Implications of Sales Tax Enforcement on E-commerce: Evidence from Nielsen Consumer Panel Data [*]

Abstract

How sensitive are e-commerce purchases to state sales taxes? Understanding the interplay of online consumer behavior, state sales tax policy changes, and competitive dynamics of online retail consumption relies on empirical elasticity estimates. This paper exploits timing variation in the imposition of state sales tax onto online purchases to estimate demand elasticities for online and traditional brick and mortar retail shopping. Elasticities of demand for goods sold online with respect to prices for online goods of 1.255 and 1.227 were found for uncompensated and compensated demands, respectively, when evaluated at their sample mean for the unconstrained preferred demand estimation specification. The large elasticities imply that collecting sales taxes from online retailers shifts consumption partially back to brick and mortar retailers. For example, if California did not impose sales on online retailers, panelists expenditure shares would be 8.9% larger in this state.

Keywords: `demand estimation, quadratic almost ideal demand system, sales tax, online sales`

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[*]Researcher's own analyses based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

1 Introduction

1.1 Research Question and Motivation

How do online state sales tax changes affect consumer shopping decisions? This research endeavors to better understand retail consumer behavior dynamics under policy shocks to state sales tax policy. More broadly this research may help to better compare state-level shocks to online retail sales. The motivation for pursuing this research question are the intersection of the competing interests of consumer welfare, tax regime application consistency, tax revenues, and competitive fairness in the retail shopping sector. Often products sold online might be the same as at a brick and mortar retail store, but the nature of the shopping experience is quite different with online systems offering convenient and streamlined services for pricing, ordering, and delivery. Additionally, overall cost considerations favored online goods which had no sales taxes imposed initially. The question of whether the success of online retailers was due to a fundamentally better shopping experience or an unfair sales tax disadvantage of brick and mortar retailers became an issue of public debate. Consequently, determining empirical estimates of elasticities for online goods is an important step in helping parse the sales tax component's contribution to these consumer trends from other competitive factors.

1.2 Overview

While e-commerce is currently a mainstay of facilitating everyday transactions, growth to its present state as a principle source of economic activity may be related to utilizing legal technicalities that stem from a once opaque legal notion of *physical nexus* which led to a situation where no sales taxes were collected for online sales. Previous mail-order catalog retailers had touched on the legal issue, but the economic impact of the legal complications were minimal until the meteoric rise of online retail marketplaces. Eventually states developed the technological infrastructure required for sales tax collection and individually legislated sales tax laws governing online sales between 2008 and 2017 before the Wayfair (2018) case taken up by the Supreme Court in 2018 settled the issue. In this paper, these state adoption dates along with the respective sales tax rates are used together with household purchases with the exception of grocery items to estimate price elasticities of demand for online goods. Non-grocery items are focused on because states often have grocery exemptions to reduce the tax burden on lower income households. Sales tax modified prices of non-grocery goods are analyzed using methods developed by Blundell and Robin (1999) and Lecocq and Robin (2015) that expand the capabilities of the demand systems developed by Deaton and Muellbauer (1980) and Banks et al. (1997).

1.3 Legislative Background

From the Commerce Clause in Article I of the United States' constitution, the Dormant Commerce Clause is a legal doctrine established to prevent interstate protectionism and promote interstate commerce. For example, the Dormant Commerce Clause prevents a state from unlawfully adopting legislation governing product safety that applies only to products imported from other states and countries while exempting producers within the state. States attempting to pass legislation discriminating against interstate or international commerce must overcome a significant legal burden of proof to justify a legitimate local purpose for which no other recourse is available. A legal *nexus* describes the type and extent of a connection between a business and a taxing jurisdiction.

HessvIllinois (1967) in 1967 was one of the first cases to address the application of *nexus* to state use taxes on mail-order retailers, with the Supreme Court ruling remittance of sales or use taxes were not required of a seller without any physical presence in that state. The physical presence component of *nexus* was again tested with QuillvND (1992) in 1992 just as fundamental internet infrastructure for e-commerce was beginning to take shape, so it would have been difficult to have sufficient legal foresight that could anticipate the future growth of e-commerce. The Supreme Court's decision forbade states from compelling remote sellers to remit sales tax collections unless they had a physical presence in the state as well as highlighting two pragmatic enforcement challenges, undue compliance burden on remote sellers among different state laws and technological infrastructure to remit sales taxes data. States organized to address this with the Streamlined Sales and Use Tax Agreement (SSUTA) in 2005.

Retail e-commerce growth continued concurrently with the absence of online sales tax collections. Traditional brick and mortar establishments argued that online retailers had an unfair competitive advantage, with small business owners being especially disadvantaged while jurisdictions considered the effects on the labor force as well as forgone sales and property tax revenues. Other legal cases followed until the Wayfair (2018) case where the Supreme Court overturned the physical presence requirement for establishing a jurisdictional nexus in 2018. By this time many online retailers had expanded their physical nexus via distribution centers rendering the issue less consequential. In this paper, to estimate price elasticities of demand for online goods, the variation in timing of states passing online sales tax and use policies throughout the period from 2001 to 2017 is exogenous to consumers and is utilized in concert with household consumer panel data for the continental United States.

2 Literature Review

There are three areas of literature that are particularly relevant. The first relates to economic analysis of sales tax policy. This literature is reviewed to determine the scope of research involving online consumption and sales tax policy. The second area of literature relates to demand systems and their implementation in applied work. This is reviewed to better understand the econometric framework of demand systems and how underlying structural equations can be estimated with different approaches to compare elasticity estimates for relevant categories of goods. Additionally demand system literature serves as a platform to discuss how the underlying assumptions of microeconomic theory might be tested by such structural models with recent improvements in software and computing capability. The third area of literature pertains to the intersection of demand systems with policy such as changes in sales tax policy. Since the emergence of online retail sales is a relatively new change in the nature of economic transactions, even for early adopters of online shopping, most applicable sales-tax related literature has been published after the year 2000.

Often due to historical necessity, prior demand estimation literature depended on various aggregation levels and collection methods that were available such as expenditure surveys, industry reporting, or aggregated government records which may have been less granular and precise compared to household transaction level panel data. This analysis contributes to the existing body of literature by using transaction level direct purchase panel data in conjunction with sales tax data to determine the expenditure shares and price elasticities of household panelists for online goods. The methods used in this paper can be applied in future work with further granularity of goods categories. Specifically, instead of examining broad categories of online or traditional goods, product categories within these two broad categories might be explored such as apparel or electronics categories.

2.1 Sales Tax and E-commerce Literature

Much of the prior literature focuses on particular e-commerce vendors such as Einav et al. (2014) who examines eBay data to estimate retail purchase sensitivity. Their work differs in that they employ an item level empirical method which looks at eBay specifically and uses the "tax table" feature from eBay's website. While this tax data is relevant for their application, the Neilsen data used in this research necessitates a tax data source that can be applied more generally to the purchases of many online vendors. Similarly, Alm et al. (2010) look exclusively at eBay seller tax compliance for specific commodities.

