frac{\delta+r}{2}P_{t_{ss}}C_{t_{ss}}}}.$$

Higher transaction fixed cost as a fraction of total spending per trip lead to less frequent shopping, while higher user costs (depreciation and forgone interest) lead to more frequent shopping. However, in general with $\sigma > 0$ this is not a good approximation.

[Figure 4 about here]

5.2 Shopping Response to an Anticipated Sales Tax Increase

Figure 4 shows the evolution of composite consumption and inventories (left y-axis), the increase in the price index due to an anticipated sales tax increase (right y-axis) and endogenously chosen transaction intervals (x-axis). To make this example as stark as possible, we use a very large tax change of 10 percentage points and an unrealistically large elasticity of intertemporal substitution of 6 and a low fixed cost of \$2. Both choices are made only for this figure.

Because the sales tax increase is fully anticipated by forward-looking consumers, the problem of choosing consumption, inventories, and transaction dates is non-stationary and standard inventory models cannot easily be applied to this setting. However, as the figure shows, we can divide the solution into three stages: (i) the pre-period shopping intervals (Δt_{ss-q} for $q \geq 2$) that occur while the consumer faces the old sales tax rate in the current and the next shopping trip,

(ii) the interim shopping interval Δt_{ss-1}, which is the last trip before the tax increase, and (iii) the final stationary state of shopping intervals Δt_{ss} that occur under the new sale tax rate.

5.2.1 Tax Elasticities

Next we derive analytic expressions for the tax elasticities of the key variables in the model—consumption, inventory, and shopping intervals—and map them to the observed spending and trip elasticities estimated in Section 4.

Consumption Elasticity The consumption Euler equation governs the wealth-compensated consumption elasticity to an anticipated sales tax increase at the time of the tax change (i.e., after the consumer has been informed about the new tax rate and hence after the wealth effect on the steady-state consumption level has been incorporated),

$$\begin{aligned}\varepsilon_{c_i} \equiv \frac{d\ln\big(c_i(t_{ss})/c_i(t_{ss-1})\big)}{d\ln(1+\tau_{t_{ss}})} &= -(\sigma-\eta)\frac{d\ln(P_{t_{ss}}/P_{t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} - \eta\frac{d\ln(p_{i,t_{ss}}/p_{i,t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} \\ &= -(\sigma-\eta)B_\tau - \eta\ 1_{\{i=\tau\}}.\end{aligned} \tag{10}$$

The second line uses $d\ln(P_{t_{ss}}/P_{t_{ss-1}})/d\ln(1+\tau_{t_{ss}}) = B_\tau$, where $B_\tau = p_{\tau,t_{ss}}s_{\tau,t_{ss}}/(P_{t_{ss}}S_{t_{ss}})$ is the expenditure share of taxable goods in steady state. For taxable goods, the reduced-form consumption elasticity is unambiguously negative (or non-positive), while the sign of the elasticity of tax-exempt consumption depends on the relative size of the two structural elasticities, the *inter*temporal substitution elasticity σ and the *intra*temporal substitution elasticity η.

Shopping Elasticity The two reduced-form consumption elasticities ε_{c_τ} and ε_{c_e} are not directly observable in the data since consumption differs from spending. Moreover, substitution of consumption is not the only or even the main adjustment margin available to consumers. Instead, consumers can also respond by bringing spending forward and thereby extending the time until the first transaction under the higher tax rate. Using (7) and (9), the increase in the length of the interim shopping interval Δt_{ss-1} (and hence the start date t_{ss} of the steady state under the higher tax rate) can be expressed in closed form as

$$\Delta t_{ss-1} - \Delta t_{ss} = \frac{\ln(P_{t_{ss}}/P_{t_{ss-1}})}{\delta + r}.$$

The consumer trades off the marginal return from bringing spending forward before taxes increase (numerator) against the additional user cost incurred during the shopping interval (denominator). The shopping interval does not change unless the price level is expected to change. Therefore, the structural interpretation of the short-run elasticity of the shopping trip interval is

$$\varepsilon_{\Delta t_{ss-1}} \equiv \frac{d\ln(\Delta t_{ss}/\Delta t_{ss-1})}{d\ln(1+\tau_{t_{ss}})} \approx -\frac{B_\tau}{(\delta+r)\Delta t_{ss}}. \tag{11}$$

Spending Elasticity Combining (7) with (11), the short-run elasticities of taxable and exempt spending are

$$\varepsilon_{s_{i,t_{ss}-1}} \equiv \frac{d\ln(s_{i,t_{ss}}/s_{i,t_{ss}-1})}{d\ln(1+\tau_{t_{ss}})} \approx \varepsilon_{\Delta t_{ss}-1} + \varepsilon_{c_i} \tag{12}$$

and the long-run spending elasticities are well approximated by the corresponding consumption elasticities,

$$\varepsilon_{s_{i,\infty}} \equiv \frac{d\ln(s_{i,t_{ss}}/s_{i,t_{ss}-q})}{d\ln(1+\tau_{t_{ss}})} \approx \varepsilon_{c_i} \tag{13}$$

for $q \geq 2$.

5.2.2 Calibration and Aggregation

We calibrate the model to match steady state values, the long-run responses, and one short-run elasticity: the fall of taxable spending in the month of the tax increase relative to steady state. We then assess the model along two dimensions. First, we analyze whether the model can generate the short-run spending dynamics for both taxable and tax-exempt goods shown in the left panel of Figure 3. Second, while matching the short-run dynamics is an important test for the model to pass, it does not tell us whether the magnitudes of the observed responses are economically reasonable. To answer this question, we calculate the revealed reservation wage implied in the shopping fixed costs necessary to match the short-run spending dynamics.

The long-run response of tax-exempt spending is close to zero as seen in Figure 3. Looking at equations (10) and (13), this implies that intertemporal and intratemporal consumption substitution elasticities σ and η must be of similar size. To assess whether both are small or large, we calculate the relative difference between the long-run spending elasticities of taxable and tax-exempt, which equals the intratemporal consumption elasticity. The estimated difference is small and hence we set both elasticities to 0.29 (the long-run difference), although this difference is not statistically different from zero.

The two remaining parameters calibrated to steady state values are the share parameters b_i and the steady-state transaction interval Δt_{ss}. The share parameters are set to match the average expenditure shares of taxable and tax-exempt goods in months without sales tax changes: 0.55 and 0.45, respectively. We set the steady state interval to 0.27 months, corresponding to the sample average of 8.3 days between two shopping trips. The effective annual risk-free rate is 3% and the depreciation rate is set such that the steady state equation (9) holds. Relative pre-tax prices are normalized to one.

Before calibrating the remaining parameter κ to match the decline in taxable spending in the month of the tax increase, we need to adjust for the fact that model time is measured at trips frequency rather than monthly frequency (which did not matter for steady state calibrations).

To eliminate artificial lumpiness resulting from the allocation of trips to months,[22] we distribute shopping start dates of a unit mass of otherwise identical consumers uniformly on an interval that starts at date 0 and has length Δt_{ss-2}.[23] We can then aggregate per trip quantities s_{i,t_n} (valued at pre-tax prices normalized to 1) to monthly spending quantities $s_{i,t}$, where t measures event time, as follows:

$$\begin{aligned} s_{i,-2} &= \frac{s_{i,t_{ss-2}}}{\Delta t_{ss-2}} \\ s_{i,-1} &= (1-\Delta t_{ss-2})\frac{s_{i,t_{ss-2}}}{\Delta t_{ss-2}} + s_{i,t_{ss-1}} \\ s_{i,0} &= [1-(\Delta t_{ss-1}-\Delta t_{ss-2})]\frac{s_{i,t_{ss}}}{\Delta t_{ss}} \\ s_{i,1} &= \frac{s_{i,t_{ss}}}{\Delta t_{ss}}. \end{aligned}$$

In month -1, the rate of spending over the initial fraction $(1-\Delta t_{ss-2})$ of the month is $s_{i,t_{ss-2}}/\Delta t_{ss-2}$ (spending per trip $s_{i,t_{ss-2}}$ times shopping frequency $1/\Delta t_{ss-2}$). The rate of spending over the remaining fraction Δt_{ss-2} of the month is $s_{i,t_{ss-1}}/\Delta t_{ss-2}$. In month 0, the rate of spending is initially 0 on an interval of length $\Delta t_{ss-1} - \Delta t_{ss-2}$ because each household stocked up more on interim shopping trip t_{ss-1} in month -1. The spending rate on the remaining fraction of month 0 is $s_{i,t_{ss}}/\Delta t_{ss}$.[24]

With this aggregation, setting $\kappa = \$5.2$ matches the decline of 1.45% in taxable spending in the month of the tax increase relative to the steady state (left panel of Figure 3). These fixed costs per trip enter the model solution as a fraction of total spending per trip, which we set to its sample average of $P_{t_{ss}}S_{t_{ss}} = \$83$.[25]

5.2.3 Model Evaluation

The right panel of Figure 3 shows that the model is successful in producing the short-run spending patterns surrounding a 1 percentage point sales tax increase, both qualitatively and quantitatively. The simple model fits the data well even though it only uses three data points for the calibration (the long-run spending changes of 0 and -0.29 and the short-run deviation of taxable

[22] To see the issue arising from time aggregation of a single consumer, suppose that $\Delta t_{ss} = \Delta t_{ss-2} = 0.25$, which holds approximately in the data, but $\Delta t_{ss-1} = \Delta t_{ss} + \varepsilon$ for an arbitrarily small $\varepsilon > 0$ due to additional stockpiling. This consumer would therefore only make 3 trips in month -1 but 4 trips in any other month, which would lead to very large monthly spending changes even though spending per trip in the continuous-time model would increase only very little on trip t_{ss-1} relative to all other trips (i.e., $s_{i,t_{ss-1}} \approx s_{i,t_n}\ \forall\ t_n \neq t_{ss-1}$).

[23] Equivalently, we could endow consumers with different inventory levels at date 0.

[24] Technically, starting with a unit mass of consumers that have completely unsynchronized shopping cycles, a systematic change in long-run shopping intervals Δt_{ss} relative to Δt_{ss-2} in response to a sales tax increase introduces small echo effects in aggregate monthly steady state spending either due to a recurring hole in the distribution of shoppers over a small interval of length $|\Delta t_{ss-2} - \Delta t_{ss}|$ or a small amount of excess mass (bunching) over an interval with the same length. However, this difference is very small in practice such that our aggregation procedure yields a very good approximation of average monthly spending dynamics.

[25] We exclude small transactions from this calculation in order to identify shopping trips rather than say lunch purchases for immediate consumption for example, which are not captured by the model.

spending from the steady state of -1.45).

We assess the economic magnitude of these responses using auxiliary data from the American Time Use Survey (ATUS) to calculate the reservation wage implied in the estimated fixed costs. Across our sample period, people in the ATUS report spending on average 0.1 hours per day on grocery shopping. The average and median number of days between two trips to a grocery store by consumers in the Nielsen data are 6 and 4 (which is lower than the 8.3 days for general store visits used above to match the response of all spending, not just grocery spending), implying that the typical household spends about half an hour per trip. These estimates transform the shopping fixed costs of $\kappa = \$5.2$ into an economically reasonable range for the hourly reservation wage of \$9 to \$13 (after income and payroll taxes).

6 Shopping Complementarity

The reduced-form response of tax-exempt spending in Section 4.6 is consistent either with non-salience of tax-exemption status (i.e., consumer confusion about which goods are exempt), complementarity of consumption, or with complementarities between taxable and tax-exempt spending arising from the short-run shopping cost savings achieved by also stockpiling tax-exempt goods while shopping for taxable goods before the tax increase.

In this section, we provide evidence for the role of shopping trip complementarities in explaining the observed patterns. We document this novel mechanism along three dimensions, taking advantage of the detailed information regarding merchant type and household shopping trips.

First, we exploit heterogeneity in "revealed costs" of shopping across consumers, reflected in the consumer's average shopping frequency in the sample. Consumers that shop infrequently in the absence of a tax change reveal that they face higher shopping costs than frequent shoppers and hence should increase tax-exempt spending relatively more. This may reflect both higher reservation wages as well as higher direct costs like gasoline or public transit fees.

Second, we test the extent to which the exempt spending response depends on the degree to which consumers can bundle their exempt and taxable spending. Intuitively, consumers that shop at stores that sell solely exempt or solely taxable goods should have lower exempt spending responses given the lower levels of shopping complementarities. Finally, we implement a form of a placebo test by looking at the relative response of taxable and tax-exempt online spending, since shopping complementarities are likely minimal when shopping online.

[Table 6 about here]

We see these results as evidence for shopping complementarities driven the response of tax-exempt goods rather than confusion on the part of the household or srong consumption complementarities across taxable and tax-exempt goods. If households are simply confused about which items are exempt, we likely would not see as stark a difference across households in the size of the tax-exempt goods' spending response. Similarly, if tax-exempt goods responded due to *con-*

sumption complementarities with taxable goods, they should respond similarly across households (eg. those with both high and low shopping costs and separate or combined shopping patterns).

6.1 Differential Exempt Response by Shopping Costs

Table 6, Panel A investigates whether households with different 'revealed shopping costs' behave differently following a change in sales taxes. We first calculate the average number of shopping trips they make in a month for each household. We then assign the top 25% of households (with more than 19 trips per month) as 'low-shopping-cost' households and the bottom 25% of households (with fewer than 9 trips per month) as the 'high-shopping-cost' households. We propose that the average number of shopping trips a household takes per month correlates negatively with the total costs of the trip, including transportation costs, inventory costs, and time costs, in line with the model in Section 5.

Columns 1 and 2 estimate the spending response of exempt and taxable goods for households with low shopping costs following a sales tax increase. We find no impact on exempt spending, while taxable spending declines 2.2%. In contrast, for households we deem to be high-cost shoppers, both exempt and taxable spending fall nearly identically (Columns 3 and 4), suggesting that these households bundle their purchases to minimize the number of shopping trips that they must undertake.

