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SALES TAXES AND INTERNET COMMERCE

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ABSTRACT

We estimate the sensitivity of Internet retail purchasing to sales taxes using data from the eBay marketplace. Our first approach exploits the fact that seller locations are revealed only after buyers have expressed interest in an item by clicking on its listing. We use millions of location "surprises" to estimate price elasticities with respect to the effective sales tax. We then use aggregated data to estimate cross-state substitution parameters, and substitution between offline and online purchases, relying on the variation in state and local sales taxes, and on changes in these rates over time. We find substantial sensitivity to sales taxes. Using our item-level approach, we find a price elasticity of around -2 for interested buyers. Using our aggregate approach, we find that a one percentage point increase in a state's sales tax increases online purchases by state residents by just under two percent, but decreases their online purchases from home-state retailers by 3-4 percent.

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1 Introduction

Internet retail amounts to well over a hundred billion dollars annually in the United States and accounts for a growing share of overall retail commerce (US Census Bureau, 2011). The majority of internet transactions occur across state lines, with striking tax consequences. While online sellers located in a particular state must collect sales tax on in-state sales, states currently cannot compel out-of-state sellers to collect tax on sales to state residents. Instead, resident consumers are obligated to pay an equivalent use tax, but enforcement is sufficiently lax that cross-state internet sales generally go untaxed.[1] As a result, even conservative guesses about purchasing elasticities suggest that taxes may play a significant role in shaping the geography and dynamics of online retail trade.

Recently, the tax treatment of internet commerce has generated considerable attention.[2] Sales and use taxes account for more than 30% of state tax revenues. Foregone taxes on internet sales could amount to $10 billion a year, and this number is likely to grow (Maguire, 2011). Nevertheless, empirical evidence that might inform a discussion about internet taxation remains rather limited, despite some notable efforts that we discuss below (Goolsbee, 2000a; Smith and Brynjolfsson, 2000; Alm and Melnik, 2005; Scanlan, 2007; Hortacsu et al., 2009; Ellison and Ellison, 2009; Goolsbee et al., 2010; and Anderson et al., 2010).

We provide some fresh evidence using data from eBay's online marketplace. In the United States, eBay's marketplace accounts for a significant fraction of internet retail commerce, roughly $30 billion annually. The marketplace is large and diverse, with millions of buyers and a huge array of sellers and product categories. We take advantage of this size and diversity to observe buyers choosing across sellers located in different states, with correspondingly different tax treatments and changes in those treatments over time, in order to

[1] Varian (2000) provides useful background on the tax treatment of internet commerce. A key Supreme Court decision in 1992 found that, absent explicit federal legislation, the Commerce Clause does not allow states to compel sellers without presence (or "nexus") in the state to collect use tax on sales to state residents (Quill Corp. v. North Dakota (91-0194), 504 U.S. 298 (1992)). About half of the states with use taxes ask taxpayers to report use tax obligations on individual income tax returns, but this effort is largely unsuccessful. Less than two percent of taxpayers report any use tax in states with this type of self-reporting (Manzi, 2010).

[2] As an indication of popular interest, a Google News search for `internet OR online OR e-commerce "sales tax"` returned more than a thousand articles published in the first two months of 2012. Many of these articles discuss internet sales taxes in relation to state budgets.

estimate the effect of sales taxes on purchasing behavior. Although our data is limited to a single platform, its overall market share is sufficiently robust that our analysis hopefully provides insight extending more broadly across online retail.

Our estimates rely on three sources of sales tax variation. The first is the difference, for online buyers, between in-state purchases that are taxed and out-of-state purchases that are not. Of course, a direct comparison of intrastate and interstate purchase propensities may understate the effect of taxes if consumers have preference for their "home state" goods or sellers. One way to address this is to use variation across states in sales tax rates, and compare the relative intrastate purchase propensity across low tax and high tax states. Thankfully, there is considerable rate variation: as of January, 2010, state sales taxes ranged from zero (in Alaska, Delaware, Montana, New Hampshire, and Oregon) to seven percent or more (California, Indiana, Mississippi, New Jersey, Rhode Island, and Tennessee). The variation becomes even greater after accounting for county and local sales taxes. Figure 1 shows the cross-sectional variation in sales and use tax rates by state and county. Finally, a third source of identifying variation comes from the frequent changes in state and local tax rates. Figure 2 shows states and counties in which there was a change in the sales tax rate during 2008-2010.

We use these three sources of variation to estimate the effect of sales taxes along different decision margins. Our first approach exploits the fact that most consumers shopping on eBay only observe a seller's location, and hence the relevant sales tax treatment, after they click on a listed item. We use data from millions of location "surprises" to estimate the tax sensitivity of purchasing conditional on being interested in a given item. This approach allows us to control tightly for the preferences of buyers and the desirability of items located in different states. Following this "micro" approach, we estimate an average tax-price elasticity of around -2, conditional on being interested in an item. We also use search and purchase histories following adverse tax surprises to trace out substitution patterns.