Often research is quite product specific. Ellison and Ellison (2006) examines memory device sales online where they try to analyze internet and traditional commerce channels for substitution effects which would be important for future competition between retail channels. They also consider the de facto sales tax advantage for online retail as well as geographical considerations. The data from Pricewatch.com used in their analysis does not capture all purchase observations, but only from two website listings so traditional retail purchases are unknown.

Other authors such as Goolsbee (2000) estimate the lower bound of sales tax revenue losses due to e-commerce sales from both retail business to consumer (B2C) and business to business (B2B) e-commerce. Their data comes from the U.S. Census 2006 Annual Retail Trade Report. Since this survey data is aggregated, their fiscal impact is calculated from an estimate of e-commerce taxes due less taxes collected. They use a complex but indirect method of calculating e-commerce sales via regressing e-commerce shipments on GDP and GDP growth. While a laudable approach, it is more advantageous to be able to measure e-commerce expenditures directly, as is possible with the Nielsen consumer panel data.

Ballard and Lee (2007) also empirically tests the effect of retail sales tax rates in local and neighboring counties on Internet purchases from the Current Population Survey between 1997 and 2001. At the time this research was done the nexus issue was of relevance, but this was before the 2018 Wayfair ruling. Ballard and Lee (2007) use a binary dependent variable for whether or not individuals engage in online purchases with sales tax rates as the explanatory variable. This analysis differs in that it addresses what Ballard and Lee (2007) wrote would be better in their footnote 8, using data that reports how much consumers spent on online purchases. Furthermore, this analysis can look at the expenditure share of online goods relative to the remainder of consumer purchases.

In the legal literature space there has been a focus on examining larger retailers such as Amazon and on the further examination of the legal paradigm. Gordon (2009), for example, examines "entity isolation" tactics leveraged by online retailers to avoid being forced to collect sales taxes as well as other legal cases and state responses to tax affiliates that were part of entity isolation tactics.

Baugh et al. (2014) investigates the effects of online sales taxes on purchases in comparison to main street retailers for a number of states. This analysis is done midway through the process of states adopting laws and as shown in the first column of Table 1, a large portion of states did not adopt until after their NBER working paper was published. They employ a differences-in-differences approach using household level data. Their data is transaction level data from an unnamed financial institution. They note the danger of bias generated by parallel trend assumption, caused by sellers engaging in price discrimination geographically in response to state sales tax initiatives. It may be difficult to determine whether the data from the financial institution is a representative sample of the United States population. Nielsen Consumer Panel data is nationally representative when using their projection factor as a sample weight.

Alm and Melnik (2005) use the special supplement in the Current Population Survey (CPS) published by the U.S. Bureau of Labor Statistics (BLS) as a more robust and representative dataset in comparison to the Forrester Research data used in Goolsbee (2000). They obtain the same qualitative result, higher sales tax yielding higher probability of an online purchase although the impact elasticity of online purchase probability is quantitative smaller (0.52) compared to (2.3) in Goolsbee (2000). The elasticities estimated, approximately 1.2 in this analysis fall within the range of these two publications.

Other literature focuses more on state revenue losses from e-commerce sales prior to legislative amelioration for brick and mortar establishments. Bruce and Fox (2001) estimate revenue estimates for 2001, 2006, and 2011. They predict a

$16 billion revenue loss for policy implications for state and local governments due to the impact of a narrowing tax base on future rate increases that may be imposed by state and local governments to supplement budgetary shortfalls.

2.2 Demand Estimation Literature

The primary variable of interest is the household expenditure share of online shopping goods. Since the data available includes the consumer's state of residence, the hypothesis is that for panelist households residing in a particular state that collects sales tax for online purchases, the expenditure share of online spending as a proportion of their total recorded expenditure would decrease as consumers adjust to the sales tax regime being enforced onto their online purchases. The demand estimation literature is foundational to this analysis, and this literature spans a wide breadth of economic disciplines such as agriculture economics, energy, and industrial organization (I.O.). This literature often uses demand estimation techniques because it is amenable for numerous policy applications. For example, demand estimation can address challenges of consumption inequality presented by Attanasio and Pistaferri (2016) as done by DeDad (2019). Among the various demand estimation methods, among the first to be proposed was the Almost Ideal Demand System (A.I.D.S) by Deaton and Muellbauer (1980). This demand estimation framework has been used in numerous applied areas and to numerous product categories, such as the Japanese (Jing et al. (2004)) and the United States' (Gallet (2010)) meat markets, Italian tobacco (Jones and Mazzi (1996)), Saudi honey imports (Alnafissa and Alderiny (2020)) and groups of consumer goods Hausman et al. (1994).

After the inception of (A.I.D.S), a number of different modifications have been proposed. The first of which extends the robustness of the (A.I.D.S) by including demographic characteristics and was first proposed by Deaton and Muellbauer (1980) though data limitations prevented them from implementing the idea at that time and was later pursued in Subramanian and Deaton (1996). A commonly used modification is the addition of a quadratic term, proposed by Banks et al. (1997) which is known as Quadratic Almost Ideal Demand System (Q.U.A.I.D.S) and will be implemented for this analysis.

Another modification includes using consumer taste preferences among different regions as aptly demonstrated by Atkin (2013) for regional tastes in India as well as by De Sousa et al. (2018) for regional consumption convergence in French dairy markets. Other modifications incorporate ideological differences as measured by tastes as in DeDad (2019). Finally, some literature involved the technical programming aspects of (A.I.D.S) such as Poi (2002), Poi (2008), Poi (2012), and Lecocq and Robin (2015).

2.3 Demand Systems Intersected with Policy

Some tax literature connects policy analysis to the consumer demand systems. Brännlund and Nordström (2004) uses demand estimation to analyze consumer responses after environmental policy changes. Tax policy is also of particular interest in application to using demand system estimation methods. Madden (1996) examines the sensitive nature to the demand system that underlies a tax proposal by comparing four different demand estimation methods. Similarly, using Belgian consumer survey and national account data, Decoster and Schokkaert (1990) compare the effects of indirect taxes using price elasticities generated by different demand systems.

Walls and Ashenfarb (2022) also look at policy effects using a two stage QUAIDS for recreation goods and then simulating a hypothetical 5% tax increase to determine potential tax revenues that can help fund the use of public lands. Taxable items that broaden this base such as hunting and fishing fees and taxes on related sporting goods are some of the potential tax channels that could better match public goods use to the industries that most directly benefit from their use. This work is related in that it examines tax policy using a demand system but differs in that its primary focus is on the public land that is complementary to the particular products being taxed.

3 Data

3.1 Overview

The primary sources of data are the Nielsen Consumer Panel data and the sales tax data from the Tax Foundation and applicable state departments of revenue. The period under examination is from 2011 to 2017 for the continental United States because 2011 is the earliest year available for the combined tax rate data and the consumer panel data does not include Hawaii or Alaska. Overall, in a panel year over the observation period, in the Nielson data there are about 60,000 panelists who make approximately 9 million trips yielding 50 to 60 million purchase item observations. About 40% of panelists in a particular panel year had made at least one online trip. Analysis will focus on the intensive margin of online consumption by these consumers who will be referred to as "Online Shoppers" and excludes common sales tax exempt items such as groceries when possible.