6.2 Differential Exempt Response by Shopping Complementarity

Panel B examines the response of exempt spending across two different types of households. Using the granular Nielsen purchase data, we determine how skewed a given household's average shopping trip is towards either exempt or taxable purchasing:

$$\text{Trip Complementarity}_i = 1 - \frac{\sum_j |(T_{ij} - 0.5)| \times 2}{\sum_j \mathbf{1}}.$$

That is, if all of household i's trips (indexed by j) are for 100% taxable ($T_{ij} = 1$) or 100% exempt goods ($T_{ij} = 0$), his average trip complementarity measure would receive a value of 0. If each trip was composed of 50% taxable goods and 50% exempt goods ($T_{ij} = 0.5$), the measure would take on a value of 1.

In Column 5, we look at the highest quartile of households along this measure. We find that exempt spending for this group responds strongly to changes in sales taxes. In contrast, the quartile of households whose taxable and exempt spending is conducted at largely different stores sees a much smaller (and insignificant) change in spending on exempt goods shown in Column 6.

6.3 Differential Exempt Response with Online Spending

Finally, Panel C tests for the asymmetric response of online spending and mail order purchases to sales tax changes as predicted by models with shopping trip costs. When shopping online, there are fewer gains to bundling multiple purchases at once, since no transportation costs need be incurred across different websites and online purchases are often made of single goods rather than a cart full of goods. Just as with the low-cost shoppers, we find that, following an increase in sales taxes, spending on exempt goods from online merchants is largely unaffected (Column 7), while spending on taxable goods increases significantly (Column 8). This response suggests that consumers evade sales taxes by substituting to online platforms.

6.4 Identifying Demand with Shopping Complementarity

These results suggest that shopping complementarities play an important role in affecting the purchasing decisions of households. It also demonstrates the caution one must take when estimating price elasticities in a difference-in-differences framework, even in the absence of general equilibrium effects. Despite the fact that some goods' prices are unaffected, demand for them may shift due to changes in shopping behavior. This is true in our setting with tax changes, but also may be true when stores put portions of their goods on sale, or an appreciable number of items at a store undergo a price change at the same time.

7 Long-Run Responses to Persistent Tax Incentives

Section 4 has shown that intertemporal substitution is only a temporary response and spending quickly reverts back to pre-change levels. In the model, this happens because the intertemporal consumption substitution elasticity and the intratemporal substitution elasticity between taxable to tax-exempt products are both low. An alternative explanation of the small long-run responses is that it might reflect consumers forgetting about sales tax rates over time. We test this explanation by analyzing the spending response to changes in tax incentives that are more persistent. Specifically, we first test whether consumers who can shop in another tax jurisdiction with lower rates increasingly do so after a sales tax increase in their home ZIP code, and whether this response persists in the long run. We then extend our analysis of online shopping in Section 6 to test whether the effect of a sales tax increase on online spending is also persistent.

While our empirical approach is the first to leverage highly-local changes in sales taxes in this setting, we are far from the first to approach the question of how cross-border and online spending reacts to differences in sales tax rates. Previous work has thoroughly analyzed some of these impacts across a range of goods and empirical specifications (e.g., Goolsbee 2000, Agrawal 2015, and other studies cited in the introduction). We see our own estimates of cross-border and online tax avoidance as pushing this literature further and placing these results into a broader context of household tax avoidance across several avoidance channels.

[Table 7 about here]

7.1 Jurisdictional Tax Avoidance: 'Cross-Border' Shopping

One way to avoid paying more sales taxes is by engaging in cross-border shopping, taking advantage of lower rates in neighboring tax jurisdictions. To analyze this mechanism, we leverage one benefit of the Nielsen Consumer Panel, its ability to observe details of the shopping trips that households took including the type and location of a retailer. The NCP identifies stores by their three-digit ZIP code. In conjunction with the location of the household, this allows us to determine what fraction of household spending was conducted in an 'alternative' three-digit ZIP code or state (outside one's 'home' ZIP code or state).

Table 7, Panel A analyzes such cross-border shopping behavior. Column 1 tests whether this ratio responds to changes in local sales taxes, finding no significant effect. However, it is generally difficult for most households to switch to shopping in a different three-digit ZIP code given that the average three-digit ZIP code spans over 1,000 square miles. So, we might expect that households who are already able to conduct such shopping trips (e.g., those who might live or commute near a state or three-digit ZIP code boundary) might be more sensitive along this margin. In order to test this, we estimate (1) by regressing the fraction of a household's total spending in an alternative three-digit ZIP code outside its own home ZIP code (i.e., residential five-digit ZIP code) on log-changes in the gross sales tax rate interacted with the average alternative three-digit ZIP spending over all household-months.

Column 2 shows precisely this mechanism, a increase in alternative-ZIP spending in the month of the tax change for households who had already been conducting some of their shopping in alternative three-digit ZIP codes. Columns 3 and 4 show the same pattern for purchases across state lines, which are less common (average spending share of less than 2% compared to the 8% spending share in alternative three-digit ZIP codes). This signals that, for households who could conceivably substitute spending into a different tax jurisdiction, an increase in the sales tax in their residential tax jurisdiction makes them shift additional spending to that alternative tax jurisdiction.

The short-run month-to-month behavior in Columns 1-4 is estimated only imprecisely and the interaction terms are not statistically significant. One reason is that in contrast to the significant intertemporal substitution of short-run spending shown in Section 4, consumers should rationally only increase cross-border spending *after* sales taxes have increased in their home ZIP code, not before. Since most products in the Nielsen data are fairly storable or durable, the next cross-border shopping trip might be months away such that this adjustment occurs only gradually over time. Columns 5 and 6 show that the long-run response is indeed larger. The interaction effects are now two to three times larger than in the short-run and statistically significant for shopping across ZIP-3 borders.

An important note about substitution across jurisdictions is that while this pattern of behavior is evidence for strong impacts of sales tax changes on spending behavior, actual household consumption is affected to a much smaller degree. A recent study by Davis et al. (2016) also looks at the geographical substitution patterns surrounding sales taxes. Using credit card spending data to examine how ZIP code level spending is impacted by changes in sales taxes on both sides of the border of the tax jurisdiction, they estimate an elasticity of approximately 4.2 in ZIP codes that are located on state borders. Our results here align with their own. They also note persistent substitution to online retailers following sales tax increases, another persistent adjustment margin to which we turn next.

7.2 Use Tax Evasion: Online Shopping

Another potential way for households to avoid increases in sales taxes is to shop online or via catalog and mail order (hereafter just referred to as 'online spending' or 'online merchants'). Online merchants are generally not required to collect sales taxes if the merchant does not maintain a physical presence in the same state as the purchaser. During our sample period, most online purchases were done without purchasers paying sales tax. Instead, households are officially required to pay a 'use tax' to their home state when completing their annual taxes. However, compliance with the use tax is extremely low. For instance, only 0.3% of California tax returns reported *any* use tax related purchases in 2009. Because of this, households may shift purchases online where possible when sales taxes increase.

Fortunately, the Nielsen Consumer Panel data categorizes purchases made from online merchants separately from brick-and-mortar retailers. Panel B shows the result of this analysis. We find that household shift spending to these online merchants in the month following a sales tax increase (Column 7) and this substitution persists in the long run (Column 8).[26]

These coefficients suggest that online spending by an affected household increases 1.6% following an increase in the sales tax rate of 1 percentage point. Our estimates are consistent with recent estimates of the effect of taxation on online commerce. For instance, using state sales tax rate changes and purchase data from eBay, Einav et al. (2014) find an online-offline substitution elasticity of 1.8, which is in line with our estimate of 1.6. Similarly, Baugh et al. (2015) estimate a tax elasticity of online purchases of -1.1 using Amazon's staggered introduction of sales tax collection across different states in different months. This estimate is consistent with the ones reported above given that their experiment is a relative *increase* in the taxation of online purchases, while the previous experiments are relative *decreases* in the taxation of online purchases, i.e., an increase in the taxation of purchases from brick-and-mortar stores.

8 Discussion and Conclusion

From 2004 to 2014, there were more than 2,000 changes in state and local tax rates in the United States. Understanding how households respond to tax changes has important implications both for optimal taxation and for the effectiveness of consumption taxes as a tool to stimulate the economy.

[26] We also find positive effects when looking at the fraction of spending done online.

Our analysis speaks to the efficiency of taxation in the long run and the effectiveness of sales taxes in stimulating the economy in the short run. Since many consumers are forward-looking and sales tax changes appear to be salient for a substantial fraction of them, they strongly respond in the short run by stocking up on storable and durable consumer goods. This intertemporal *spending* elasticity and, hence, the stimulative effect of the tax change, is larger for more durable and storable goods. At the same time, we find that this effect is relatively short lived, which implies a small intertemporal *consumption* elasticity. This small long-run effect, while imprecisely estimated, would suggest that sales taxes are also a relatively efficient form of taxation.

We also find that households are, on average, aware of other methods to avoid sales taxes, increasing trips to locations with lower tax rates after a tax increase in their home ZIP code and increasing online purchases. These additional adjustment margins also affect the long-run efficiency of sales taxes and the short-run effectiveness of sales taxes as a macroeconomic stabilization tool. On the one hand, tax leakage (cross-border or online shopping) increases the responsiveness of demand in the short run and thus enhances the stimulus effect. On the other hand, tax leakage also reduces the long-run efficiency of the tax by increasing deadweight losses. However, we show that the aggregate effect of these leakages is quantitatively small.

Our estimates mainly capture intertemporal substitution of spending. The effectiveness of sales tax changes as a macroeconomic stimulus tool also depends on income and wealth effects, which are difficult to identify in our setting because we are unable to identify the exact date at which households become aware of the upcoming tax changes.[27] However, a sales tax stimulus program could be designed to be revenue neutral, either over the business cycle or by having compensating income tax changes such as the Japanese VAT change in 1997 (Cashin 2017).

We also find that tax-exempt spending is affected to much the same degree as spending on taxable goods. To explain this seemingly irrational behavior, we build and calibrate a model of inventory and shopping complementarities where households rationally bundle purchases of different types of goods into single shopping trips. We show that this shopping complementarity mechanism has support in the data, with households possessing lower revealed shopping costs tend to bundle purchases less than households with higher costs.

Finally, our analysis suggests that the spending response to foreseeable sales tax changes might be very different than to unexpected posted price changes. This has potentially important implications both for tax incidence analysis but also more generally for structural models of consumer demand.

[27] In Appendix C we discuss some evidence for income effects for a subset of sales tax changes where we know the approval date. Two other factors that affect the effectiveness of the stimulus are the fraction of liquidity constrained households and the price response of retailers. While our data does not measure liquid assets directly, we see slightly larger responses among higher-income consumers. Similarly, while prices in our data do not substantially respond to tax changes (see Table 4), this could change if sales taxes are used systematically as a counter-cyclical policy tool.

References

Agarwal, Sumit, John C. Driscoll, Xavier Gabaix, and David Laibson. 2013. "Learning in the Credit Card Market." *Working Paper.*

Agarwal, Sumit, Nathan Marwell, and Leslie McGranahan. 2017. "Consumption Responses to Temporary Tax Incentives: Evidence from State Sales Tax Holidays." *American Economic Journal: Economic Policy.*

Agrawal, David R. 2015. "The Tax Gradient: Spatial Aspects of Fiscal Competition." *American Economic Journal: Economic Policy*, 7(2): 1–29.

Baker, Scott R., Lorenz Kueng, Leslie McGranahan, and Brian T. Melzer. 2018. "Do Household Finances Constrain Unconventional Fiscal Policy?" *Northwestern University Working Paper.*

Baugh, Brian, Itzhak Ben-David, and Hoonsuk Park. 2015. "The 'Amazon Tax': Empirical Evidence from Amazon and Main Street Retailers." *Working Paper.*

Broda, Christian, and David E. Weinstein. 2010. "Product Creation and Destruction: Evidence and Price Implications." *American Economic Review*, 100(3): 691–723.

Büttner, Thiess, and Boryana Madzharova. 2017. "Sales and Price Effects of Pre-announced Consumption Tax Reforms: Micro-level Evidence from European VAT." *University of Erlangen-Nuremberg Working Paper.*

Cabral, Marika, and Caroline Hoxby. 2013. "The Hated Property Tax: Salience, Tax Rates, and Tax Revolts." *Working Paper.*

Cashin, David. 2014. "The Intertemporal Substitution and Income Effects of a Consumption Tax Rate Increase: Evidence from New Zealand." *Working Paper.*

Cashin, David. 2017. "The Household Expenditure Response to a Consumption Tax Increase." *Working Paper.*

Cashin, David, and Takashi Unayama. 2016. "Measuring Intertemporal Substitution in Consumption: Evidence from a VAT Increase in Japan." *Review of Economics and Statistics*, 98(2): 285–297.

Chen, Xiu, Harry M. Kaiser, and Bradley J. Rickard. 2014. "The Salience of Excise vs. Sales Taxes on Healthy Eating: An Experimental Study." *Working Paper.*

Chetty, Raj, Adam Looney, and Kory Kroft. 2009. "Salience and Taxation: Theory and Evidence." *American Economic Review*, 99(4): 1145–1177.

Coglianese, John, Lucas W. Davis, Lutz Kilian, and James H. Stock. 2017. "Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand." *Journal of Applied Econometrics*, 32(1): 1–15.

Crossley, Thomas F., Hamish W. Low, and Cath Sleeman. 2014. "Using a Temporary Indirect Tax Cut as a Fiscal Stimulus: Evidence from the UK." *Working Paper.*

D'Acunto, Francesco, Daniel Hoang, and Michael Weber. 2018. "Unconventional Fiscal Policy." *AEA Papers and Proceedings*, 108 519–23.