Our second approach uses more aggregated data on sales from one location to another. It is closer to earlier work on internet tax sensitivity, so that our main contribution is improved data and the use of tax changes as well as cross-sectional differences in tax levels. We consider an econometric specification based on a constant elasticity (CES) model of online purchasing that allows us to map tax sensitivities into substitution parameters governing choices between online goods, and the choice to purchase online. Using different sources of tax variation, we estimate that a one percentage point increase in a state's sales tax leads to an increase of just under 2 percent in online purchasing, and a 3-4 percent decrease in the volume of online purchases from home-state sellers. We connect these estimates to our item-level "surprise" elasticities using a simple accounting framework that accounts for the effect of taxes on consumer search patterns.

Existing work on sales taxes and internet commerce dates back to the influential work of Goolsbee (2000a,b). Using data from a 1997 Forrester Research survey, Goolsbee looked at whether respondents in high-tax areas were more likely to have made an online purchase. He estimated that up to 24 percent of online purchasers would not have purchased online if internet transactions were taxed. Later studies by Alm and Melnik (2005) and Scanlan (2007) performed a similar exercise using questions in the 2001 Current Population Survey. The former estimates a tax sensitivity only a fourth as large as that of Goolsbee, while the latter suggests there is minimal tax sensitivity in low tax jurisdictions but very substantial sensitivity in high tax areas. Apart from pre-dating the widespread use of the internet, one limitation of these studies is that the data is very coarse; the authors effectively project a yes/no indicator of e-commerce participation on home-state sales tax and household characteristics.

Other studies have taken a more targeted approach using data for a particular retailer or product. Ellison and Ellison (2009) examine detailed data on the sale of computer memory modules by a retailer located in California. Using price search data, they estimate that consumers searching for certain memory modules are highly price-sensitive, with price elasticities on the order of -50 and tax-price elasticities on the order of -10. They also use data on the retailer's distribution of sales across states to estimate how sales vary with (offline) tax rates. They find that states with a one percentage point higher tax rate have almost 6% more purchases from the retailer, but caution that their controls may not adequately isolate tax effects from other cross-state differences. Smith and Brynjolfsson (2001), Anderson et al. (2010) and Goolsbee et al. (2010) also find relatively high tax sensitivities for specific types of products, namely online books, clothing, and cigarettes.

Finally, in an interesting paper that relates closely to the first half of our analysis in Section 3, Hortacsu, Martinez-Jerez, and Douglas (2009) use a sample of eBay transactions collected between February and May 2004 to estimate a gravity model of cross-state trade flows. They focus mainly on the relationship between trade volume and distance, but one of their specifications accounts for the sales tax on home-state transactions. Their results indicate that, holding online expenditures fixed, a one percentage point increase in state sales tax decreases same-state online purchases by 10% or more, about twice the magnitude of the effect we estimate. We discuss their estimates in more detail below.

2 Individual Responses to Tax "Surprises"

Our first approach to estimating consumer sensitivity to online sales tax takes an item-level empirical approach. We exploit a particular feature of the search process on eBay, namely that buyers observe seller locations and the sales tax they will be charged only after they click on an item listing. Prior to clicking on a listing, buyers may have an expectation as to whether the seller is located in their same state, in which case sales tax is due, or not, in which case the transaction is effectively tax-free. Only after clicking the listing, however, can the buyer observe the seller location and eventually the exact sales tax. In what follows, we use data on consumer browsing sessions to identify millions of these "surprises" and estimate an average item-level sensitivity to sales tax.

2.1 Research Design

Consumers shopping on eBay see items displayed on listings pages, which they can reach by browsing the site or entering search queries. Figure 3(a) displays a typical listings page. Each listing contains a thumbnail picture of the item, a short description, its price (or the current high bid if the sale is by auction), and the time until the listing expires. By default, listings are ranked by relevance (determined by eBay's "best match" algorithm); users also can sort listings by price or expiration date. Seller location (and hence sales tax) is not displayed and is not factored into the sort order unless buyers explicitly specify a local search, which is very uncommon. Indeed, the only information about sellers on a listings page are flags indicating that particular sellers are "top rated".

Potential buyers click on listings to learn more or make a purchase. A click reveals an item page (Figure 3(b)) that contains more details, including the seller's location (shown in the bottom right corner of Figure 3(b)). In principle, this is enough to determine if tax will be due, but buyers can also click on the "shipping and payment" tab where many sellers list more detailed tax information, and tax information is displayed after the buyer initiates a purchase and before it is confirmed.