3.2 Nielsen Consumer Panel Dataset

Household non-grocery purchases are used from the Consumer Panel Dataset by the Nielsen Company made available by the University of Chicago's Kilts Center Archive Nielsen (2019).

A smartphone application or scanner is provided by Nielsen to household participants in order to record their transactions. The dataset is nationally representative to the demographic composition of U.S. Census estimates, once sample weights provided in the data are used. Universal Product Code (UPC) level purchase data of trips taken by participating panelists are aggregated over the panel year to calculate $w_{i,h,t}$, expenditure shares for i (online and traditional) aggregated goods of household h in a given year t. Additional household demographic characteristics, product attributes, and hierarchical levels of product categorical granularity, the broadest of which are called "departments", are features of the dataset. The type of retail channel is recorded for trip purchases and importantly for this analysis as one such retail channel denotes online purchases.

3.3 Sales Tax Data

Sales tax data is compiled for each state and procured from the Department of Revenue of applicable states. Additionally, combined sales tax rates which are defined as the state plus average local sales tax rates, available for the 2011 to 2020 period were provided by the Tax Foundation as with Fritts (2020). The associated combined state and local sales tax rate is applied to these household purchases if sold in a state that collects sales tax and if the purchase was a traditional brick and mortar purchase. State and local sales tax rate figures are applied to online prices according to whether the date of purchase occurred after states adopted online sales tax policies and began collecting online sales taxes. Thus, the legislated adoption year is used for applying sales taxes to applicable purchases from the consumer panel data. Though it may be argued that consumers may anticipate incoming sales taxes upon first public knowledge of legislative intent, legislative outcomes were uncertain as well as when the information was known to all consumers. As the legal case history for many states elucidates, it is also likely knowledgeable consumers would postpone their consumption response until a final court determination was made.

There are many details that vary by state as to the types of goods and services that are taxable or exempt organizations such as charities. While it seems to be reasonable to assume none of the panelists as households qualify for such exemptions, the different products under a state sales tax regime is more troublesome. Prescription medication, non-prescription medication, and groceries are the most common exempt categories, where 32 of the states exempt groceries outright and of those that tax groceries, some tax at a lower rate or have exemption exclusions stipulated for certain products like candy and soda. To avoid an intractable application of state level grocery sales tax conditions to millions of product purchases, grocery items were excluded in the demand system.

4 Descriptive Statistics

Figure 1 uses U.S. Census data via FRED to give external figures for the share of e-commerce in total retail sales. This figure documents a very strong growth of online retail sales over the period of analysis.

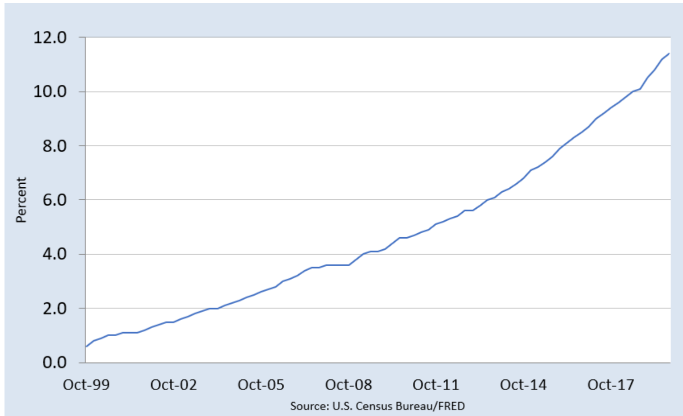

Figure 1: E-Commerce Retail Sales as a Percent of Total Sales

4.1 Sales Tax Adoption and Average State Online Expenditure Shares

There does appear to be promising variation for elasticity estimation purposes as we see not only different magnitude increases in sales tax rates, but also some situations where one state is decreasing its sales tax rate while its neighbor increases theirs. This variation likely contributes to the state trends in online expenditure shares. In 2011, California had a combined sales tax rate of 9.08% which decreased to 8.48% by 2017. In contrast, Nevada's combined sales tax rate increased from 7.96% in 2011 to 8.32% by 2017.Table 1 displays the year in which a state adopted an online sales tax regime in the first column.

Consumer tastes over this period may have shifted toward a preference for an online ordering mechanism that outweighs the price effects of online taxation which would otherwise reduce the expected online expenditure share. In California, the online expenditure share increased from 4.77% in 2011 to 5.28% in 2017. Meanwhile, Nevada had a mean online expenditure share of 4.14% in 2011 which increased to only about 4.32% by 2017. In Alabama, the combined state and average local sales tax rate increased from 8.03% in 2011 to 9.22% by 2020 which is a larger magnitude increase than in Nevada the combined state and average local sales tax rate increased from 7.96% in 2011 to 8.32% in 2020. These are some of the several interesting examples of sales tax rate variation.

Given this increase in the online expenditure share after the implementation of online sales taxes, one might expect shifting online preferences to support more inelastic online prices which is contrary to what is estimated. These elasticities can be more confidently estimated now that it is known that there is a sufficient variation of sales tax rates between states in concert with their online sales tax policy adoption year.

Table 1: State Online Sales Tax Adoption Year

State	Adoption Year	State	Adoption Year	State	Adoption Year	State	Adoption Year
AL	2016	KY	2005	NJ	2013	VA	2017
AR	2011	LA	2017	NM	2017	VT	2013
AZ	2013	MA	2013	NV	2014	WA	2013
CA	2012	MD	2013	NY	2017	WI	2013
CO	2016	ME	2017	OH	2015	WV	2008
CT	2013	MI	2015	OK	2017	WY	2017
DE	None	MN	2014	OR	None		
FL	2014	MO	2017	PA	2012		
GA	2013	MS	2017	RI	2017		
IA	2017	MT	None	SC	2016		
ID	2017	NC	2014	SD	2017		
IL	2015	ND	2001	TN	2014		
IN	2014	NE	2017	TX	2012		
KS	2005	NH	None	UT	2017		

4.2 Panelist Household Profile

With some descriptive statistics, we can better outline the characteristics that describe the Nielsen panelist households. These descriptive statistics are partitioned by variables relating to the econometric structure of QUAIDS demand system, head of household characteristics, and general household characteristics.Table 2 displays the price and expenditure variables that are canonical components of QUAIDS demand systems.

Table 2: QUAIDS Demand System Variable Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Online Expenditure Share	148363	0.045	0.089	0	1
Traditional Expenditure Share	148321	0.955	0.088	0	1
Median Online PUC with Tax*	148363	4.575	1.241	2.5	9.222
Median Traditional PUC with Tax	148321	2.701	0.177	2.25	3.233
Total Expenditure	148363	6223.85	3792.465	3.99	94112.3

Table 3 displays the distribution of age ranges for heads of household. It shows many households are within the prime working age although there is a heavier representation in the 55 to 64 years and over 65 years old brackets.

*PUC stands for Per Unit Cost. Tax is State Sales Tax applied if traditional goods or online goods with purchase date after the state sales tax adoption year.

This may be indicative of the self-selection of panelists who may be retired and more inclined to participate in using the Nielsen scanner in this case using the projection factor provided by Nielsen to ensure a representative sample might be advisable.