Davis, Trevor, Dan Knoepfle, Stephen Sun, and Constantine Yannelis. 2016. "Greener on the Other Side: Estimating Consumer Sensitivity to Local Sales Tax Changes." *Working Paper.*

Einav, Liran, Dan Knoepfle, Jonathan Levin, and Neel Sundaresan. 2014. "Sales Taxes and Internet Commerce." *American Economic Review*, 104(1): 1–26.

Einav, Liran, Ephraim Leibtag, and Aviv Nevo. 2010. "Recording Discrepancies in Nielsen Homescan Data: Are they Present and Do They Matter?" *QME*, 8(2): 207–239.

Farhi, Emmanuel, and Xavier Gabaix. 2017. "Optimal Taxation with Behavioral Agents." *Working Paper.*

Feldman, Naomi E., and Bradley J. Ruffle. 2015. "The Impact of Including, Adding, and Subtracting a Tax on Demand." *American Economic Journal: Economic Policy*, 7(1): 95–118.

Finkelstein, Amy. 2009. "EZTax: Tax Salience and Tax Rates." *Quarterly Journal of Economics.*

Gabaix, Xavier. 2016. "Behavioral Macroeconomics Via Sparse Dynamic Programming." *Working Paper.*

Goolsbee, Austan. 2000. "In a World without Borders: The Impact of Taxes on Internet Commerce." *Quarterly Journal of Economics*, 115(2): 561–576.

Griffith, Rachel, Ephraim Leibtag, Andrew Leicester, and Aviv Nevo. 2009. "Consumer Shopping Behavior: How Much do Consumers Save?" *Journal of Economic Perspectives*, 23(2): 99–120.

Hendel, Igal, and Aviv Nevo. 2006a. "Measuring the Implications of Sales and Consumer Inventory Behavior." *Econometrica*, 74(6): 1637–1673.

Hendel, Igal, and Aviv Nevo. 2006b. "Sales and Consumer Inventory." *RAND Journal of Economics*, 37(3): 543–561.

Hendel, Igal, and Aviv Nevo. 2013. "Intertemporal Price Discrimination in Storable Goods Markets." *American Economic Review*, 103(7): 2722–2751.

Howitt, Peter. 1977. "Intertemporal Utility Maximization and the Timing of Transactions." *American Economic Review*, 67(2): 156–165.

Keynes, John Maynard. 1936. *The General Theory of Employment, Interest and Money.*: Macmillan Cambridge University Press.

Kueng, Lorenz. 2018. "Tax News Shocks and Consumption." *Northwestern University Working Paper.*

Mian, Atif, and Amir Sufi. 2012. "The Effects of Fiscal Stimulus: Evidence from the 2009 Cash for Clunkers Program." *Quarterly Journal of Economics*, 127(3): 1107–1142.

Nakamura, Emi, and Jón Steinsson. 2017. "Identification in Macroeconomics." *Working Paper.*

Nakamura, Emi, and Jón Steinsson. 2018. "High Frequency Identification of Monetary Non-Neutrality: The Information Effect." *Working Paper.*

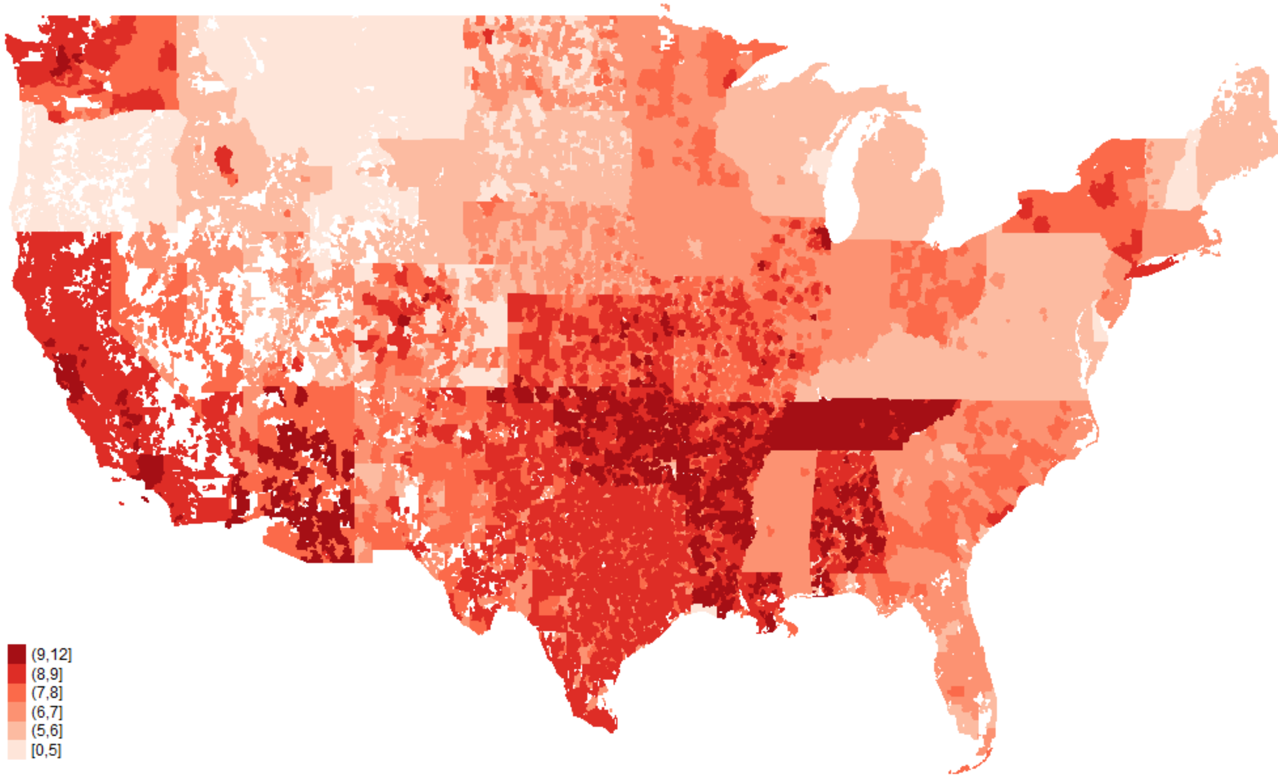
Ogaki, Masao, and Carmen M. Reinhart. 1998. "Measuring Intertemporal Substitution: The Role of Durable Goods." *Journal of Political Economy*, 106(5): 1078–1098.

Samphantharak, Krislert, and Robert M. Townsend. 2010. *Households as Corporate Firms: An Analysis of Household Finance Using Integrated Household Surveys and Corporate Financial Accounting.*(46): : Cambridge University Press.

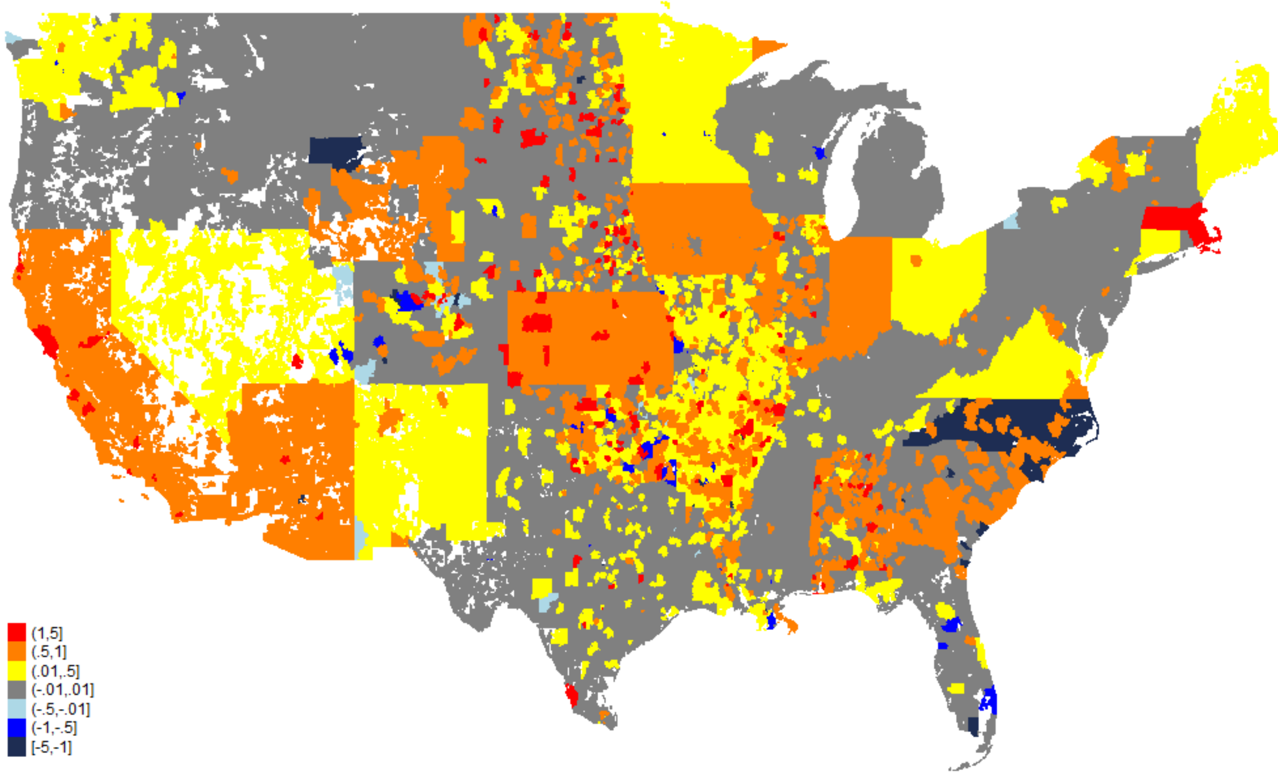
Stephens-Davidowitz, Seth. 2013. "The Cost of Racial Animus on a Black Presidential Candidate: Evidence Using Google Search Data." *Working Paper.*

Figure 1: ZIP Code Level Sales Tax Rates

(a) Sales tax rates



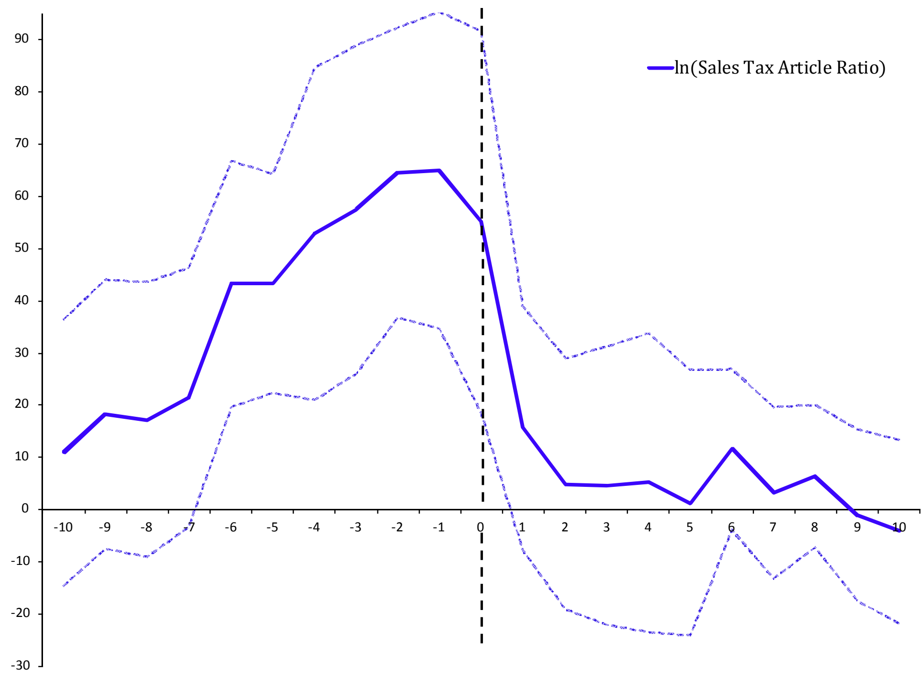
(b) Tax rate changes, 2008-14



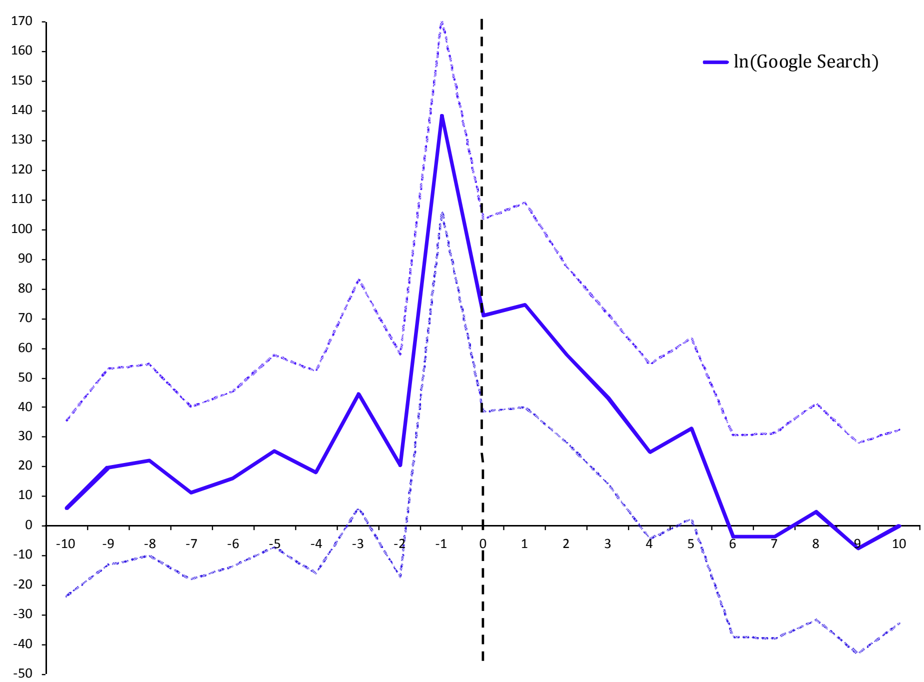
Notes: Maps plot the maximum level (a) respectively change (b) of total sales tax rates in each five-digit ZIP code for years 2008-14, matching the sample period of the Nielsen Consumer Panel. Sales tax rates are expressed in percentages. Total sales tax rate changes may be driven by changes in state, city, county, or special district sales tax rates. White ZIP codes have missing sales tax rates or are not covered by Nielsen.