The idea of our research design is to compare buyers who arrive at the same item page, some of whom are located in the same state as the seller (and would be charged tax) and some of whom are not. In this way we compare like-minded buyers considering the same item, only with different tax-inclusive prices. Of course, for sales tax to matter, at least some consumers must take note of it. Chetty, Looney, and Kroft (2009) and Ellison and Ellison (2009) have made the point that sales taxes often may not be as salient as retail prices, and we have seen in our own research (Einav et al., 2011) that eBay consumers appear not to fully internalize shipping fees, which if anything are displayed more prominently than taxes. For this reason, tax price sensitivity may understate retail price sensitivity.

2.2 Data

We assemble detailed browsing and purchasing data for several hundred thousand items available on eBay. We start with the set of all items listed between January 1 and December 31, 2010. From this universe, we select all items that were offered at a posted price with at least ten available units, by sellers who use eBay's "tax table" application. We focus on listings with a relatively large available quantity so that we can observe multiple purchases for each item (almost all transactions on eBay are single unit purchases) and avoid any potential issues that might arise from listings selling out after one or a few purchases. We focus on sellers who use the tax table so we can be confident of their tax collection practices. The tax table is used by retailers who list significant numbers of items: it allows a seller to enter the tax rate it wishes to charge buyers in states where it has nexus, and the seller can apply this rate easily to all its listings.

We sort through trillions of user interaction events to identify, for each item, all page views by logged-in eBay users during the observation period.[3] We restrict attention to users located in the United States. We use the respective ZIP codes of the buyer and seller to determine the applicable sale tax. We assume that for an in-state sale, the seller charges the combined state and local sales tax in its own ZIP code, while for out-of-state sales no tax is charged.[4] We also calculate the great-circle distance between the centroids of the buyer and seller ZIP codes. Finally, for each page view we determine if the user subsequently purchased the item during the browsing session.

Table 1 presents summary statistics for the items in the data. We report statistics only for those items that had at least one qualifying purchase because in the fixed-effects specifications we use below, items with zero purchases provide no identifying information and hence are dropped from the analysis. The resulting data consist of 275,020 listed items posted by 10,347 different sellers. The average base price of these items is $37. The average combined state and local sales tax in the seller's ZIP code is just under 8%. We observe an average of around 25 page views for each item. This gives us a total of 6,796,691 page views. Overall, for the average item in our sample, about one in five of these page views results in a purchase.

2.3 Consumer Tax Sensitivity

We estimate consumer sensitivity to sales tax using a fixed-effects logit model of the purchase decision. Let k index the items, and i index the viewers of each item. We assume that

$$\Pr(i \text{ buys } k \mid i \text{ views } k) = \frac{\exp(u_{ik})}{1 + \exp(u_{ik})}, \tag{1}$$

where

$$u_{ik} = \alpha_k + \beta \log(1 + \tau_{ik}) + g(d_{ik}) + \gamma \mathbf{1}\{\text{state } i = \text{state } k\}. \tag{2}$$

[3] We focus on logged-in users so we can reliably identify each consumer's location, and discard observations with incomplete or ambiguous location information. Note that we require that the user logged in prior to having viewed the item in that browsing session, to eliminate the concern that users might log in specifically to complete a particular purchase. Also, if a user viewed a sample item in a given browsing session and then viewed that same item in the subsequent session, we only use the data from the first session. We do this to simplify the analysis, as it allows us to consider a cross-section of encounters for each item.

[4] In the event that some sellers charge tax in more than one state, or adjust the local tax to reflect the precise location of in-state buyers, this will introduce some measurement error in the "effective tax rate" we use below in our regressions.

Here the first term α_k is a fixed effect that captures each item's general desirability, including its pre-tax price.[5] The second term is the effect of the relevant tax rate τ_{ik}, which is equal to the combined sales tax in the item's ZIP code if i is a same-state buyer, and zero otherwise. We include the distance between the buyer and seller, denoted d_{ik}, as a control to account for the possibility that buyers may prefer nearby items, for instance because they expect faster shipping or have more trust in local sellers.

Our first specification includes only these first three terms. In this specification, the primary source of variation in τ_{ik} is between in-state buyers who are taxed and out-of-state buyers who are not, holding fixed their physical distance to the item. One concern, however, is that buyers may prefer in-state items even controlling for distance. Such "border effects" are common in the international trade literature (Anderson, 2011), and appear in Hortacsu et al.'s (2009) eBay study. Focusing on consumers who already have clicked on an item should rule out many obvious examples of home-state preference (e.g. Nebraska residents preferring Cornhuskers t-shirts), but any residual preference might bias an estimate of β toward zero. In our preferred specification, we include a dummy variable indicating whether the buyer is located in the same state as the item. With this control, the tax parameter β is identified from differences in the same-state "avoidance" of buyers in high and low tax states.