Table 3: Male and Female Head of Household Age

	Female Head Age										
Male Head Age	No Head	Under 25	25-29	30-34	35-39	40-44	45-49	50-54	55-64	65+	Total
No Head	-	190	755	1,563	2,249	2,669	3,684	5,181	12,207	11,390	39,888
Under 25	64	114	45	20	8	10	9	11	12	5	298
25-29	305	172	1,100	331	67	21	14	16	38	10	2,074
30-34	581	41	1,008	2,596	626	110	46	35	45	20	5,108
35-39	764	10	241	1,829	3,016	771	194	77	85	28	7,015
40-44	1,078	10	96	548	2,139	3,437	1,093	320	146	93	8,960
45-49	1,679	7	43	182	713	2,465	4,014	1,308	522	138	11,071
50-54	2,289	6	29	85	257	925	3,075	5,135	2,023	219	14,043
55-64	4,754	13	37	59	149	425	1,600	5,385	16,991	1,755	31,168
65+	4,039	13	6	32	49	76	230	770	7,366	16,157	28,738
Total	15,553	576	3,360	7,245	9,273	10,909	13,959	18,238	39,435	29,815	148,363

In Table 4 we see the distribution of hours worked by the male and female head of household. We can see from the totals that there are many panelists who are not employed for pay which may allow a head of household more time to participate as a panelist. Of the heads of household who do work, working over 35 hours is the most prevalent.

Table 4: Head of Household Hours of Employment

	Female Head Employment					
Male Head Employment	No Head	Under 30 hours	30-34 hours	35+ hours	Not Employed for Pay	Total
No Head	-	4,462	1,790	16,884	16,752	39,888
Under 30 hours	1,289	1,261	290	1,928	2,178	6,946
30-34 hours	610	503	333	1,066	1,074	3,586
35+ hours	7,514	8,904	3,071	22,171	20,128	61,788
Not Employed for Pay	6,140	2,656	907	6,393	20,059	36,155
Total	15,553	17,786	6,391	48,442	60,191	148,363

4.3 Intensive Margin

This section starts with a cursory determination as to whether there is enough variation between states' sales tax rates in concert with their respective years of e-commerce taxation adoption for the demand estimation. An area of interest is the time trends in the adoption rate of online sales by consumers in the panel. The primary source of variation for traditional goods is due to standard legislative changes in the level of both the state and local sales tax rates over time as seen in Table 1. This source of variation for traditional goods is the variation that might be expected in absence of any online sales tax adoption policy. This cross-sectional variation in sales taxes between states includes states without sales taxes. The variation includes some states which increased their sales tax rates while others decreased over the period.

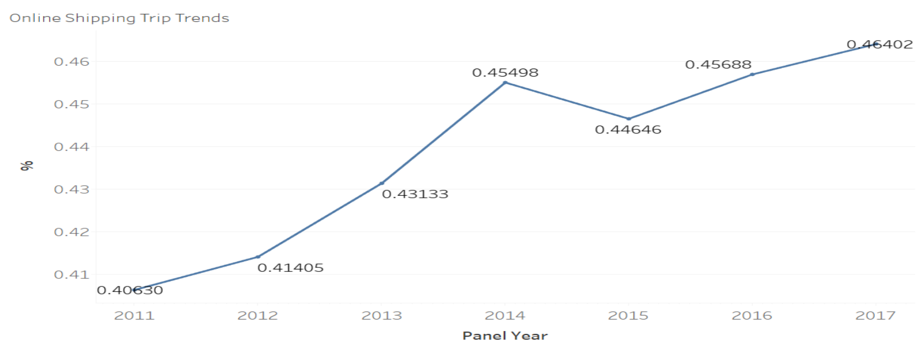

Figure 2: Nielsen Consumer Panel Intensive Margin Percentage of 1 Minimum Online Shopping Trip Per Year

The extensive margin criterion, having at least one online shopping trip in the panel year, is important to parse the relevant data for further analysis. Figure 2 displays the percentage of panelists who had a minimum of one online shopping trip per year. It can be seen the growth trend in online shopping has been modest but consistently positive. Just because panelists made at least one online trip, it does not tell us how often online shoppers make online trips. Consequently, another question that might be asked is: “How often do panelists go on online shopping trips compared to traditional brick and mortar establishments per year?”

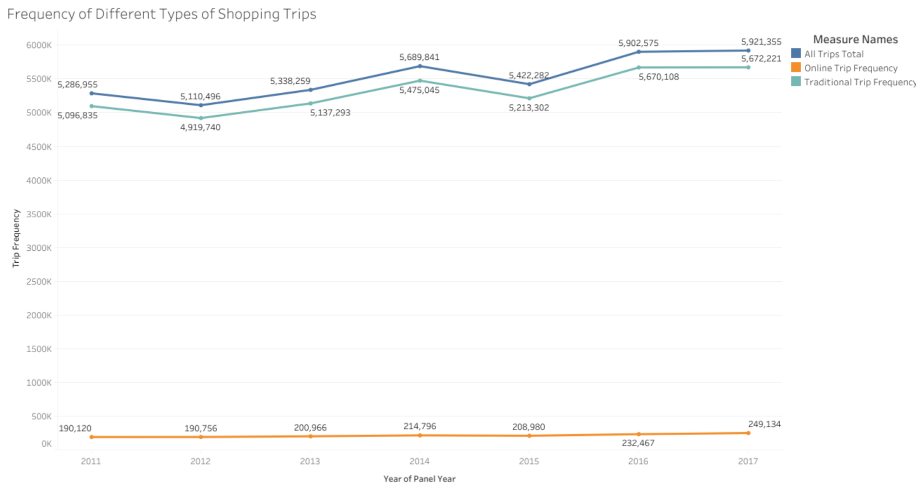

Figure 3: Nielsen Consumer Panel Trip Frequencies Per Year

Figure 3 shows that online shopping is a relatively small proportion of shopping trips, which is due to a majority of the trips going to grocery stores and discount stores. Figure 4 shows the year-over-year (YoY) changes in the number of shopping trips by type. It demonstrates that online shopping trips overall have a higher growth rate, or as in 2015, incur a milder downturn than their traditional counterparts.

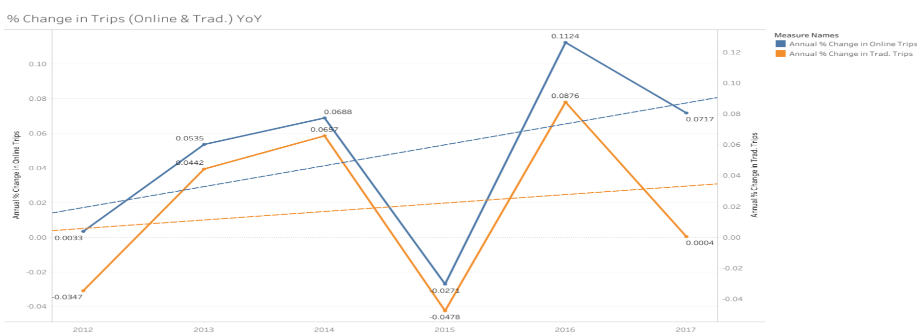

Figure 4: Nielsen Consumer Panel Shopping Trip Year-over-year Change

Trips while useful, does not tell use everything we might like to know about online shopping trends. The YoY change in the value of products sold online is provided in Figure 5.Figure 4 demonstrates similar growth patterns in online expenditures as Figure 5, including the resilience of online sales to expenditure contraction in 2015.