Figure 2: Response of Newspaper Coverage and Google Searches to State Tax Changes

(a) News article ratio around state sales tax rate changes (in %)



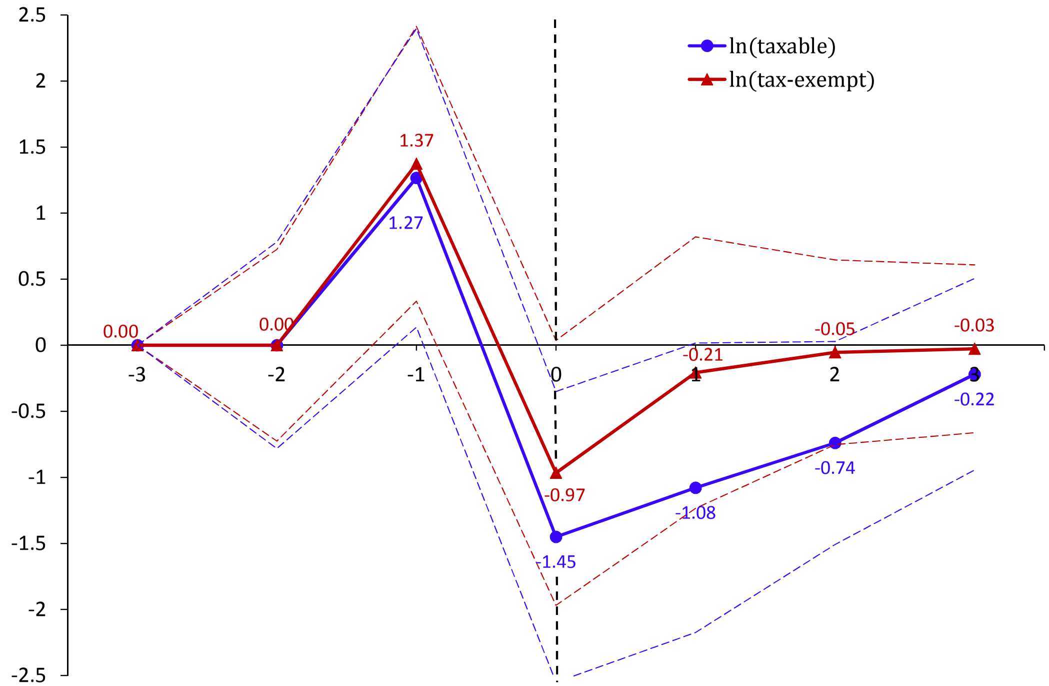
(b) Google Search around state sales tax rate changes (in %)



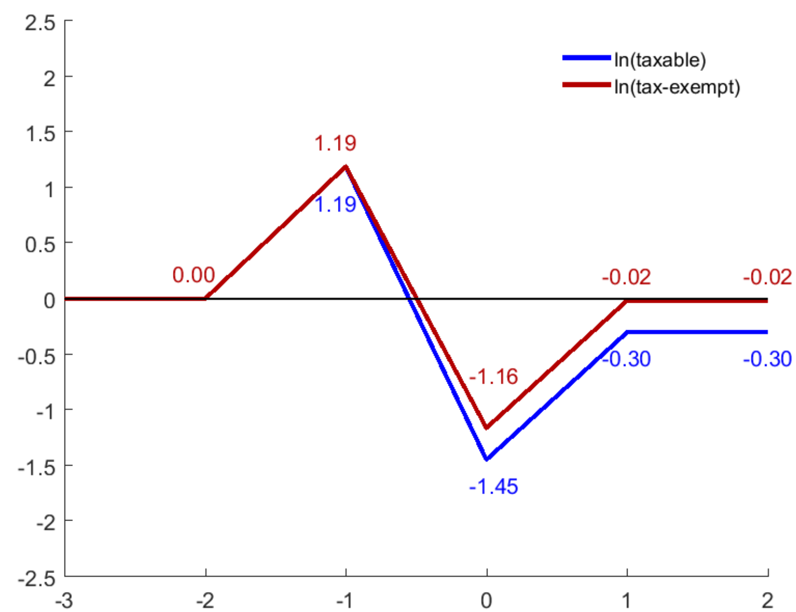
Notes: Top panel plots coefficients from a regression of the ratio of news articles that contain the term 'sales tax' or 'sales taxes' as a fraction of all newspaper articles in a given month across newspapers in that state. Y-axis units are percentage points. News articles taken from Access World News and cover approximately 3,000 US newspapers ranging from large national papers to local papers. Bottom panel plots coefficients from a regression of logged Google search activity from Google Trends. Y-axis units are percentage deviations from baseline. Household and period fixed effects are included. Standard errors clustered by state. Red vertical lines denote 'time 0', where a state level sales tax rate change occurs.

Figure 3: Spending Dynamics around a Sales Tax Increase: Estimation and Model

(a) Estimation: β coefficients from log-level regression

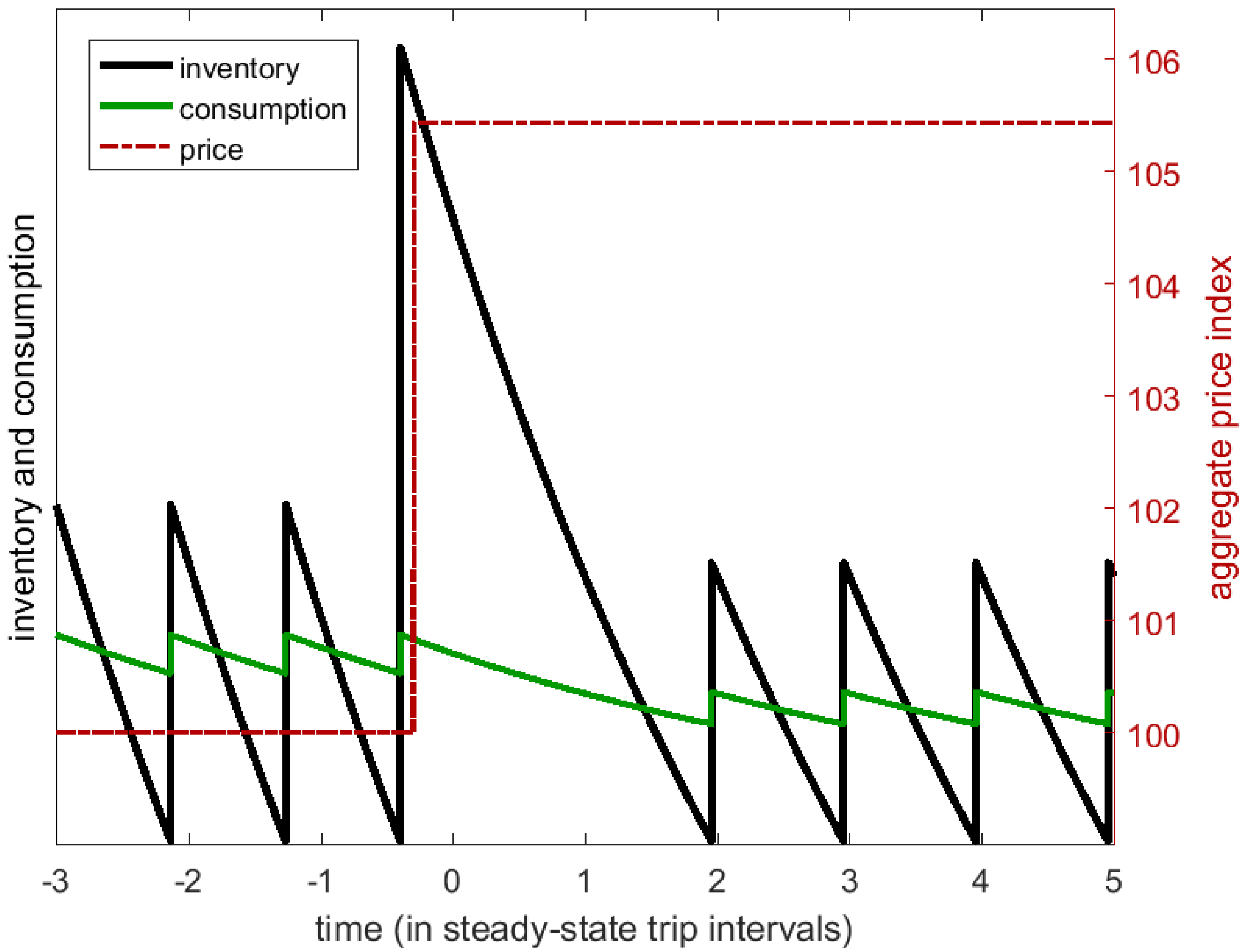


(b) Model: Log-levels in discrete time (monthly)



Notes: Left panel plots coefficients of a regression of the logged amount of pre-tax household retail spending on taxable and exempt products on leads and lags of total sales tax rate increases. All coefficients are scaled to an increase in sales taxes of 1 percentage point. Dashed lines represent 95% confidence intervals from standard errors clustered at the zipcode level. Periods -1, 0 and 1 reflect the three months around the tax increase and periods -2, 2 3 reflect the surrounding three quarters. Coefficients are normalized to be zero in period -2. The right panel shows the corresponding monthly series of the log-levels of taxable and tax-exempt spending generated by the continuous-time model in Section 5.

Figure 4: Continuous-Time Model Dynamics around a Sales Tax Increase



Notes: Figure plots the evolution of inventory $S(t)$ and consumption $C(t)$ of the composite good and the tax-inclusive aggregate price index $P(t)$ around a sales tax increase. To make this example as stark as possible, we use a very large tax change of 10 percentage points and an unrealistically large intertemporal consumption substitution elasticity of $\sigma = 6$ and a low fixed cost of $\kappa = 2$. Otherwise, the model parameters are set as described in Section 5.

Table 1: Response of Taxable Spending and Shopping Frequency to Sales Tax Changes

	A. Spending			B. Shopping Frequency	
	Baseline	State taxes only	Tax decreases	Log(trips)	Levels (# of trips)
	(1)	(2)	(3)	(4)	(5)
Δln(1 + total sales tax rate)	-2.036***		-1.719*	-1.479***	-20.164***
	(0.648)		(0.965)	(0.449)	(5.562)
Δln(1 + state sales tax rate)		-2.185**			
		(1.031)			
Period FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Observations	4,137,927	5,928,468	4,114,413	4,137,927	4,137,927
R-squared	0.014	0.013	0.014	0.020	0.026

Notes: Total sales tax rates combine all sales taxes within a ZIP code, including state, county, city, and special districts. The dependent variable in Panels A is monthly changes in logged household taxable spending as measured by Nielsen Consumer Panel and the log and level of the number of shopping trips per month in Panel B. Taxability of household spending is defined at a state level depending on what categories of goods are exempt from sales taxes (e.g., groceries, clothing, medication). For robustness, the dependent variable is winsorized at the 1% level. Other household characteristics include fixed effects for income bins and family size. The sample average number of trips per month in column 5 is 15.1. Regressions span 2004-2014 for state sales tax rate changes (column 2) and 2008-2014 for total sales tax rate changes. Standard errors in parentheses are clustered at the level of the tax jurisdiction.

Table 2: Response of Taxable Spending and Shopping Frequency to a Sales Tax Increase

	A. Nielsen Consumer Panel					B. Nielsen Retailer Store Panel		
	Local econ. and HH char.	Drop Great Recession	State-period FE	No online spending	No border shopping	Baseline	Local econ. and store FE	State-period FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\ln(1 + \text{total sales tax rate})$	-2.082***	-2.012**	-2.269***	-2.224***	-2.145***	-2.814**	-2.794**	-3.265**
	(0.648)	(0.882)	(0.701)	(0.691)	(0.756)	(1.368)	(1.368)	(1.440)
Period FE	Yes	Yes		Yes	Yes	Yes	Yes	
Household FE	Yes	Yes	Yes	Yes	Yes			
Household characteristics	Yes	Yes	Yes	Yes	Yes			
Local unemployment rate	Yes	Yes	Yes	Yes	Yes		Yes	Yes
State-period FE			Yes					Yes
Store FE						Yes	Yes	Yes
Observations	4,137,927	3,285,747	4,137,886	3,565,145	2,926,272	2,461,491	2,461,491	2,461,491
R-squared	0.014	0.015	0.015	0.020	0.024	0.140	0.140	0.150

Notes: The dependent variable is monthly changes in logged taxable spending as measured by the Nielsen Consumer Panel and the Nielsen Retailer Panel data, spanning 2008-2014. Robust standard errors in parentheses are clustered at the level of the tax jurisdiction.