The estimates are reported in Table 2. The first column reports our initial specification with no home-state preference dummy. The second column is our preferred specification. To translate the reported estimate of the tax coefficient β into an approximate price elasticity, one needs to multiply it by one minus the purchase rate, or by approximately 0.79.[6] With that in mind, our preferred specification yields an approximate tax-price elasticity of -2. That is, for every one percentage point increase in the sales tax (one percent increase in the post-tax price), purchasing decreases by about two percent. A viewer charged a 5% sales tax is about 6% more likely to purchase than an equivalent viewer facing an 8% sales tax, and 10% less likely to purchase than one who is charged no sales tax.

[5] To see how this works, let p_k denotes the retail price and suppose that $u_{ik} = a_k + \beta \log(1+\tau_{ik}) p_k + g(d_{ik}) + \gamma \mathbf{1}\{\text{state } i = \text{state } k\}$. Defining $\alpha_k = a_k + \beta \log p_k$ yields equation (2).

[6] The elasticities reported are computed at the margin corresponding to the average purchase probability for items in our sample.

One reaction to this estimate is that, for retail items in a highly competitive marketplace, demand appears to be surprisingly inelastic. There are at least two reasons, however, to be cautious of this interpretation. First, it is very plausible that buyers pay less attention to the sales tax than to the retail price. Second, we are focusing on the response of buyers who already have identified and expressed interest in these items. If the primary effect of a retail price increase is to cause buyers not to click on the item in the first place, the relevant price elasticity for the sellers of these items could be considerably larger (i.e. more negative).[7]

The results in Table 2 on the effects of distance and home-state preference are also interesting. There is a clear and consistent relationship between distance and the probability of purchase. All else equal, a consumer who is 250 kilometers from an item is about 3% more likely to purchase than one who is 1000 kilometers from the item. One possible explanation is shipping time: the closer the item, the less delay a buyer may expect. For a small fraction of the items (just under 15%), shipping cost may also be a factor because rather than charging a flat shipping fee (typical on eBay), the seller charges a calculated rate based on the distance.

The presence of these variable shipping rate items also provides a useful opportunity to look at the salience of "add-on" prices. In column (c), we allow the effect of distance to vary depending on the type of shipping fee. Consumers are twice as sensitive to distance when it affects the shipping fee. To interpret the magnitude of the coefficient, we observe that the average variable rate shipping fee increases by around \$0.56 for every doubling in distance. If we take the distance coefficient for flat shipping rate items to be a base preference for distance and interpret the additional sensitivity for calculated shipping rate items as a price response, this suggests that for a typical item in the sample, the \$0.56 increase in the shipping fee from a doubling of distance reduces the probability of purchase by around 1.4%. For a good priced at \$43 (which is our sample average, calculated shipping included), a \$0.56 increase in the shipping fee corresponds to a price elasticity of about -1.1.[8]

Finally, the estimates in Table 2 suggest a substantial home-state preference. Controlling for distance to an item, consumers are about 10% more likely to buy if the seller is located

[7] Dinerstein, Einav, Levin and Sundaresan (in progress) explore the relationship between prices and consumer search behavior using variation in prices that arises due to the timing of retail price posting.

[8] This elasticity estimate is about half of our estimated tax elasticity. This appears reasonable given that calculated shipping rates, unlike flat shipping rates, depend on distance in a non-transparent way.

in the same state. The positive effect is consistent with the results in Hortacsu et al. (2009) and in our Table 5, but perhaps more surprising given that we are focusing only on interested buyers. It may be useful in thinking about this effect to consider how it is identified. Note that we can group the second and fourth terms in our logit specification, equation (2), as $\mathbf{1}\{\text{state } i = \text{state } k\} \left[\gamma + \beta \log\left(1 + \tau_k\right)\right]$, where τ_k is item k's combined state and local sales tax. By comparing buyers located similar distances from an item but on either side of the state border we can identify the combined effect $\gamma + \beta \log\left(1 + \tau_k\right)$. We estimate this to be close to zero on average (i.e. $\gamma + \beta\overline{\log(1 + \tau)} \approx 0$). The variation in individual item tax rates then allows us to identify β, so that γ falls out as an intercept. Identifying γ, however, requires some extrapolation because nearly all the items have a combined tax rate between five and ten percent. As a result, our home-state preference estimate varies a bit across specifications, although it appears in all cases to be substantial.

2.4 Heterogeneity in Tax Sensitivity

Our baseline results yield an average tax-price elasticity for a wide range of retail items. We also can take advantage of the rich data by splitting the sample and comparing purchasing behavior for goods in different retail categories or at different price points. Such an exercise is interesting in part because not many studies have been able to provide reliable and comparable price elasticity estimates for large numbers of retail goods.[9]

Table 3(a) reports separate estimates for the six largest product categories in our sample. We estimate the largest elasticity for electronics (-4.3), followed by sporting goods (-3.3). Three other categories (cell phones, computers, and clothing) are estimated to have a tax-price elasticity of about -2. The "home and garden" category is an exception, as we estimate essentially no tax sensitivity. Although the estimates are not sufficiently precise to be definitive, the results generally conform to the intuitive idea that price sensitivity might be greater in more "commodity" type product categories than in categories with greater