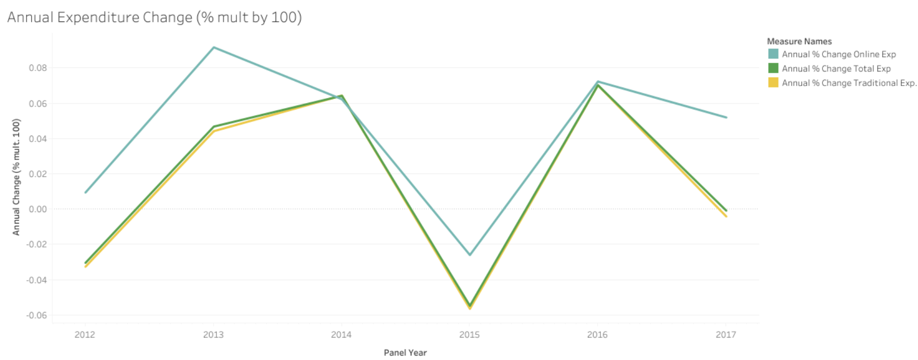

Figure 5: Nielsen Consumer Panel Online and Traditional Expenditure Change

Finally, Table 5 shows for the 2011 to 2017 period the number and percent of purchased items bought by panelists who made none or at least one online trip in the given panel year. It can be seen that for this set of panelists, online purchased items increases over time as one might expect with the increasing prevalence of online shopping over the period with a similar trend as when looking at trips.

Table 5: Panelists Who Made None or at Least One Online Purchase in Panel Year

Panel Year	None	One or More	Total	None (%)	One or More (%)
2011	44,544,026	21,777,822	66,321,848	67.16%	32.84%
2012	41,461,998	21,490,273	62,952,271	65.86%	34.14%
2013	40,077,286	23,065,539	63,142,825	63.47%	36.53%
2014	39,884,696	24,832,424	64,717,120	61.63%	38.37%
2015	39,678,860	24,111,887	63,790,747	62.20%	37.80%
2016	41,326,261	26,441,125	67,767,386	60.98%	39.02%
2017	39,415,929	27,038,277	66,454,206	59.31%	40.69%

5 Conceptual Framework and Methodology

Following Lecocq and Robin (2015), the analysis uses Stone's Price index (Stone (1954)), proper linearized, and quadratic variants of the Almost Ideal Demand System under unconstrained as well as price parameter homogeneity constrained circumstances. The quadratic variant became the preferred specification. Chi-squared testing for Slutsky symmetry was performed after the demand estimation. The demand system's approach assumes the household optimizes its resource allocation between online and traditional goods. The expenditure shares calculated from the panel data are akin to disposable expenditure as not all household expenditures are recorded in the data (e.g. rent & utilities).

Expenditure shares $w_{i,h,t}$, are defined as the amount spent on a good relative to the expenditure budget $x_{h,t}$ available $w_{i,h,t} = \frac{p_{i,h,t} * q_{i,h,t}}{x_{h,t}}$, where $p_{i,h,t}$ and $q_{i,h,t}$ are the price and quantity of good i purchased by household h in year t and are estimated following Banks et al. (1997). For expenditure period t, household h's expenditure share function for good i is specified as:

$$w_{i,h,t} = \alpha_{i,h,t} + \gamma_{\mathbf{i,t}}^{'} \mathbf{p}_{s,t} + \beta_{i,t}\{x_{h,t} - a(\mathbf{p}_{s,t}, \theta)\} + \lambda_{i,t} \frac{\{x_{h,t} - a(\mathbf{p}_s, \theta)\}^2}{b(\mathbf{p}_s, \theta)} + u_{i,h,t} \quad (1)$$

where $\mathbf{p}_{s,t}$ is a log median price N-vector indexed by $i \in 1, 2$ for online and traditional goods which includes sales taxes where applicable. That is $\mathbf{p}_{s,t}$ is comprised of $p_{i,s,t}$ which is the log median price of the good in state jurisdiction s for year t, otherwise denoted $\mathbf{p}_{s,t} \in \{p_{on,s,t} \ , \ p_{tr,s,t}\}$. θ is the set of all parameters while $x_{h,t}$ is log total expenditure of household h in year t, and $u_{i,h,t}$ is an error term.

Additionally, nonlinear price aggregators are:

$$a(\mathbf{p}_{s,t},\theta) = \alpha_0 + \alpha^{'}\mathbf{p}_{s,t} + \frac{1}{2}\mathbf{p'}_{s,t}\mathbf{\Gamma}\mathbf{p}_{s,t} \tag{2}$$

$$b(\mathbf{p}_{s,t},\theta) = \exp(\beta^{'}\mathbf{p}_{s,t}) \tag{3}$$

where $\alpha_t = (\alpha_1, ..., \alpha_N)^{'}_t, \beta_t = (\beta_1, ..., \beta_N)^{'}_t, \mathbf{\Gamma}_t = (\gamma_1, ..., \gamma_N)_t$. α_t, β_t, and $\mathbf{\Gamma}_t$ must satisfy the additivity ($\sum_{i=1}^{n}\alpha_i = 1$ and $\sum_{i=1}^{n}\beta_i = 0$), homogeneity ($\sum_{i=1}^{n}\gamma_{i,j} = 0$ $\sum_{i=1}^{n}\lambda_i = 0$), and Slutsky symmetry ($\gamma_{i,j} = \gamma_{j,i}$) conditions for a canonical almost ideal demand system, though the unconstrained model is also examined. Demographic variables use the translating approach presented first by Pollak and Wales (1981) by entering the demand system via the α's whereby $\alpha_{h,t} = \alpha^{'}_{\mathbf{i,t}}\mathbf{s}_{h,t}$ and $\mathbf{s}_{h,t}$ is the set of household demographic variables observed in the panel data.

6 Pooled Results

6.1 Unconstrained and Homogeneity Constrained Regression Results

To begin the analysis, pooled results from the panel period are used to examine whether the timing of a state's implementation of sales enforcement affected the price (including sales tax) and thereby the quantity of goods sold online. After initial unconstrained results are obtained, the homogeneity constraint is imposed on the model to see if the results are robust when imposing these conditions as well as using the chi-squared test results to determine whether symmetry holds for the dataset. Table 6 presents the Q.U.A.I.D.S results for the expenditure share of online goods. The residual expenditure share is spent on goods bought at traditional brick and mortar retail[†].

The γ coefficients for both price parameters are statistically significant with signs that would be expected. An increase in the log median price of online goods corresponds to a decrease in online expenditure shares while an increase in the log median price of traditional goods corresponds to an increase in the expenditure share of online goods as expected for traditional and online goods baskets that are substitutable.