Table 3: Storability and Intertemporal Substitution

	A. Average Effect		B. Response by Storability			C. Purchase Frequency of Taxable Products	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δln(1 + sales tax rate)	-2.185**	-2.021**	-1.206	-1.538	-1.476	CARBONATED BEVERAGES	1.942
	(1.031)	(0.934)	(1.257)	(1.240)	(1.324)	CANDY	1.700
Δln(1 + sales tax rate), lead		1.826***	0.092	-0.010	0.015	PAPER PRODUCTS	1.615
		(0.550)	(0.812)	(0.649)	(0.658)	PET FOOD	1.382
						ICE CREAM, NOVELTIES	0.967
Δln(1 + sales tax rate) × I(durable)			-2.979			SOFT DRINKS, NON-CARB.	0.906
			(2.915)			DETERGENTS	0.726
Δln(1 + sales tax rate) × I(durable), lead			1.629*			WRAPPING MATERIALS	0.612
			(0.927)			STATIONERY, SCHOOL SUP.	0.604
						ORAL HYGIENE	0.602
Δln(1 + sales tax rate) × Storability				-2.209		PET CARE	0.591
				(1.792)		HAIR CARE	0.558
Δln(1 + sales tax rate) × Storability, lead				1.802*		LAUNDRY SUPPLIES	0.516
				(1.037)			
						...	...
Δln(1 + sales tax rate) × Storability							
- Quartile 2					1.652*	BABY NEEDS	0.147
					(0.916)	ICE	0.146
- Quartile 3					-5.543*	FLORAL, GARDENING	0.143
					(2.911)	CHARCOAL, LOGS	0.110
- Quartile 4					-12.678**	COOKWARE	0.106
					(6.272)	FEMININE HYGIENE	0.099
Δln(1 + sales tax rate) × Storability, lead						FRAGRANCES - WOMEN	0.081
- Quartile 2					-0.300	PHOTOGRAPHIC SUPPLIES	0.076
					(0.489)	MEN'S TOILETRIES	0.075
- Quartile 3					1.951*	CANNING, FREEZING SUP.	0.069
					(1.127)	TOYS & SPORTING GOODS	0.065
- Quartile 4					14.910*	GRT CARDS/PARTY NEEDS	0.049
					(8.885)	SEWING NOTIONS	0.044
						SEASONAL	0.042
Period FE	Yes	Yes	Yes	Yes	Yes	SHOE CARE	0.041
Household FE	Yes	Yes	Yes	Yes	Yes		
State FE			Yes	Yes	Yes		
Product FE			Yes	Yes	Yes		
Observations	5,928,468	4,129,999	307,520	307,520	307,520	Sample mean (weighted)	0.846
R-squared	0.013	0.014	0.064	0.064	0.064	Sample standard deviation	0.602

Notes: The dependent variable is the monthly log change in taxable retail spending by product group and state across all households in the Nielsen Consumer Panel, 2004-2014. The main independent variable is changes in state sales tax rates. We drop "magnet data", leaving 53 unique product groups. Storability is the inverse of purchase frequency in Panel C. Purchase frequency is the number of pruchases per month. Regressions in columns 3-5 are estimated using least squares weighted by average sales per product group. Robust standard errors in parentheses are clustered at the state level.

Table 4: Quantity and Price Response

	A. Quantity Response				B. Price Response			
Dependent variable:	Δln(taxable)	Δln(exempt)	Δln(taxable)	Δln(exempt)	Δln(retail price)		Δln(wholesale price)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(1 + total sales tax rate)	-2.330***	-1.458***			-0.215***		-0.008*	
	(0.479)	(0.458)			(0.036)		(0.004)	
Δln(1 + state sales tax rate)			-2.245**	-1.744***		-0.171**		-0.007
			(0.908)	(0.566)		(0.069)		(0.015)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes				
Product FE					Yes	Yes	Yes	Yes
ZIP3 FE					Yes	Yes	Yes	Yes
Observations	4,140,969	4,142,698	5,928,529	5,928,499	4,333,000	5,862,621	4,333,000	5,862,621
R-squared	0.014	0.014	0.013	0.013	0.011	0.010	0.189	0.177

Notes: Dependent variables in columns 1 to 4 are monthly changes in logged quantities (items) purchased by each household in the Nielsen Consumer Panel. Dependent variables in column 5 to 8 are monthly changes in sales-weighted average prices by product group and ZIP-3 code for all retailers in the Nielsen Retail Scanner Panel. For robustness, the dependent variables are winsorized at the 1% level. Regressions span 2004-2014 for state sales tax rate changes using the Nielsen Consumer Panel (columns 3 and 4) respectively 2006-2014 using the Nielsen Retail Scanner Panel (columns 6 and 8), and 2008-2014 for total sales tax rate changes (columns 1, 2, 5, and 7). Standard errors in parentheses are clustered at the ZIP-3 code for total sales tax rate changes and at the state level for state sales tax rate changes.

Table 5: Tax-Exempt Spending Response to a Sales Tax Increase

	Baseline	State taxes only	Local econ. and HH char.	State-period FE
	(1)	(2)	(3)	(4)
$\Delta\ln(1 + \text{total sales tax rate})$	-1.395***		-1.329***	-1.215**
	(0.513)		(0.513)	(0.557)
$\Delta\ln(1 + \text{state sales tax rate})$		-1.618**		
		(0.656)		
Period FE	Yes	Yes	Yes	
Household FE	Yes	Yes	Yes	Yes
Household characteristics			Yes	Yes
Local unemployment rate			Yes	Yes
State-period FE				Yes
Store FE				
Observations	4,095,406	5,865,177	4,095,406	4,095,406
R-squared	0.015	0.014	0.015	0.016

Notes: See the description in Table 2. The dependent variable is the log change of monthly tax-exempt retail spending.

Table 6: Evidence of Shopping Complementarity

	A. Revealed Cost Approach				B. Trip Complementarity		C. Placebo Test	
	frequent shoppers		infrequent shoppers		combined trips	separate trips	online purchases	
Dependent variable:	Δln(exempt)	Δln(taxable)	Δln(exempt)	Δln(taxable)	Δln(exempt)	Δln(exempt)	Δln(exempt)	Δln(taxable)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(1 + sales tax rate)	-0.010	-2.202**	-2.236*	-2.406*	-2.109**	-0.813	0.145	1.592**
	(0.756)	(0.910)	(1.191)	(1.451)	(0.828)	(1.16)	(0.464)	(0.709)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,086,921	1,091,667	934,657	951,890	1,049,599	895,365	6,868,924	6,868,924
R-squared	0.016	0.017	0.022	0.020	0.017	0.018	0.004	0.005

Notes: Sales tax rates in columns 1 to 6 combine all sales taxes within a ZIP code, including state, county, city, and special districts, while Columns 7 and 8 use state sales tax rates. The dependent variable is the monthly log-change of exempt or taxable retail spending as measured by Nielsen Consumer Panel data. Frequent shoppers in Columns 1 and 2 are consumers with average monthly trips above the 75th percentile (19 trips), while infrequent shoppers in Columns 3 and 4 have average monthly trips below the 25th percentile (9 trips). Columns 5 and 6 split the sample into households who possess the most disparate (column 6) and most combined (column 5) shopping trips in terms of taxable and exempt purchases. For robustness, the dependent variables are winsorized at the 1% level. Regressions span 2008-2014 for total sales tax rate changes and 2004-2014 for state sales tax rate changes. Standard errors in parentheses are clustered at the level of the tax jurisdiction.

Table 7: Long-Run Response to Persistent Tax Incentives

	A. Fraction Spent in Alternative Tax Jurisdiction						B. Online Spending	
	short-run response (one-month change)				long-run (12-month change)		short-run	long-run
Dependent variable:	Δln(frac. alt. ZIP)		Δln(frac. in alt. state)		Δln(alt. ZIP)	Δln(alt. state)	Δln(online spending)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(1 + total sales tax rate)	-0.075	-0.182***			-0.674***			
	(0.072)	(0.056)			(0.093)			
Δln(1 + total sales tax rate)		1.497			5.484***			
× avg. fraction in alt. ZIP3		(0.951)			(1.507)			
Δln(1 + state sales tax rate)			-0.003	-0.017		-0.199***	1.703**	1.591**
			(0.027)	(0.019)		(0.034)	(0.824)	(0.791)
Δln(1 + state sales tax rate)				1.334		4.731		
× avg. fraction in alt. state				(2.639)		(3.907)		
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,231,065	4,231,065	6,049,454	6,049,454	2,510,373	4,010,860	6,868,924	3,010,794
R-squared	0.005	0.005	0.005	0.005	0.119	0.101	0.005	0.044
Average of interaction variable		0.079		0.017	0.079	0.016		

Notes: Panel A examines changes in the monthly fraction of a household's retail spending in an alternative tax jurisdiction outside the household's residential 3-digit ZIP code, either an alternative 3-digit ZIP code or an alternative state. The dependent variable in Columns 1 to 4 are monthly changes while Columns 5 and 6 use 12-moth changes (e.g., change from March 2013 to March 2014). Panel B examines changes in the log of total online spending, including mail orders. Standard errors in parentheses are clustered at the level of the tax jurisdiction.

Online Appendix of
"Shopping for Lower Sales Tax Rates"

Scott R. Baker Stephanie Johnson Lorenz Kueng

A. Additional Data

A.1 Nielsen Retail Scanner (Retail Prices)

With the Nielsen Retail Scanner Panel (NRP), price and quantity information is available at the store level for each UPC carried by a covered retailer and span the years 2006-2014. An average (quantity weighted) price is reported, by UPC, for each store every week.[28] NRP covers 125 product groups with more than 3.2 million individual UPCs. Units are consistently standardized and most products are measured in ounces (OZ, 51%), count (CT, 45%) or ml (ML, 2%).

A.2 PromoData (Wholesale Prices)

We use PromoData to measure wholesale prices for grocery and retail goods. Promo obtains its information from one (confidential) major wholesaler in each market.[29] One downside to this approach is that, since no single wholesaler carries every SKU in a given market, information about the universe of goods is not observed. Overall, Promo prices are available for 32 markets after removing redundant markets and combining overlapping markets.[30]

Data on wholesale prices are available from 2006 - 2012. However, during 2012 the data loses a significant amount of coverage. For this reason, we perform robustness tests excluding 2012 data from our sample. PromoData contains all changes in price or deals that are run by the wholesaler. Thus, we take prices as constant between observations, based on the last observed price data. We then are able to collapse prices to a monthly level for each product group. To arrive at consistent unit prices within type of product (eg. product groups), we scale the observed wholesale prices by the number of goods in a 'pack' and by the size of the unit (eg. number of ounces in a candy bar and number of candy bars in a box). To make meaningful unit price comparisons we need to know the units associated with each good. Unfortunately unit information is often not provided

[28] For a given store, coverage over time is stable and relatively complete across all years. Unit prices are calculated as $price/(prmult \times size1\_amt)$.

[29] By only using one wholesaler, Promo relies on the Robinson–Patman Anti-Price Discrimination Act of 1936 that prohibits price discrimination. In particular, it prevents wholesalers from offering special discounts to large chain stores but not to other, smaller retailers.

[30] Leveraging this regional information provides additional variation but introduces more measurement error given less complete coverage in any given market both with respect to corresponding Nielsen product groups in the cross-section and time-series coverage of specific products.

or is inconsistently coded (e.g., CT, PACK, EACH, OZ, O etc.). We use the modal unit within UPC to impute missing values. The intuition is that if a product is recorded as being measured in OZ most of the time units are reported, it is probably measured in OZ.

A.3 Matching Wholesaler and Retailer Data

Given the large number of products in the retailer dataset we aggregate retail unit prices to the product group level before matching with wholesale prices. We assign products in the wholesaler data to Nielsen product groups by matching at the UPC level. The mapping is not one-to-one due to differences in end-digits when shifting to UPCs of different levels of granularity (e.g., some are reported with retailer specific end-digits, etc.). This leads to multiple Nielsen UPCs corresponding to a single Promo UPC for some goods. However, this appears to have little effect when merging Nielsen product groups to their Promo equivalents.

As a consistency check we also match retail and wholesale prices by UPC at a single point in time. The implied markup distribution supports the accuracy of both the raw data and our unit price calculations, with 90% of markups falling between -7% and 135%. We calculate Promo coverage of Nielsen product groups as the percentage of UPCs in each Nielsen product group that can be found in Promo. Overall, we see that about 4% of overall UPCs in Nielsen are also covered directly in the wholesale data for a given market. Aggregating across markets to the national level, this coverage increases somewhat.

The two datasets are merged based on the weekly date. That is, Promo prices are those associated with the week containing the Nielsen week-ending Saturday. For a Nielsen retailer using a 7-day period ending on Saturday the periods correspond closely. However, as mentioned above this is not the case for all retailers. For a retailer using a Thursday to Wednesday week, the Nielsen prices would pre-date the Promo prices by a few days.

Comparing unit prices is not completely straightforward as Promo units are missing for many products. As discussed above, we impute some missing units based on the modal unit reported in Promo for that UPC. When merging, we retain only UPCs for which the imputed Promo unit matches the Nielsen unit. A coarse attempt is made to standardize the more common Promo units before matching. In particular we assume O and Z refers to OZ and $C, CNT, PK, EA, EACH, STK, ROL, RL, PC, \#, CTN$ refer to CT.

A.4 State Ballot Propositions

To study tax salience, we focus on sales tax changes triggered by state-level ballot propositions. Using Ballotpedia.com we identify all state ballot propositions that involve changes in state sales taxes from 2004-2015. These data include propositions in Arizona, Arkansas, California, Colorado, Georgia, Maine, Massachusetts, Michigan, Minnesota, Missouri, South Dakota, and Washington, with some states having multiple ballots regarding sales taxes.

In total, we observe 20 propositions with potential effects ranging from a decline in sales taxes of 3.25ppt to an increase in sales taxes of 1ppt. 10 of the 20 propositions were successful, 9 were unsuccessful, and one was partially successful (took effect in a subset of state counties). 9 of the 20 propositions took place in November with the remaining propositions spread across February, May, June, and August.