[9] One exception is the marketing literature that uses grocery-store scanner data to estimate price elasticities for a variety of goods. For instance, a well-cited paper by Hoch, Kim, Montgomery and Rossi (1995) reports average own-price price elasticities for eighteen categories of goods sold at Dominick's grocery stores. They lie in a remarkably narrow range, from -0.79 to -2.59.

product differentiation.[10]

Table 3(b) splits the sample based on the retail prices of the sample items. The estimated tax coefficient is larger in magnitude for more expensive items, which also have a lower purchase rate. Translated into tax-price elasticities, we find the elasticity of the cheapest items (selling for less than 6 dollars) to be just under -1.5, compared to -2.7 for items that are priced at $24 or more. One hypothesis is that taxes are more salient for the expensive goods because their dollar effect is larger and perhaps noticed by more consumers. The differing estimates could also reflect differences in the retail price elasticities, which also would be interesting because it is not a priori clear that demand should be more elastic for more expensive items.[11]

In addition to exploring differences across items, we also considered the possibility that different buyers would be systematically more or less sensitive to taxes. In particular, we looked separately at experienced and inexperienced buyers, using a segmentation developed by eBay that correlates roughly with the number of past purchases a buyer has made. To our surprise, we found only very minor differences in tax sensitivity across buyers with different amounts of experience, and no differences that were statistically significant.

2.5 Substitution Effects

Our final exercise in this section uses the tracking allowed by the clickstream data to investigate whether buyers who receive a "tax surprise" are likely to substitute to an alternative item. To do this, we rely on the same set of user-item observations as in the analysis above, but for each user, track whether he or she subsequently purchased a different item, and if so, the characteristics of this purchase.[12] We use this expanded data to investigate the generalized response of browsing consumers who receive an adverse price shock. We view

[10] One may notice that the estimated home-state effect varies substantially across product categories. Recall, however, our discussion in the end of the previous section, which makes it clear why this estimate is mechnically (and negatively) affected by the estimated tax elasticity.

[11] To the extent that the higher price reflects a higher optimal mark-up, one might expect more expensive goods to be less price elastic. On the other hand, if elasticities reflect search costs, it is plausible that buyers might exert more search effort for more expensive goods, making them more price-elastic.

[12] Here, "subsequently" means subsequently in the same browsing session, where a session is defined (by eBay) as a string of events from the same user in the same browser. A session ends if 30 minutes pass without an event.

this exercise as interesting in its own right, but also as a way to validate that the tax effect documented above is capturing a behavioral response and is not merely a statistical anomaly.

The top panel of Table 4 reports the results of a series of logit regressions. Each column corresponds to a different outcome variable, but the regressors are identical and associated with the original page view in Table 2. The positive tax coefficients in columns (a), (b), (d) and (e) suggest significant substitution: individuals who receive a negative tax surprise are noticeably more likely to purchase a different item subsequently in the session, more likely to purchase an item from a different seller, and more likely to purchase an item from a different seller that is in the same product category as the original item. The negative tax coefficient in column (c) is also interesting. The estimate indicates that consumers who receive a large negative tax surprise are less likely to purchase some other home state item (which should also have a high tax) than consumers who receive smaller tax surprises.

These results are consistent with the idea that when users experience a negative tax surprise, their response is not simply to avoid the original purchase, but to keep searching and perhaps buy a similar item from a different seller. In the bottom panel of Table 4, we attempt to hone in on the substitution effect by relating subsequent purchasing to whether a consumer purchased the original item. We report two types of results based on linear probability models. In the top row we regress an indicator for a subsequent purchase on an indicator for whether or not the consumer purchased the original item. There is little raw correlation between the two purchase decisions. In the bottom row, we report the results from an instrumental variables specification in which we use the location regressors from Panel A as instrumental variables to identify a causal effect of purchasing the first item on the decision of whether or not to make a different purchase. Here we find relatively clear and strong substitution effects. Indeed, the estimated effect is surprisingly large (probably too large): purchasing the first good essentially eliminates the chance some later good is purchased.

3 Aggregate Responses to Sales Taxes

The item-level tax sensitivity estimates reported above have the advantage of coming from a well-controlled research design, but they are also a step removed from the relevant policy questions, which concern changes in tax rates or tax treatment at the state or national level. In this section, we pursue a second approach that brings us closer to a direct estimate of the policy-relevant parameters. We use aggregated data on trade flows to estimate the effect of sales taxes on online purchasing shares, and on the overall volume of online purchases. As we explain below, we rely on a difference-in-differences strategy which exploits the variation in sales tax rates to identify cross-state substitution in online purchases, while making use of tax changes over time to identify the overall effect on online purchases.