Demographic variables include several types of household composition with heads of households being married, living alone, or with other related or unrelated parties. Many of these demographic variables are statistically significant, of which some of the more economically significant are household composition, residence type, employment of the head of the household, and household size. Of the head of household demographic features (age, employment, education,

[†]Using the traditional expenditure share as the dependent variable leads to identical estimates with flipped signs of the coefficients.

and occupation), all are significant for the female heads of household. Only age and employment are significant for a male head of household. In earlier panel years, more panelists use scanners that upload via phone line as opposed to smartphone applications now typically used. The type of internet is not measured though whether they have an internet connection or not is measured. Because it is possible panelists who are early adopters of online shoppers are also early adopters of an internet connection, it may be endogenous.

The homogeneity-constrained results are similar to the unconstrained model but with slightly smaller standard errors in most cases.

Table 6: Unconstrained and Homogeneity Constrained QUAIDS for Online Goods

Online Expenditure Share	Unconstrained	Homogeneity Constrained
$\gamma_{\mathbf{p_{Online,t}}}$	-0.110***	-0.109***
	(0.00580)	(0.00580)
$\gamma_{\mathbf{p_{Trad,t}}}$	0.126***	0.109***
	(0.00709)	(0.00580)
βlnx	-0.165***	-0.165***
	(0.00486)	(0.00487)
λlnx^2	0.00975***	0.00975***
	(0.000302)	(0.000303)
The Alphas α's		
HH Income	0.000128**	0.000145**
	(0.0000494)	(0.0000492)
HH Size	-0.00116***	-0.00115***
	(0.000263)	(0.000263)
Type of Residence	0.00124***	0.00128***
	(0.000134)	(0.000134)
HH Composition	0.00136***	0.00136***
	(0.000211)	(0.000211)
Age and Pres. Children	0.000415***	0.000415***
	(0.000120)	(0.000120)
Race	0.00195***	0.00209***
	(0.000318)	(0.000316)
Hispanic Origin	0.000222	-0.000113
	(0.000976)	(0.000973)
Male Head Age	-0.000813***	-0.000821***
	(0.000164)	(0.000164)
Male Head Employment	0.000473**	0.000462**
	(0.000154)	(0.000154)

Male Head Education	0.0000795	0.0000781
	(0.000227)	(0.000227)
Male Head Occupation	-0.000115	-0.000103
	(0.0000955)	(0.0000955)
Female Head Age	0.00172***	0.00175***
	(0.000161)	(0.000160)
Female Head Employment	0.000821***	0.000825***
	(0.000155)	(0.000155)
Female Head Education	0.00107***	0.00109***
	(0.000251)	(0.000251)
Female Head Occupation	-0.0000599	-0.0000584
	(0.000110)	(0.000110)
Kitchen Appliances	-0.00147***	-0.00147***
	(0.000151)	(0.000151)
Tv Items	0.00000975	0.000108
	(0.000296)	(0.000295)
Cons	0.694***	0.710***
	(0.0201)	(0.0197)
obs.	130275	130275
R^2	0.0318	0.0317

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Uncompensated and Compensated Own-price, Cross-price, and Budget Elasticities

While the gamma price coefficients are informative, they are complemented by their respective elasticity calculations. The budget or expenditure elasticity as well as uncompensated and compensated price elasticities for two comparison goods i and j are derived by differentiating the household budget share equation with respect to x_h and $p_{j,s,t}$ giving:

$$\mu_{i,h,t} = \beta_{i,t} + 2\lambda_{i,t}\frac{x_{h,t} - a(\mathbf{p_s}, \theta)}{b(\mathbf{p_s}, \theta)} \tag{4}$$

$$\mu_{i,j,h,t} = \gamma_{i,j,t} - \mu_{i,h,t}(\alpha_{\mathbf{j,h,t}} + \gamma_{\mathbf{j,t}}\mathbf{p}) - \lambda_{i,t}\beta_{i,t}\frac{x_{h,t} - a(\mathbf{p_s}, \theta)^2}{b(\mathbf{p_s}, \theta)} \tag{5}$$

In turn, from these partial derivatives, expenditure, uncompensated, and compensated elasticities are given by:

$$e_{i,h,t} = \frac{\mu_{i,h,t}}{w_{i,h,t}} + 1 \tag{6}$$

$$e^u_{i,j,h,t} = \frac{\mu_{i,j,h,t}}{w_{i,h,t}} - \delta_{i,j,h} \tag{7}$$

$$e^c_{i,j,h,t} = e^u_{i,j,h,t} + e_i w_{j,h,t} \tag{8}$$

where $\delta_{i,j,h}$ is the Kronecker delta.

Table 7 and Table 8 present the corresponding uncompensated and compensated price elasticities for the unconstrained and homogeneity-constrained models. The rows of these two tables denote the prices of online and traditional goods, $\gamma_{\mathbf{p_{Online,t}}}$ and $\gamma_{\mathbf{p_{Trad,t}}}$, respectively. Columns one and three display the corresponding own and cross-price elasticities derived from the associated expenditure shares. Columns two and four report the associated standard errors. The absolute magnitude of the uncompensated own-price elasticity for online goods varies between 1.255 and 1.221 for the unconstrained (Table 7) and homogeneity-constrained (Table 8) models, respectively. Similarly, the compensated own-price elasticity for online goods varies between 1.227 and 1.19. Traditional goods as to be expected are less elastic. The estimated uncompensated own-price elasticity ranges between magnitudes of 1.039 to 1.021. Notably, unlike the estimate for online goods, the estimate for traditional goods differs between uncompensated and compensated elasticities. It goes from nearly unit elastic for uncompensated to quite an inelastic range of 0.067 to 0.048 in the unconstrained and homogeneity-constrained cases for compensated own-price elasticity.

Additionally, the table presents cross-price elasticities. This indicates that an online goods basket may be sensitive to price changes in a traditional brick-and-mortar goods basket as indicative of a substitute goods basket. The cross-price elasticity for online goods with respect to traditional goods basket prices ranges between 0.971 with uncompensated and 1.647 with compensated demand in the unconstrained model. For the homogeneity-constrained model, the estimate varies between 0.522 and 1.194 for uncompensated and compensated respectively. Traditional expenditure shares on the other hand are consistently inelastic with respect to changes in online prices.