B. Derivation of the Shopping Model

B.1 Supporting Calculations

B.1.1 Within-Period Value Function, $U(C_{t_n}, \Delta t_n)$

Define $f(\Delta t;\alpha) = \frac{e^{\alpha\Delta t}-1}{\alpha}$ with $f' = e^{\alpha\Delta t}$, $f^{(n)} = \alpha^{n-1}e^{\alpha\Delta t}$, $f(0) = 0$, $\lim_{\alpha\to 0} f(\Delta t;\alpha) = \Delta t$ and a second-order approximation around $\Delta t = 0$ is $f(\Delta t;\alpha) \approx (1+\frac{\alpha}{2}\Delta t)\Delta t$. The Lagrangian of (3) is $\int_{x=0}^{\Delta t_n}\left[e^{-\rho t}u(C(t_n+x)) - \lambda e^{\delta x}C(t_n+x)\right]dx + \lambda S_{t_n}$. Defining $F(C, C', t) = e^{-\rho t}u(C(t_n+t)) - \lambda e^{\delta t}C(t_n+t)$, the general form of the Euler condition of this problem is $F_C = \frac{dF_{C'}}{dt} = F_{C'C}C' + F_{C'C'} + F_{C't}C''$. Since $F_{C'} = 0$, this reduces to $F_C = 0$, which implies $e^{\delta x}\lambda = e^{-\rho x}u'(C(t_n+x)) = e^{-\rho x}C(t_n+x)^{-1/\sigma}$. Hence $C(t_n+x) = \lambda^{-\sigma}e^{\gamma x}$ and $C_{t_n} = C(t_n) = \lambda^{-\sigma}$, where $\gamma = -(\delta+\rho)\sigma$,

$$C(t_n+x) = C_{t_n}e^{\gamma x}.$$

Plugging into the constraint yields $S_{t_n} = \int_0^{\Delta t_n} e^{\delta x}C(t_n+x)dx = \lambda^{-\sigma}\int_{x=0}^{\Delta t_n} e^{(\delta+\gamma)x}dx = \lambda^{-\sigma}f(\Delta t_n;\phi)$, with $\phi = \delta+\gamma = \delta - \sigma(\delta+\rho)$, so that

$$S_{t_n} = C_{t_n}\cdot f(\Delta t_n;\phi).$$

Plugging into the objective function and integrating yields[31]

$$\begin{aligned} U(C_{t_n}, \Delta t_n) &= \int_{x=0}^{\Delta t_n} e^{-\rho x}u(C(t_n+x))dx = u(C_{t_n})\int_{x=0}^{\Delta t_n} e^{-\rho x}e^{\frac{\sigma-1}{\sigma}\gamma x}dx \\ &= u(C_{t_n})\int_{x=0}^{\Delta t_n} e^{\phi x}dx \\ &= u(C_{t_n})\cdot f(\Delta t_n;\phi). \end{aligned}$$

B.1.2 Inventories, S_{t_n}, s_{i,t_n}

Between shopping transactions, inventory evolves according to the first-order ordinary differential equation $\dot{s}_i(x) = -\delta s_i(x) - c_i(x)$, with boundary conditions $s_i(t_n) = s_{i,t_n}$ and $s_i(t_{n+1}^-) = 0$. The solution for $x \in [t_n, t_{n+1})$ is

$$s_i(t_n+x) = e^{-\delta x}\left[s_{i,t_n} - \int_{z=0}^{x} e^{\delta z}c_i(t_n+z)dz\right] \tag{14}$$

[31] Also note that $U(C_{t_n}, \Delta t_n) = U(S_{t_n}, \Delta t_n) = u(S_{t_n})\cdot f(\Delta t_n;\phi)^{1/\sigma}$.

Hicksian demand $c_i(t)$ is a function of the relative price at the transaction date t_n, $p_{i,t_n}/P_{t_n}$ such that $c_i(t_n+z) = b_i\big(\frac{p_{i,t_n}}{P_{t_n}}\big)^{-\eta} C(t_n+z) = b_i\big(\frac{p_{i,t_n}}{P_{t_n}}\big)^{-\eta} C_{t_n} e^{\gamma z}$. We can use individual inventories $s_i(t_n)$ to define inventories of the composite consumption good

$$
\begin{aligned}
S(t_n+x) \equiv \frac{\sum_i p_{i,t_n} s_i(t_n+x)}{P_{t_n}} &= e^{-\delta x}\Big[S_{t_n} - \int_{z=0}^{x} e^{\delta z} \underbrace{\frac{\sum_i b_i\Big(\frac{p_{i,t_n}}{P_{t_n}}\Big)^{-\eta} p_{i,t_n}}{P_{t_n}}}_{=1} C(t_n+z)dz\Big] \\
&= e^{-\delta x}\Big[S_{t_n} - C_{t_n}\int_{z=0}^{x} e^{(\delta+\gamma)z}dz\Big] \\
&= e^{-\delta x}\Big[S_{t_n} - C_{t_n} f(x;\phi)\Big].
\end{aligned}
$$

The condition $s_i(t_n+\Delta t_n) = s_i(t_{n+1}^-) = 0$ implies $S(t_n+\Delta t_n) = S(t_{n+1}^-) = 0$ and

$$S_{t_n} = C_{t_n} f(\Delta t_n;\phi).$$

Similarly, using $s_i(t_{n+1}^-) = 0 = e^{-\delta\Delta t_n}\Big[s_{i,t_n} - \int_{z=0}^{\Delta t_n} e^{\delta z} c_i(t_n+z)dz\Big]$, beginning-of-period inventories for the individual goods are

$$
\begin{aligned}
s_{i,t_n} &= \int_{z=0}^{\Delta t_n} e^{\delta z} c_i(t_n+z)dz \\
&= b_i\big(\frac{p_{i,t_n}}{P_{t_n}}\big)^{-\eta} C_{t_n}\int_{z=0}^{\Delta t_n} e^{(\delta+\gamma)z}dz = b_i\big(\frac{p_{i,t_n}}{P_{t_n}}\big)^{-\eta} C_{t_n} f(\Delta t_n;\phi) \\
&= b_i\left(\frac{p_{i,t_n}}{P_{t_n}}\right)^{-\eta} S_{t_n}
\end{aligned}
$$

and the expenditure share of good i is

$$B_{i,t_n} = \frac{p_{i,t_n} s_{i,t_n}}{P_{t_n} S_{t_n}} = b_i\left(\frac{p_{i,t_n}}{P_{t_n}}\right)^{1-\eta}.$$

B.1.3 Tax Elasticity of the Price Index

The effective cost-of-living price index is $P(\tau) = [b_\tau(1+\tau)^{1-\eta}\tilde{p}_\tau^{1-\eta} + b_e\tilde{p}_e^{1-\eta}]^{1/(1-\eta)}$, where $\tilde{p}_i$ is the pre-tax price so that $p_\tau = (1+\tau)\tilde{p}_\tau$ and $p_e = \tilde{p}_e$. Hence

$$
\begin{aligned}
\frac{d\ln P(\tau)}{d\ln(1+\tau)} &= \frac{1+\tau}{P}\frac{dP}{d(1+\tau)} \\
&= \frac{1+\tau}{P}\frac{1}{1-\eta}P^{\eta}(1-\eta)(1+\tau)^{-\eta} b_\tau \tilde{p}_\tau^{1-\eta} \\
&= b_\tau\left(\frac{(1+\tau)\tilde{p}_\tau}{P}\right)^{1-\eta} = b_\tau\left(\frac{p_\tau}{P}\right)^{1-\eta}.
\end{aligned}
$$

The taxable expenditure share is

$$B_\tau = \frac{p_\tau s_\tau}{PS} = \frac{p_\tau}{PS} b_\tau \left(\frac{p_\tau}{P}\right)^{-\eta} S = b_\tau \left(\frac{p_\tau}{P}\right)^{1-\eta}.$$

Hence,

$$\frac{d \ln P(\tau)}{d \ln(1+\tau)} = B_\tau.$$

B.2 Model Solution

B.2.1 Transaction Interval, Δt_n

Define $C = C_{\Delta t}$ with consumption flow $C_{\Delta t} = \int_{x=0}^{\Delta t} C(t_n + x)dx = C_{t_n} f(\gamma)$ so that $S = C\frac{f(\phi)}{f(\gamma)}$ and

$$\begin{aligned} U &= u(C) \cdot f(\gamma)^{\frac{1}{\sigma}-1} \cdot f(\phi) = u\big(C/f(\gamma)\big) \cdot f(\phi) = u(S) \cdot f(\phi)^{\frac{1}{\sigma}} \\ K &= \kappa + PC \cdot \frac{f(\phi)}{f(\gamma)} = \kappa + PS. \end{aligned}$$

The partial derivatives of U and K with respect to C are

$$\begin{aligned} \partial_C K' &= P\frac{f(\phi)}{f(\gamma)} = \frac{PS}{C} \\ \partial_C U' &= u'(C) \cdot f(\gamma)^{\frac{1}{\sigma}-1} f(\phi) = U \cdot \frac{u'(C)}{u(C)} \end{aligned}$$

such that (6) becomes

$$V' = \frac{\partial_C U'}{\partial_C K'} = \frac{(1-\frac{1}{\sigma})U}{PS}.$$

The partial derivatives of U and K with respect to Δt are

$$\partial_{\Delta t} K' = PC\big[-f(\gamma)^{-2} f(\phi) e^{\gamma \Delta t} + f(\gamma)^{-1} e^{\phi \Delta t}\big] = PS\big[\frac{e^{\phi\Delta t}}{f(\phi)} - \frac{e^{\gamma\Delta t}}{f(\gamma)}\big]$$

and

$$\begin{aligned} \partial_{\Delta t} U' &= u(C)\big[(\frac{1}{\sigma}-1) f(\gamma)^{\frac{1}{\sigma}-2} f(\phi) e^{\gamma\Delta t} + f(\gamma)^{\frac{1}{\sigma}-1} e^{\phi\Delta t}\big] \\ &= u(C) f(\gamma)^{\frac{1}{\sigma}-1} f(\phi)\big[\frac{e^{\phi\Delta t}}{f(\phi)} - (1-\frac{1}{\sigma})\frac{e^{\gamma\Delta t}}{f(\gamma)}\big] \\ &= U\big[\frac{e^{\phi\Delta t}}{f(\phi)} - \frac{e^{\gamma\Delta t}}{f(\gamma)} + \frac{1}{\sigma}\frac{e^{\gamma\Delta t}}{f(\gamma)}\big] = U\big[\frac{\partial_{\Delta t} K}{PS} + \frac{1}{\sigma}\frac{e^{\gamma\Delta t}}{f(\gamma)}\big]. \end{aligned}$$

Necessary condition for Δt_n Necessary condition (8) can also be written as

$$\partial_{\Delta t} U'_{t_n} - e^{-\rho\Delta t_n}\rho V_{t_{n+1}} = \big[\partial_{\Delta t} K'_{t_n} - e^{-r\Delta t_n} r w_{t_{n+1}}\big] e^{(r-\rho)\Delta t_n} V'_{t_{n+1}}.$$

The right-hand side is

$$\begin{aligned} e^{(r-\rho)\Delta t_n} V'(w_{t_{n+1}})\big[\partial_{\Delta t} K'_{t_n} - r(w_{t_n} - K_{t_n})\big] &= e^{(r-\rho)\Delta t_n} V'(w_{t_{n+1}})\big[\partial_{\Delta t} K'_{t_n} - e^{-r\Delta t_n} r w_{t_{n+1}}\big] \\ &= (1-\frac{1}{\sigma})U_{t_n}\big[\frac{\partial_{\Delta t_n} K'_{t_n}}{P_{t_n} S_{t_n}} - \frac{e^{-r\Delta t_n} r w_{t_{n+1}}}{P_{t_n} S_{t_n}}\big] \\ &= (1-\frac{1}{\sigma})U_{t_n}\big[\frac{e^{\phi\Delta t_n}}{f(\phi)} - \frac{e^{\gamma\Delta t_n}}{f(\gamma)} - \frac{e^{-r\Delta t_n} r w_{t_{n+1}}}{P_{t_n} S_{t_n}}\big] \end{aligned}$$

and the left-hand side is

$$\begin{aligned} \partial_{\Delta t} U'_{t_n} - e^{-\rho\Delta t_n}\rho V(w_{t_{n+1}}) &= U_{t_n}\big[\frac{\partial_{\Delta t} K'_{t_n}}{P_{t_n} S_{t_n}} + \frac{1}{\sigma}\frac{e^{\gamma\Delta t_n}}{f(\gamma)}\big] - e^{-\rho\Delta t_n}\rho V(w_{t_{n+1}}) \\ &= U_{t_n}\big[\frac{e^{\phi\Delta t_n}}{f(\phi)} - (1-\frac{1}{\sigma})\frac{e^{\gamma\Delta t_n}}{f(\gamma)}\big] - e^{-\rho\Delta t_n}\rho V(w_{t_{n+1}}). \end{aligned}$$

Hence, necessary condition (8), which implicitly defines Δt_n, can be rewritten as

$$\frac{\rho e^{-\rho\Delta t_n} V(w_{t_{n+1}})}{U(S_{t_n}, \Delta t_n)} - \big(1-\frac{1}{\sigma}\big)\frac{r e^{-r\Delta t_n} w_{t_{n+1}}}{P_{t_n} S_{t_n}} = \frac{1}{\sigma}\frac{e^{\phi\Delta t_n}}{f(\Delta t_n;\phi)} \tag{15}$$

or substituting out inventories,

$$\frac{\rho e^{-\rho\Delta t_n} V(w_{t_{n+1}})}{u(C_{t_n})} - \big(1-\frac{1}{\sigma}\big)\frac{r e^{-r\Delta t_n} w_{t_{n+1}}}{P_{t_n} C_{t_n}} = \frac{1}{\sigma} e^{\phi\Delta t_n}.$$

B.2.2 Final Stationary State (starting at t_{ss})