3.1 Data and Preliminary Evidence

We construct measures of online trade flows using all eBay.com transactions during the years 2008-2010, excluding Autos and Real Estate. We aggregate these data in two ways.

Our first dataset consists of annual state-to-state trade flows. Observations in this dataset are at the ijt level, where i represents the buying state, j the selling state, and t the year. We define the applicable tax rate for state i in year t to be the (population weighted) average combined state and local tax rates for state residents, with the average taken across state resident-months.

Our second dataset, which we use to look at overall online purchasing, groups eBay transactions into total monthly purchase counts by county and by ZIP code. Observations in this dataset are at the it level, where i indexes the buying county or ZIP code and t the month. In this case, the applicable tax rate for ZIP i in month t is the combined state and local sales tax for residents in that ZIP-month, and for the county it is the (population weighted) average combined state and local tax rates for county residents.

We use the data on state-state trade flows to look at the propensity of state residents to make online purchases out of state, relative to their overall online purchasing and the quantity and general attractiveness of goods available from different locations. To see roughly how this approach works, let s_{ij} denote the share of state i's online purchases that are from sellers located in state j. Let s_j denote the overall share of eBay purchases that are from sellers in state j. With this notation, the ratio s_{ij}/s_j captures state i's relative preference for state j goods, and a natural way to look for tax sensitivity is to relate the relative preference of state i buyers for home-state sellers, that is, s_{ii}/s_i, to the state's applicable tax rate.

Figure 4 presents a first-pass analysis. For each state, we calculate the share of state purchases that were home-state purchases and divide this by the state's share of overall eBay sales. We then plot this measure against the state's average sales tax. We construct purchasing and sales shares using sales counts rather than transaction value; the plot looks very similar using value shares. Two points are immediately apparent. First, all fifty states exhibit a home bias in purchasing, i.e. $s_{ii}/s_i > 1$. Second, consumers in high tax states do notably less home-state purchasing, consistent with tax shifting purchases out of state. Of course, this analysis doesn't account for potentially confounding factors such as state size (intrastate distance) or the distance to states with attractive goods, but we will see below that adding more detailed controls leaves the basic relationship intact.

The second question of interest is whether sales taxes increase overall online purchases, presumably due to substitution away from taxed offline (local) purchases. This question is more challenging with a purely cross-sectional approach. Intuitively, while the overall share of eBay purchases made from Iowan sellers might be a reasonable proxy for the share of purchases that Iowans should make from these sellers, absent any home-state preference or sales taxes, it is less obvious that the overall online (or eBay) purchasing by residents of other states should be a good proxy for that of Iowans, absent any incentive from sales tax differences. Indeed, Figure 5 provides a simple plot of each state's per-capita eBay purchases against the state's average sales tax. The raw correlation is negative, indicating that high tax states generally do less eBay purchasing, a surprising correlation unless other factors apart from taxes are at work.

One way to address this is to control better for cross-state differences. Roughly speaking, this is the approach taken by Goolsbee (2000a,b), Alm and Melnik (2005), Scanlan (2007), and in the first half of Ellison and Ellison (2009), all of whom regress some statistic of online purchasing on home sales tax and a set of controls. Nevertheless, one may worry that even relatively rich covariates will not suffice to control for underlying heterogeneity in preferences, prices, or patterns of retail behavior or internet use across states. With this in mind, we also report results that rely on the variation in tax rates caused by changes at the state and local level (shown in Figure 2).

3.2 Sales Taxes and Cross-State Substitution

We start by considering the relationship between taxes and cross-state purchasing patterns. As is common in empirical studies of trade flows, we work with a CES representation of consumer demand (Anderson, 2011). We think of each state as having a representative buyer and selling a single composite good. Let i index buyer locations and j index "goods", or equivalently seller locations. Let q_{ij} denote the quantity purchased by state i from state j, and let p_{ij} denote the unit price including any sales tax.

With the CES representation, the quantities q_{ij} solve, for each i,

$$\max_{q_{i1},\ldots,q_{iJ}} \left(\sum\nolimits_j \left(q_{ij}/\zeta_{ij}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \qquad \text{s.t.} \qquad \sum\nolimits_j p_{ij}q_{ij} \leq w_i. \tag{3}$$

Here w_i is i's expenditure on online retail goods, the ζ_{ij} are preference parameters, and σ is the elasticity of substitution. The CES demands are

$$q_{ij} = \frac{p_{ij}^{-\sigma}\zeta_{ij}^{1-\sigma}}{P_i^{1-\sigma}} w_i, \tag{4}$$

where P_i is the CES price index for online goods.[13] Assuming that this general demand structure applies in each period t, and taking logs, we have:

$$\log q_{ijt} = a_{it} - \sigma \log p_{ijt} + (1-\sigma)\log \zeta_{ijt} - (1-\sigma)\log P_{it} + \log w_{it}. \tag{5}$$