Table 7: Unconstrained Own and Cross-Price Elasticities

	w_{Online}	(b/se)	$w_{Traditional}$	(b/se)
Uncompensated				
Online	-1.255***	0.026	0.010***	0.001
Traditional	0.971***	0.11	-1.039***	0.004
Compensated				
Online	-1.227***	0.026	0.050***	0.001
Traditional	1.647***	0.11	-0.067***	0.004

* p<0.05,** p<0.01, ***p<0.001

Median per unit cost with state sales tax used. Columns are the elasticity of good being and corresponding standard errors examined while the row is the respective price

Table 8: Homogeneity Constrained Own and Cross-Price Elasticities

	w_{Online}	(b/se)	$w_{Traditional}$	(b/se)
Uncompensated				
Online	-1.221***	0.025	0.009***	0.001
Traditional	0.522***	0.027	-1.021***	0.001
Compensated				
Online	-1.194***	0.025	-0.048***	0.001
Traditional	1.194***	0.025	-0.048***	0.001

* p<0.05,** p<0.01, ***p<0.001

Median per unit cost with state sales tax used. Columns are the elasticity of good being and corresponding standard errors examined while the row is the respective price

The budget elasticities for the unconstrained and homogeneity-constrained models are presented in Table 9 below. The expenditure share of online goods is inelastic with respect to the consumer budget in both cases at 0.704 and 0.699, respectively. If a 10% increase in budget corresponds to about a 7% increase in demand for online goods, this elucidates the differential between the uncompensated and compensated demand price elasticities for online expenditure shares in Table 7 and Table 8. In both the unconstrained and homogeneity-constrained tables the compensated online own price elasticity is less elastic than the uncompensated elasticity.

Table 9: Budget Elasticities

	Unconstrained	Homogeneity Constrained
w_{Online}(b/se)	0.704***	0.699***
	0.11	0.011
$w_{Traditional}$(b/se)	1.012***	1.012***
	0.00	0.00

* p<0.05,** p<0.01, ***p<0.001

It should be noted that when comparing the unconstrained model to the homogeneity-constrained model, a chi-squared test can be applied in concert with the unconstrained model to determine whether or not the homogeneity constraint holds. For the unconstrained model, the calculated chi-squared value of 17.92 is greater than all conventional critical value thresholds, so homogeneity is rejected. Similarly, when homogeneity is imposed on the model, a χ^2 test for Slutsky symmetry is calculated to be 11,451.82 so symmetry is rejected at typical confidence levels as well. Finally, the predicted online and traditional expenditure shares were 3.9% and 96.1% in both the unconstrained and homogeneity-constrained models.

6.3 Sales Tax Policy Implications of Elasticities

Using estimated elasticities, it is possible to estimate how different expenditure shares would be if states had never implemented sales taxes on online retail goods. With sales taxes remaining on traditional brick-and-mortar goods, we would expect that the level of online expenditure share would be greater.

Examining the elasticities for selected states of online goods we can not only compare the differences in uncompensated and compensated elasticities between states but the elasticity value can be multiplied by the prevailing sales tax rate in the state to determine an overall effect of sales tax enforcement for online purchases on the expenditure share of online goods in each state. The figures presented are likely an upper bound of policy potential as the estimated sample is indicative of the intensive margin of online shoppers and not retail consumption overall. The results appear in Table 10.

We first estimate the Q.U.A.I.D.S. for five selected states to assess whether elasticities vary over states. We choose the large states Texas and California with the other West Coast states such as Nevada for comparison. The compensated own price elasticity for online goods is -1.227 in the pooled sample. In the table, the state-level elasticities of a Q.U.A.I.D.S. model with demographics are calculated and presented with the state's prevailing sales tax rate in 2022. If consumers are consistent in their consumption behavior, policymakers can multiply their state sales tax by the state-level elasticity to determine the overall effect of the sales tax on online retail consumption. Oregon, which has no state sales tax, provides a reference for comparison.

The uncompensated state elasticity estimates of this selection of states are highest in Texas at 1.27 in absolute terms while California has the lowest at 1.225. Interestingly, Oregon has a value of 1.263 which is higher than both its neighboring states (Washington 1.243). Texas has the lowest state sales tax besides Oregon and has the second-highest state-level uncompensated elasticity.

Table 10: Elasticities of Online Expenditure Share and Sales Tax Impact by State

State	Budget Elas.	Uncomp.	Comp.	Sales Tax	Uncomp*Sales Tax
CA	0.674	-1.225	-1.194	7.25%	-8.881%
	0.009	0.021	0.022		
OR	0.62	-1.263	-1.238	0.00%	0.000%
	0.01	0.026	0.026		
WA	0.649	-1.243	-1.215	6.50%	-8.080%
	0.01	0.023	0.023		
NV	0.626	-1.259	-1.233	6.85%	-8.624%
	0.01	0.026	0.026		
TX	0.612	-1.27	-1.245	6.25%	-7.938%
	0.011	0.027	0.028		

6.4 Variance Inflation Factors

We ascertain the presence and extent of multicollinearity among expenditure terms, and the models' variance inflation factors (VIFs) are used for this purpose. Table 11 presents the VIF results and using the traditional rule of thumb of a VIF greater than 10 being indicative of multicollinearity, it is readily apparent that both the total expenditure term and quadratic total expenditure term at 183.67 and 168.89 respectively, exhibit strong multicollinearity. This is not surprising as the quadratic term is correlated with the level by design in the quadratic AIDS framework, so this is not a cause of concern. The only other variable that reaches slightly above the threshold of 10 is the log median online price at 10.73. These figures are close to VIF figures obtained from other readily available commodity data sets. The estimation results suggest that collecting sales tax from online retailers reduces the expenditure share of online goods substantially: by 7.9% in Texas and by 8.9% in California (keeping the sales tax on traditional retail channels constant).

Table 11: Variance Inflation Factors (VIFs) for Unconstrained and Homogeneity Constrained Models

Variable	Unconstrained VIFs	Homogeneity Constrained VIFs
ln(Median Online PUC w/tax)	10.73	10.68
ln(Median Traditional PUC w/tax)	1.44	1.44
lnx	183.6	183.67
lnx2	169.07	168.89
household income	1.64	1.64
household size	2.16	2.16
type of residence	1.11	1.11
household composition	2.73	2.73
age and presence of children	1.89	1.89
race	1.14	1.14
hispanic origin	1.12	1.12
male head of household age	6.79	6.79
male head of household employment	5.07	5.07
male head of household education	4.6	4.6
male head of household occupation	4.07	4.07
female head of household age	1.94	1.94
female head of household employment	5.21	5.21
female head of household education	1.31	1.31
female head of household occupation	5.6	5.6
kitchen appliances	1.08	1.08
TV items	1.07	1.07

7 Individual Panel Year Results

7.1 Unconstrained Estimates

In this extension, we ask whether consumers became more or less price-sensitive over time in their online shopping behavior, as the overall volume of online sales increased strongly (Figure 1). We estimate separate models for each year. The quadratic unconstrained estimates are presented in Table 12. The estimated γ coefficient has the anticipated negative sign that indicates an online price increase leads to a lower online expenditure share. That magnitude of the γ coefficient for online shopping has a slightly positive trend over the 2011 to 2017 period with the greatest uptick in 2017, where γ reached -0.138. Thus online shoppers have become sensitive as online purchases have increased over time.

The type of residence, age of the female head of household, and kitchen appliances are among several demographic variables of interest that were statistically significant over the period. Other demographic variables such as race, household size, and household composition have varying levels of statistical significance in some but not all years in the period.

Along with the output from the unconstrained model is also reported a joint χ^2 test for homogeneity. The results are mixed with four out of seven years in the period rejecting the null at conventional levels.