In the stationary state with $r=\rho$, (4) implies

$$V_{t_{ss}} = (1-e^{-\rho\Delta t_{ss}})^{-1} U_{t_{ss}} \tag{16}$$

$$w_{t_{ss}} = (1-e^{-r\Delta t_{ss}})^{-1} K_{t_{ss}} = (1-e^{-r\Delta t_{ss}})^{-1}(\kappa + P_{t_{ss}} S_{t_{ss}}) \tag{17}$$

Plugging the stationary-state value function and wealth into (15) and evaluating at the stationary state $\rho = r$, noting that $e^{-r\Delta t} r(1-e^{-r\Delta t})^{-1} = f(\Delta t; r)^{-1}$, yields (9),

$$(1-\sigma)\frac{\kappa}{P_{t_{ss}} S_{t_{ss}}} = e^{\phi\Delta t_{ss}}\frac{f(\Delta t_{ss}; r)}{f(\Delta t_{ss}; \phi)} - 1$$

or in terms of consumption,

$$(1-\sigma)\frac{\kappa}{P_{t_{ss}} C_{t_{ss}}} = e^{\phi\Delta t_{ss}} f(\Delta t_{ss}; r) - f(\Delta t_{ss}; \phi). \tag{18}$$

Furthermore, by plugging (17) into (9), we can express the optimal shopping cycle in the stationary state instead as a function of the total level of wealth in stationary state, $w_{t_{ss}}$,[32]

$$(1-\sigma)\Big[\frac{\kappa}{(1-e^{-r\Delta t_{ss}})w_{t_{ss}}-\kappa}\Big] = e^{\phi \Delta t_{ss}}\frac{f(\Delta t_{ss};r)}{f(\Delta t_{ss};\phi)} - 1. \tag{19}$$

Approximate steady-state trip interval ("square-root formula") Define the right-hand side of (18)

$$F(\Delta t) = e^{\phi\Delta t} f(\Delta t; r) - f(\Delta t;\phi).$$

Taking a second-order Taylor expansion of F around $\Delta t = 0$

$$F(\Delta t) \approx F(0) + F'(0)\Delta t + F''(0)\frac{(\Delta t)^2}{2},$$

noting that

$$\begin{aligned}
F(0) &= 0 \\
F'(\Delta t) &= \phi e^{\phi\Delta t} f(\Delta t;\phi) + e^{(\phi+\delta)\Delta t} - e^{\phi\Delta t} && \Rightarrow F'(0) = 0 \\
F''(\Delta t) &= \phi^2 e^{\phi\Delta t} f(\Delta t;\phi) + (2\phi + r)e^{(\phi+r)\Delta t} - \phi e^{\phi\Delta t} && \Rightarrow F''(0) = (1-\sigma)(\delta + r)
\end{aligned}$$

yields

$$F(\Delta t) \approx (1-\sigma)(\delta + r)\frac{(\Delta t)^2}{2}.$$

If $\sigma = 0$ (which we cannot reject based on our estimates of the long-run spending response), then consumption is constant, in particular $C_{t_n} = C$, and does not depend on Δt. Hence the left-hand side of (18) is not affected by the Taylor expansion around $\Delta t = 0$. Therefore, substituting the approximation of the right-hand side into (18) yields the approximate square root formula in the text,

$$\Delta t_{ss} \approx \sqrt{\frac{\kappa}{\frac{\delta+r}{2}P_{t_{ss}}C_{t_{ss}}}}.$$

B.2.3 Interim Shopping Period (starting at t_{ss-1})

A. Change of the iterim-period interval (Δt_{ss-1}) Using (15) we have

$$\frac{1}{\sigma}\frac{e^{\phi\Delta t_{ss-1}}}{f(\Delta t_{ss-1};\phi)} = \frac{\rho e^{-\rho\Delta t_{ss-1}}V(w_{t_{ss}})}{U(C_{t_n},\Delta t_n)} - \big(1-\frac{1}{\sigma}\big)\frac{re^{-r\Delta t_{ss-1}}w_{t_{ss}}}{P_{t_{ss-1}}S_{t_{ss-1}}}$$

[32] Note that if $\sigma = 1$ (i.e., income effect equals substitution effect) then Δt_{ss} is not defined by (9) since the LHS=RHS=0 independent of Δt_{ss}, but instead is pinned down by the steady-state budget constraint.

$$= \frac{\rho e^{-\rho\Delta t_{ss-1}}(1-e^{-\rho\Delta t_{ss}})^{-1}U_{t_{ss}}}{U_{t_{ss-1}}} - (1-\frac{1}{\sigma})\frac{re^{-r\Delta t_{ss-1}}(1-e^{-r\Delta t_{ss}})^{-1}(\kappa+P_{t_{ss}}S_{t_{ss}})}{P_{t_{ss-1}}S_{t_{ss-1}}}$$
$$= re^{-r\Delta t_{ss-1}}(1-e^{-r\Delta t_{ss}})^{-1}\Big[\frac{U_{t_{ss}}}{U_{t_{ss-1}}} - (1-\frac{1}{\sigma})(\frac{P_{t_{ss}}S_{t_{ss}}}{P_{t_{ss-1}}S_{t_{ss-1}}} + \frac{\kappa}{P_{t_{ss-1}}S_{t_{ss-1}}})\Big].$$

Using (7) we find an expression for $U_{t_{ss}}/U_{t_{ss-1}}$,

$$\frac{U_{t_{ss}}}{U_{t_{ss-1}}} = \frac{u(S_{t_{ss}})f(\Delta t_{ss};\phi)^{1/\sigma}}{u(S_{t_{ss-1}})f(\Delta t_{ss-1};\phi)^{1/\sigma}} = \left(\frac{S_{t_{ss}}}{S_{t_{ss-1}}}\right)^{1-1/\sigma}\left(\frac{f(\Delta t_{ss};\phi)}{f(\Delta t_{ss-1};\phi)}\right)^{1/\sigma}$$
$$= e^{(\sigma-1)(r-\rho)\Delta t_{ss-1}}\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{1-\sigma}\frac{f(\Delta t_{ss};\phi)}{f(\Delta t_{ss-1};\phi)}$$

and

$$\frac{P_{t_{ss}}S_{t_{ss}}}{P_{t_{ss-1}}S_{t_{ss-1}}} + \frac{\kappa}{P_{t_{ss-1}}S_{t_{ss-1}}} = \frac{P_{t_{ss}}S_{t_{ss}}}{P_{t_{ss-1}}S_{t_{ss-1}}}(1+\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}})$$
$$= e^{\sigma(r-\rho)\Delta t_{ss-1}}\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{1-\sigma}\frac{f(\Delta t_{ss};\phi)}{f(\Delta t_{ss-1};\phi)}(1+\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}}).$$

Plugging back in and evaluating at $\rho = r$,

$$\frac{1}{\sigma}\frac{e^{\phi\Delta t_{ss-1}}}{f(\Delta t_{ss-1};\phi)} = e^{-r(\Delta t_{ss-1}-\Delta t_{ss})}f(\Delta t_{ss};r)^{-1}\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{1-\sigma}\frac{f(\Delta t_{ss};\phi)}{f(\Delta t_{ss-1};\phi)}\Big[1-(1-\frac{1}{\sigma})(1+\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}})\Big]$$
$$= e^{-r(\Delta t_{ss-1}-\Delta t_{ss})}f(\Delta t_{ss};r)^{-1}\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{1-\sigma}\frac{f(\Delta t_{ss};\phi)}{f(\Delta t_{ss-1};\phi)}\frac{1}{\sigma}\Big[1+(1-\sigma)\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}}\Big].$$

Therefore,

$$(1-\sigma)\frac{\kappa}{P_{t_{ss}}S_{t_{ss}}} = e^{\phi\Delta t_{ss-1}+r(\Delta t_{ss-1}-\Delta t_{ss})}\frac{f(\Delta t_{ss};r)}{f(\Delta t_{ss};\phi)}\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{-(1-\sigma)} - 1.$$

Substituting the left-hand side with (9)

$$\left(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\right)^{(1-\sigma)} = e^{(\phi+r)(\Delta t_{ss-1}-\Delta t_{ss})} = e^{(1-\sigma)(\delta+r)(\Delta t_{ss-1}-\Delta t_{ss})}$$

and taking logs yields

$$\Delta t_{ss-1} - \Delta t_{ss} = \frac{\ln\left(P_{t_{ss}}/P_{t_{ss-1}}\right)}{\delta+r}.$$

Elasticity Hence, we obtain (11) by the following approximation,

$$\frac{\ln\left(P_{t_{ss}}/P_{t_{ss-1}}\right)}{(\delta+r)\Delta t_{ss}} = \frac{\Delta t_{ss-1}-\Delta t_{ss}}{\Delta t_{ss}} \approx -\ln\left(\Delta t_{ss}/\Delta t_{ss-1}\right)$$

such that

$$\varepsilon_{\Delta t_{ss-1}} = \frac{d\ln(\Delta t_{ss}/\Delta t_{ss-1})}{d\ln(1+\tau_{t_{ss}})}\Big|_{\Delta t_{ss}\ cons} = -\frac{1}{(\delta+r)\Delta t_{ss}}\frac{d\ln\left(P_{t_{ss}}/P_{t_{ss-1}}\right)}{d\ln(1+\tau_{t_{ss}})}$$
$$= -\frac{B_\tau}{(\delta+r)\Delta t_{ss}}.$$

B. Change of iterim-period spending ($s_{i,t_{ss-1}}$) Beginning-of-period inventory of good i is

$$s_{i,t_n} = b_i\Big(\frac{p_{i,t_n}}{P_{t_n}}\Big)^{-\eta} S_{t_n}$$

such that

$$\frac{s_{i,t_{ss-1}}}{s_{i,t_{ss}}} = \Big(\frac{p_{i,t_{ss}}}{p_{i,t_{ss-1}}}\Big)^{\eta}\Big(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\Big)^{-\eta}\frac{S_{t_{ss-1}}}{S_{t_{ss}}}.$$

Substituting Euler equation (7) evaluated at $\rho = r$ yields

$$\frac{s_{i,t_{ss-1}}}{s_{i,t_{ss}}} = \Big(\frac{p_{i,t_{ss}}}{p_{i,t_{ss-1}}}\Big)^{\eta}\Big(\frac{P_{t_{ss}}}{P_{t_{ss-1}}}\Big)^{\sigma-\eta}\frac{f(\Delta t_{ss-1};\phi)}{f(\Delta t_{ss};\phi)}.$$

Using the fact that $\frac{d\ln(P_{t_{ss}}/P_{t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} = B_\tau$, the compensated short-run spending elasticity of a forward-looking consumer is

$$\begin{aligned}
\varepsilon_{s_{i,t_{ss-1}}} &\equiv \frac{d\ln(s_{i,t_{ss}}/s_{i,t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} \\
&= -(\sigma-\eta)\frac{d\ln(P_{t_{ss}}/P_{t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} - \eta\cdot\frac{d\ln(p_{i,t_{ss}}/p_{i,t_{ss-1}})}{d\ln(1+\tau_{t_{ss}})} - \frac{d\ln\left(f(\Delta t_{ss-1};\phi)/f(\Delta t_{ss};\phi)\right)}{d\ln(1+\tau_{t_{ss}})} \\
&= -(\sigma-\eta)B_\tau - \eta\cdot 1_{\{i=\tau\}} - \frac{d\ln\left(f(\Delta t_{ss-1};\phi)/f(\Delta t_{ss};\phi)\right)}{d\ln(1+\tau_{t_{ss}})} \\
&= \varepsilon_i^c - \frac{d\ln\left(f(\Delta t_{ss-1};\phi)/f(\Delta t_{ss};\phi)\right)}{d\ln(1+\tau_{t_{ss}})}.
\end{aligned}$$

Hence, the additional sensitivity of spending relative to consumption is driven by the last term.

Elasticity Evaluating the derivatives of f around $d\tau = 0$ such that $d\ln f(\Delta t_{ss-1};\phi) \approx d\ln f(\Delta t_{ss};\phi)$ and using (11) we get

$$\begin{aligned}
\frac{d\ln f(\Delta t_{ss-1};\phi)}{d\ln(1+\tau_{t_{ss}})} - \frac{d\ln f(\Delta t_{ss};\phi)}{d\ln(1+\tau_{t_{ss}})} &\approx \frac{e^{\phi\Delta t_{ss}}}{f(\Delta t_{ss};\phi)}\frac{d(\Delta t_{ss-1}-\Delta t_{ss})}{d\ln(1+\tau_{t_{ss}})} \\
&= \frac{e^{\phi\Delta t_{ss}}}{f(\Delta t_{ss};\phi)}\frac{B_\tau}{\delta+r}.
\end{aligned}$$

Taking a first order approximation of $G(\phi) \equiv \frac{e^{\phi \Delta t}}{f(\Delta t;\phi)} = \frac{\phi e^{\phi \Delta t}}{e^{\phi \Delta t}-1}$ around $\phi = 0$, $G(\phi) \approx \frac{1}{\Delta t} + \frac{1}{2}\phi$, yields

$$\frac{d\ln\left(f(\Delta t_{ss-1};\phi)/f(\Delta t_{ss};\phi)\right)}{d\ln(1+\tau_{t_{ss}})} \approx \frac{B_\tau}{\delta + r}\left(\frac{1}{\Delta t_{ss}} + \frac{\phi}{2}\right).$$

Evaluating G at $\phi = 0$ instead yields the approximation in (12).

Proof: Using de l'Hopital's rule, $G(0) = \lim_{\phi \to 0} G(\phi) = \frac{1}{\Delta t}$. After some algebra, the derivative of G simplifies to $G'(\phi) = \frac{e^{\phi\Delta t}(e^{\phi \Delta t}-1-\phi\Delta t)}{(e^{\phi\Delta t}-1)^2}$. Using de l'Hopital's rule again, $G'(0) = \lim_{\phi\to 0} G'(\phi) = \frac{1}{2}$.