This expression will be the basis for our estimates of cross-state substitution in response to the sales tax on in-state purchases. To this end, we express prices as $p_{ijt} = (1+\tau_{ijt})\, p_{jt}$, where p_{jt} is the base price on goods sold from location j, and τ_{ijt} is the ap-

[13] The CES price index is $P_i = \left(\sum_j \left(\zeta_{ij}p_{ij}\right)^{1-\sigma}\right)^{1/(1-\sigma)}$. The one property of this price index we will use is that $\partial \log P_i/\partial \log p_{ij} = x_{ij}$, where $x_{ij} = p_{ij}q_{ij}/w_i$ is the expenditure share of location i consumers devoted to location j goods.

plicable sales tax. Suppose that in addition we can write the preference parameter ζ_{ijt} as $\zeta_{ijt} = \left(h^{\mathbf{1}\{i=j\}} d_{ij}^{\gamma}\right)^{1/(1-\sigma)} \zeta_{jt}$, where h captures same-state purchasing preference, d_{ij} is the distance between location i and j, and ζ_{jt} is the general attractiveness of location j goods. With these assumptions, purchases by state i from state j at time t can be expressed as:

$$\log q_{ijt} = a_{it} + b_{jt} - \sigma \log(1 + \tau_{ijt}) + \gamma \log (d_{ij}) + h\mathbf{1}\{i = j\}. \tag{6}$$

We estimate the model as a Poisson quasi-maximum likelihood regression using our data on annual state-to-state eBay trade flows.[14] In this specification, the combined term $\sigma \log(1+\tau_{ijt}) + h\mathbf{1}\{i = j\}$ is identified by the relative propensity of buyers to purchase in-state, after controlling for distance and the attractiveness of each state's products. More narrowly, the tax effect β is identified by differences in the home bias of states with low and high sales tax rates. One difference with the earlier individual-level approach, however, is that without item-level fixed effects, we control less well for particular idiosyncrasies in the types of goods that buyers in certain states might favor.

Table 5 reports the results from four specifications with progressively tighter controls. In column (a), we allow for buyer state by year fixed effects (a_{it}'s in the above equation) and seller state fixed effects (assuming $b_{jt} = b_j$). In columns (b) and (c), we relax the latter assumption and allow for seller state by year fixed effects. In each of the first two specifications, we use both cross-sectional and time series variation in tax rates to identify the effect of tax rates. In the remaining specifications reported in columns (d) and (e), we replace our distance and same-state controls with fixed effects for each state pair (c_{ij} dummies), and rely solely on the time series variation in tax rates. In column (d) observations remain aggregated to the year level, while in column (e) we disaggregate to monthly purchase counts and tax rates.

Our main interest is in the parameter $-\sigma$ given by the estimated tax coefficient, which is similar across specifications, ranging from -3.6 to -5.9. The interpretation is that a one percentage point increase in a state's sales tax rate will be associated with a roughly 5% decrease in online home-state purchases. This calculation holds fixed the total online ex-

[14] Here we follow common practice in the empirical trade literature (Anderson, 2011), which is to use a count specification rather than a log-linear regression model.

penditure; as we discuss below, the reduction in online same-state purchases will be offset if a sales tax increase shifts purchasing from offline to online. Note that although the point estimates are fairly stable across specifications, the estimates are not terribly precise: taking column (b) as our benchmark specification, the standard error is 2.3, and the 95% confidence interval is -1.3 to -10.4.

The other coefficient estimates in Table 5 are also of interest, in part because they are quite similar to those reported in Hortacsu et al. (2009). As in their paper, we find that trade drops off with distance: state i's purchases fall by roughly 7% as the distance to the selling state doubles. There is also a substantial home state effect: after controlling for the adverse tax consequences of home state purchases, intrastate trade is about 75% higher than would be expected based on distance alone. As a comparison, Hortacsu et al. (Table 3, Model III) reported estimates that imply a doubling of distance reduces trade by about 5% and find an almost identical same-state excess trade of 75%.[15] Interestingly, the estimated distance effects for eBay purchasing are substantially smaller than what is estimated in many similar gravity-type regressions (including estimates for purchasing on MercadoLibre, a South American platform, also reported in Hortacsu et al. (2009)).

3.3 Sales Taxes and Online-Offline Substitution

The results reported in the previous section speak to the effect of sales tax on the geographic distribution of online trade, holding fixed total online spending. In this section, we consider the effect of sales tax on the overall propensity to shop online.