Table 12: Online Expenditure Shares of Unconstrained Quadratic AIDS for Panel Years

	2011	2012	2013	2014	2015	2016	2017
$\gamma_{\mathbf{POnline,t}}$	-0.113***	-0.106***	-0.115***	-0.110***	-0.116***	-0.0908***	-0.137***
	(0.0184)	(0.0174)	(0.0171)	(0.0158)	(0.0160)	(0.0121)	(0.0160)
$\gamma_{\mathbf{PTrad,t}}$	0.0759***	0.0987***	0.120***	0.112***	0.137***	0.122***	0.163***
	(0.0222)	(0.0223)	(0.0217)	(0.0200)	(0.0203)	(0.0154)	(0.0184)
βlnx	-0.165***	-0.167***	-0.168***	-0.162***	-0.160***	-0.137***	-0.183***
	(0.0150)	(0.0142)	(0.0137)	(0.0132)	(0.0137)	(0.0122)	(0.0124)
λlnx^2	0.00947***	0.00965***	0.00980***	0.00964***	0.00954***	0.00820***	0.0110***
	(0.000967)	(0.000902)	(0.000863)	(0.000827)	(0.000851)	(0.000746)	(0.000740)
Alphas α's							
HH Income	-0.000279	0.0000409	0.0000727	0.0000348	0.000128	0.000333**	0.000379**
	(0.000154)	(0.000144)	(0.000136)	(0.000126)	(0.000127)	(0.000113)	(0.000122)
HH Size	-0.000145	-0.0000351	-0.000910	-0.00117	-0.00117	-0.00186**	-0.00220***
	(0.000798)	(0.000743)	(0.000735)	(0.000696)	(0.000676)	(0.000596)	(0.000653)
Residence	0.00129**	0.000821*	0.00107**	0.00139***	0.00102**	0.00115***	0.00186***
	(0.000419)	(0.000394)	(0.000365)	(0.000340)	(0.000346)	(0.000304)	(0.000331)
HH Compos.	-0.000338	0.00202**	0.00117	0.00164**	0.00203***	0.00197***	0.00176**
	(0.000525)	(0.000629)	(0.000603)	(0.000584)	(0.000593)	(0.000486)	(0.000535)
Children	0.000773*	0.000173	0.000662*	0.000343	0.000217	0.000372	0.000421
	(0.000365)	(0.000343)	(0.000328)	(0.000311)	(0.000312)	(0.000272)	(0.000295)
Race	0.00111	0.00135	0.00420***	0.00299***	0.00155	0.00153*	0.00130
	(0.00102)	(0.000943)	(0.000896)	(0.000825)	(0.000822)	(0.000705)	(0.000747)
Hispanic	-0.00294	0.00190	0.00463	0.000486	-0.00180	0.000952	-0.00209
	(0.00317)	(0.00296)	(0.00282)	(0.00260)	(0.00248)	(0.00211)	(0.00226)
Male HH:							
Age	0.000122	0.000178	-0.000841	-0.000535	-0.000615	-0.00135***	-0.00159***
	(0.000512)	(0.000491)	(0.000463)	(0.000431)	(0.000426)	(0.000379)	(0.000412)
Employment	0.000360	0.00112*	0.000602	0.000794	0.000287	0.000604	0.000236
	(0.000567)	(0.000530)	(0.000492)	(0.000472)	(0.000332)	(0.000433)	(0.000475)
Education	-0.000332	-0.000344	0.000668	0.000141	-0.000145	0.000327	0.000332
	(0.000706)	(0.000673)	(0.000635)	(0.000585)	(0.000588)	(0.000524)	(0.000563)
Occupation	-0.000124	-0.000560	-0.000121	-0.000360	0.000219	-0.000400	-0.0000129
	(0.000388)	(0.000360)	(0.000338)	(0.000323)	(0.000189)	(0.000296)	(0.000321)

Female HH:							
Age	0.00156**	0.00263***	0.00210***	0.00158***	0.00109*	0.00165***	0.00119**
	(0.000509)	(0.000475)	(0.000451)	(0.000417)	(0.000428)	(0.000360)	(0.000387)
Employment	0.00110*	-0.0000390	0.000444	0.000835*	0.00120**	0.00108**	0.00107**
	(0.000458)	(0.000432)	(0.000405)	(0.000377)	(0.000422)	(0.000379)	(0.000414)
Education	0.000124	0.000168	0.000144	0.00104	0.00241***	0.00170**	0.00126*
	(0.000782)	(0.000742)	(0.000696)	(0.000637)	(0.000642)	(0.000567)	(0.000615)
Occupation	-0.000301	0.000326	0.000109	-0.000137	-0.000430	-0.000123	0.0000301
	(0.000325)	(0.000306)	(0.000288)	(0.000269)	(0.000301)	(0.000270)	(0.000292)
Appliances	-0.00137**	-0.00151***	-0.00184***	-0.00152***	-0.00138***	-0.00129***	-0.00107**
	(0.000481)	(0.000451)	(0.000416)	(0.000383)	(0.000384)	(0.000344)	(0.000372)
Tv Items	0.000862	-0.00107	0.000369	0.000771	-0.000808	0.000219	-0.00000174
	(0.000885)	(0.000885)	(0.000828)	(0.000789)	(0.000821)	(0.000716)	(0.000758)
State	-0.000101*	-0.0000612	-0.0000189	0.00000287	0.0000474	0.0000820*	0.0000583
	(0.0000472)	(0.0000434)	(0.0000411)	(0.0000387)	(0.0000415)	(0.0000356)	(0.0000391)
Cons	0.777***	0.731***	0.710***	0.688***	0.672***	0.554***	0.757***
	(0.0602)	(0.0578)	(0.0566)	(0.0548)	(0.0570)	(0.0511)	(0.0533)
obs.	16614	16655	17922	19452	18844	20051	20737
	Chi^2	Chi^2	Chi^2	Chi^2	Chi^2	Chi^2	Chi^2
	8.22	0.3	0.17	0.03	2.9	10.81	7.24
	Prob chi2	Prob chi2	Prob chi2	Prob chi2	Prob chi2	Prob chi2	Prob chi2
	0.0041	0.5821	0.6838	0.8645	0.0888	0.001	0.0071
Is χ^2 > Prob	Reject	Fail to Reject	Fail to Reject	Fail to Reject	Reject	Reject	Reject

8 Conclusion

The demand estimation results for the Nielsen Consumer Panel data set demonstrate that the predicted expenditure shares are within comparable shares of online sales from external data sources. Additionally, own-price elasticity for online goods consistently prices elastic at elasticity values around 1.22, indicating that consumers are price sensitive in regards to their online shopping patterns. In particular, these results indicate that consumers are sensitive to changes in state sales tax policy. For example, if California had not introduced sales taxation for online goods, the expenditure share of online goods for consumers in California would be 8.9% higher. This suggests that sales tax policy toward online retailers can substantially shift consumption between online and traditional retailers and can therefore be an effective instrument if policymakers intend to strengthen small local brick-and-mortar businesses. Since e-commerce has evolved to the point where small brick-and-mortar businesses can market their goods online just as larger online retailers, the substitutability between traditional and online goods can be further tested. Additionally, if states continue to modify the level of their sales tax rate, the effectiveness of such an instrument might be further examined using these methods.

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