B.2.4 Pre Tax Change Periods (until t_{ss-1})

Consider the problem of choosing how to space N trips planned to occur before the interim shopping trip at $t_{ss-1} = t_\tau^-$.[33] Without much loss of generality we start model time at a date that corresponds to a shopping transaction. The goal is to show that for an appropriate choice of tax change date t_τ there is a solution involving a constant trip interval $\Delta t = \Delta t_{ss-2} = \Delta t_{ss-q}$ $\forall q \geq 2$ and constant beginning-of-period consumption $C = C_{t_{ss-2}} = C_{t_{ss-q}}$ $\forall q \geq 2$. Define the start and end dates of the pre tax change period

$$\begin{aligned} t_0 &= 0 \\ t_N &= t_\tau^- = t_{ss-1}. \end{aligned}$$

There are $N+1$ transaction dates and N transaction intervals. Also define $V(w_{t_\tau^-})$ as the value of the problem starting from the interim shopping trip at t_τ^- given accumulated wealth $w_{t_\tau^-}$. The problem is

$$V(w_0) = \max_{w_{t_\tau^-}, \Delta t_0, \ldots, \Delta t_{N-1}, C_{t_0}, \ldots, C_{t_{N-1}}} \sum_{k=0}^{N-1} e^{-\rho \sum_{j=0}^{k-1} \Delta t_j} U(C_{t_k}, \Delta t_k) + e^{-\rho t_\tau^-} V(w_{t_\tau^-})$$

subject to

$$\begin{aligned} t_\tau^- &= \sum_{k=0}^{N-1} \Delta t_k \\ w_0 &= \sum_{k=0}^{N-1} e^{-r\sum_{j=0}^{k-1}\Delta t_j} K_{t_k} + e^{-r t_\tau^-} w_{t_\tau -} \end{aligned}$$

where the multiplier on first constraint is λ_1 and on second constraint is λ_2.

[33] Note that it is best for the household to take the interim trip as close to t_τ as possible, all else constant.

Necessary condition for Δt_n

$$e^{-\rho t_n}\lambda_1 = \Big[\partial_\Delta U'_{t_n} - \rho \sum_{k=n+1}^{N-1} e^{-r\sum_{j=0}^{k-1}\Delta t_j} U_{t_k}\Big] - \lambda_2\Big[\partial_\Delta K'_{t_n} - r \sum_{k=n+1}^{N-1} e^{-\rho\sum_{j=0}^{k-1}\Delta t_j} K_{t_k}\Big]. \tag{20}$$

Necessary condition for C_{t_n}

$$\partial_C U'_{t_n} = \lambda_2 \cdot \partial_C K'_{t_n}. \tag{21}$$

Necessary condition for $w_{t_\tau^-}$

$$e^{-\rho t_\tau^-} V'(w_{t_\tau^-}) = \lambda_2 e^{-r t_\tau^-} \tag{22}$$

Using (22) and $r = \rho$ we get

$$\lambda_2 = V'(w_{t_\tau^-})$$

The consumption Euler equation is

$$\frac{\partial_C U'_{t_n}}{\partial_C U'_{t_{n+1}}} = \frac{P_{t_n}}{P_{t_{n+1}}} \frac{f(\Delta t_n;\phi)}{f(\Delta t_{n+1};\phi)} \frac{f(\Delta t_n;\gamma)}{f(\Delta t_{n+1};\gamma)}$$

The transaction Euler equation is obtained using (20),

$$\partial_\Delta U'_{t_n} - \rho e^{-\rho\Delta t_n} U'_{t_{n+1}} - [\partial_\Delta K'_{t_n} - r e^{-r\Delta t_n} K_{t_{n+1}}] V'(w_{t_\tau^-}) = e^{-\rho\Delta t_n}\partial_\Delta U'_{t_{n+1}} - e^{-r\Delta t_n}\partial_\Delta K'_{t_{n+1}} V'(w_{t_\tau^-}).$$

Using the constant guess for the solution, $\Delta t_n = \Delta_{t_{ss-2}} = \Delta t$ and $C_{t_n} = C_{t_{ss-2}} = C$, we obtain a condition similar to the steady state equation for the post tax transaction interval,

$$\partial_\Delta U' - \rho \frac{e^{-\rho\Delta t}}{1 - e^{-\rho\Delta t}} U = [\partial_\Delta K' - r\frac{e^{-r\Delta t}}{1-e^{-r\Delta t}} K] V'(w_{t_\tau^-}).$$

Using similar steps as in the derivation of the steady state above, we can combine this relationship with (21) to yield

$$(1-\sigma)\frac{\kappa}{P_{t_{ss-2}} S_{t_{ss-2}}} = e^{\phi\Delta t_{ss-2}} \frac{f(\Delta t_{ss-2}; r)}{f(\Delta t_{ss-2};\phi)} - 1. \tag{23}$$

Furthermore, since $V'(w_{t_\tau^-})$ is also the multiplier in the post-tax steady state, we can relate $C_{t_{ss-2}}$ and $C_{t_{ss}}$ through (21),

$$\partial_C U'_{t_n} = V'(w_{t_\tau^-})\partial_C K'_{t_n},$$

such that

$$u'(C_{t_{ss-2}}) f(\Delta t_{ss-2};\gamma)^{1/\sigma - 1} f(\Delta t_{ss-2};\phi) = V'(w_{t_\tau^-}) P_{t_{ss-2}} \frac{f(\Delta t_{ss-2};\phi)}{f(\Delta t_{ss-2};\gamma)}$$

which reduces to

$$u'(C_{t_{ss-2}}) = V'(w_{t_\tau -}) P_{t_{ss-2}} f(\Delta t_{ss-2};\gamma)^{-1/\sigma}.$$

Hence,

$$C_{t_{ss-2}} = \Big(P_{t_{ss-2}} V'(w_{t_\tau^-})\Big)^{-\sigma}$$

and

$$C_{t_{ss}} = \Big(P_{t_{ss}} V'(w_{t_\tau^-})\Big)^{-\sigma}$$

such that

$$\frac{C_{t_{ss-2}}}{C_{t_{ss}}} = \Big(\frac{P_{t_{ss-2}}}{P_{t_{ss}}}\Big)^{-\sigma}.$$

If we use $S_{t_{ss-2}} = C_{t_{ss-2}} f(\Delta t_{ss-2};\phi)$ in (23), we have two equations in Δt_{ss-2} and $C_{t_{ss-2}}$, which we solve to get the pre tax change solution

$$(1-\sigma)\frac{\kappa}{P_{t_{ss-2}} C_{t_{ss-2}} f(\Delta t_{ss-2};\phi)} = e^{\phi \Delta t_{ss-2}} \frac{f(\Delta t_{ss-2};r)}{f(\Delta t_{ss-2};\phi)} - 1$$
$$\frac{C_{t_{ss-2}}}{C_{t_{ss}}} = \Big(\frac{P_{t_{ss-2}}}{P_{t_{ss}}}\Big)^{-\sigma}$$

To make sure $\sum_{k=0}^{N-1} \Delta t_k = t_\tau$ is satisfied we set

$$t_{\tau-} = N \cdot \Delta t_{ss-2}.$$

This solution has a straightforward interpretation: Intertemporal consumption allocation satisfies the standard consumption Euler equation (even in the presence of transaction fixed costs and product storability) and the optimal trip interval in the pre tax change period reflects the same trade-offs as in the final steady state. Figure 4 highlights these two features of optimal transaction intervals and spending and consumption plans.

C. Tax Salience and Announcement Effects

C.1 Tax Salience: Evidence from Ballot Initiative

A natural question that arises given the results displayed in Figure 2 is whether tax salience plays an additional role in consumers response to a sales tax rate chang and whether news about future sales tax changes prompt a response via an income or wealth effect. While the results in Section 4 document a significant degree of tax foresight on average, it seems reasonable that some households are not fully aware of the tax rate changes, or some aspects of the tax code such as the exemption status of certain goods is not fully salient (e.g., cookies vs. candies). In this section, we test whether more salient tax changes elicit larger spending responses. This analysis is motivated by several highly influential previous studies that document a large degree of non-salience of sales tax rates among consumers (see the literature mentioned in the introduction). Table A.1 presents the results from this analysis.

Panel A uses two measures of tax salience and examines their impact on changes in household spending. The first is the aforementioned index of sales tax news coverage in the month prior to the change. Given that the size of the sales tax change strongly impacts the level of coverage, we first obtain the residuals from a regression of the amount of sales tax news coverage on the size of the change, the squared size of the change, and time fixed effects. With this approach, we interpret the resulting residuals as a measure of news coverage of the impending sales tax change that is unrelated to the size of the change (ideally driven by the amount of other important news in that period, editorial decisions, etc.). Here, the assumption is that the more that sales taxes are written about in local newspapers, the more likely it is that a given household will be aware of the upcoming change in sales taxes and that they will be in position to react to the change.

Columns 1 to 3 interact this news-based measure with changes in state sales taxes. To facilitate the quantitative interpretation, we normalize the news measure by its standard deviation. Since it is a residual, the resulting transformation has mean zero and a unit standard deviation (i.e., a standard score). We again find that, in general, sales tax changes have a negative relationship with spending in the month of the tax change, comparable with the baseline effects reported in Column 2 of Tables 1 and 5. Moreover, changes that had more news coverage (conditional on the size of the change) also had larger declines. The coefficient on the interaction term of Column 1 shows that an increase in news coverage of one standard deviation would increase the spending response to a 1ppt sales tax change by about 20% (from -1.8% to -2.1%). The effect is again similarly shared by taxable and tax-exempt spending.

Columns 4 to 6 take a different approach to testing heterogeneity in household responses across sales tax changes with different salience. Here we utilize data on state-level ballot measures that changed state sales taxes. Our prior is that sales tax changes enacted through state-wide ballots would garner more media attention than those enacted through a vote solely by their state representatives and also would force all voters to be at least somewhat aware of the initiative that they are voting on. Consistent with this hypothesis, we find that changes in sales tax rates that were authorized by a state-wide ballot measure tended to produce much larger responses among households.

C.2 'News' Response: Income, Wealth and Substitution Effects

Panel B of Table A.1 demonstrates some evidence for an announcement effect of sales taxes. For most of the changes in our sample, we are unable to determine when exactly the sales tax change was finalized (often 3 months to 12 months prior to the change taking place). For state ballot provisions, however, we can precisely measure this date, allowing us to look for changes in household spending behavior prior to the change actually taking place.[34]

In a model with fully informed and rational consumers, households would perceive this future tax increase as a persistent increase in future prices. At the time of the announcement (which is before time 0 in the model of Section 5), this leads to a spending response that is the combination

[34]Ideally we would weigh the responses by how close the outcome of the ballot proposition was in order to interpret the spending response as a rational response to a change in expected tax rates. Unfortunately, we do not yet have this data.

of a negative income effect (the same pre-tax consumption plan is more expensive) and a positive intertemporal substitution effect (spending is temporarily cheaper in the period before the sales tax increase). In addition, there could be wealth effects that depend on the consumer's perception and valuation of what the government plans to do with the additional revenue.

Column 7 provides suggestive evidence that this effect might play a role, on average, across all ballots (whether they passed or failed), with the act of voting on the ballot being associated with a 0.5% decline in household retail spending. We further refine the analysis by separating these ballots into those that failed and those that passed, finding opposite signed coefficients. Judging the point estimates, we find a near zero effect on spending following a failed tax increase initiative, while we see a much larger decrease in spending following a successful tax increase vote. These results are consistent with forward-looking behavior on the part of consumer, although they are not statistically significant.

Table A.1: Salience and Announcement Effects

	A. Salience Effects						B. Announcement Effects	
	newspaper coverage			ballot-induced tax changes				
Dependent variable:	Δln(total)	Δln(taxable)	Δln(exempt)	Δln(total)	Δln(taxable)	Δln(exempt)	Δln(total)	Δln(total)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln(1 + sales tax rate)	-1.738***	-2.124**	-1.572**	-1.526**	-2.238*	-1.310**		
	(0.581)	(1.053)	(0.603)	(0.687)	(1.179)	(0.591)		
Δln(1 + sales tax rate) × Score(newspaper coverage)	-0.361***	-0.336	-0.439**					
	(0.110)	(0.257)	(0.166)					
Δln(1 + sales tax rate) × I(state ballot proposition)				-4.195***	-4.765**	-5.043***		
				(1.050)	(2.038)	(0.889)		
I(date tax rate change proposed)							-0.529	-1.706
							(0.330)	(1.444)
I(date tax rate change proposed) × I(ballot proposition failed)								1.434
								(1.493)
Score(newspaper coverage of state sales tax changes)	-0.001	-0.001*	0.001					
	(0.001)	(0.001)	(0.001)					
I(date ballot proposition failed)				0.022***	0.030***	0.022***		
				(0.005)	(0.009)	(0.005)		
I(ballot proposition failed)								-0.002
								(0.006)
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,822,806	5,777,878	5,865,177	5,865,949	5,928,421	5,777,966	5,860,476	5,860,476
R-squared	0.016	0.015	0.014	0.014	0.012	0.013	0.014	0.014

Notes: Columns 1-3 interact changes in state sales tax rates with the level of newspaper coverage (measured as the demeaned ratio of articles mentioning sales taxes to the total number of articles in newspapers within the state covered by Access World News, normalized by its standard deviation). Columns 4-6 interact changes in sales tax rates with an indicator for whether the change in state sales tax rates was driven by a ballot measure (as opposed to being enacted by the legislature). Columns 7 and 8 use, as independent variables, indicators for dates when ballot initiatives that would change state sales tax rates were voted on (as opposed to the dates they were enacted). Column 8 interacts these indicators with another indicator that signifies the ballot not being successfully passed (and thus resulting in no change in sales tax rates). For robustness, the dependent variables are winsorized at the 1% level. Standard errors in parentheses are clustered at the state level.