We start with a simple log-log representation of consumer demand for online purchases,

$$\log Q_{it} = \xi_{it} - \eta \log\left(P_{it}/\overline{P}_{it}\right), \tag{7}$$

[15] There are some minor differences between specifications. One is that Hortacsu et al. measure interstate distance as the great circle distance between state capitals and intrastate distance as the population weighted distance between the two most populous cities in the state, whereas we measure distance as the average eBay transaction distance with the distance of each transaction computed using the distance between buyer and seller ZIP codes. As noted in the introduction, their paper also includes state sales tax in one set of regressions (Table 7, Models II and III). Their estimated tax effects are not directly comparable to ours, as they do not account for county and local taxes, use indicators for integer state tax levels instead of a continuous regressor, and interact tax rate with distance. To first approximation, their estimated tax effect is rather larger than ours, at least -10, and perhaps -20.

where Q_{it} are counts of total online purchases by consumers in location i at time t, ξ_{it} captures local preferences and overall consumption, η is the price elasticity, and P_{it} and $\overline{P}_{it}$ are, respectively, online and offline price indices.[16] Making the assumption that "own-location" purchases comprise only a small share of online purchases, but essentially all offline purchases, we can write $P_{it}/\overline{P}_{it} = (1+\tau_{it})^{-1} R_{it}$, where R_{it} represents the relative online-to-offline prices before sales tax is imposed.

For our econometric model, we further assume that both the general level of online demand ξ_{it} and the pre-tax relative prices R_{it} can be decomposed into a location-specific component, a time component, and effects that are captured by observed covariates. So we have

$$\log Q_{it} = a_i + b_t + Z_{it}\lambda + \eta \log(1+\tau_{it}). \tag{8}$$

Implicit in this specification is an assumption that targeted changes in state or local sale tax are passed through fully to consumers. Suppose that instead sellers absorb a constant proportion of tax increases, say, $1-\rho$. Then the coefficient on $\log(1+\tau_{it})$ would be $\theta = \rho\eta$. Either way, the estimated coefficient will capture the effective response of online purchases to a tax change, but in the latter case the coefficient cannot be interpreted purely as a demand elasticity, but instead as the combined effect of (offline) price changes and substitution.

We start by attempting to use only cross-sectional variation, using county-level counts of eBay purchases during 2010. In Panel A of Table 6 we report specifications that use cross-state and within-state variation in county-level tax rates, with and without a rich set of county-level controls (see the notes to Table 6 for details). The estimated tax effect is imprecise and varies greatly across specifications, indicating the difficulty of constructing suitable controls for local purchasing propensities.

In Panel B, we consider an alternative matching approach. We restrict attention to the roughly 35% of counties that lie on state boundaries, and match adjacent counties that lie on two sides of a state border. We then re-run our regression specification with fixed effects for each border pair. Unfortunately, the estimates are imprecise, vary across specifications,

[16] Note that, for consistency with the previous section, one can think of P_{it} as the CES price index and Q_{it} as the CES aggregator of online consumption. In estimation, however, we will use overall purchase counts as our measure of Q_{it}.

and often have the "wrong" sign.

Our preferred approach, therefore, is to rely on within-locality tax changes. In this specification, we include fixed effects for each locality and each month, so that identification is based on changes in county-level or ZIP-level purchasing following a tax change as compared to the average change over that same time period for other localities that did not experience a tax change. The results are reported in Panel C of Table 6. Columns (a)-(c) report county-level purchasing specifications, and columns (d)-(f) show ZIP-level results. The estimated tax effect now has the expected sign, is estimated with some precision, and is quite similar across the different levels of aggregation.

Our baseline estimate of η (or alternatively of $\rho\eta$ if one favors the imperfect pass-through interpretation) is around 1.8, meaning that a one percentage point increase in sales tax increases online purchasing by 1.8%. In comparison, Goolsbee's (2000a) baseline estimated elasticity using cross-sectional variation in tax rates was 2.3, increasing to 3.4 with the addition of more sophisticated controls. The elasticity for memory modules reported in Ellison and Ellison (2009), again identified off cross-sectional variation in state tax rates, is even higher, roughly 6 or 7.[17] While our estimate appears to be somewhat small relative to those reported previously, it nonetheless implies substantial effects of sales taxes on online trade. Given an average combined tax rate of about 7 percent, it suggests that sales tax effects might be responsible for boosting online purchasing by 10% or more.

3.4 Combined Effects of Sales Tax Changes

So far we have considered the two margins of substitution—online-offline and online cross-state—separately. To think about the possible effect of changes in sales taxes, or changes in the current legal regime, it is useful to combine the effects. To do this, we combine our model of overall online purchasing (equation (7)) with our model of how online spending is distributed (equation (5)), noting that in the latter we can represent overall online expenditure w_i

[17] The estimates in Ellison and Ellison concern differences in purchasing from their California retailer by residents of high and low tax states, and hence combine online-offline and cross-state substitution effects. To the extent that each state represents only a small share of online sales, however, their number should reflect mainly online-offline substitution.

as P_iQ_i.[18]

Now, consider the effect of an increase in state i's sales tax τ_i, which under the current legal regime will be applied to both off-line and in-state online purchases. To the extent that state i represents a relatively small share of both online demand and sales, we can assume that this will have no direct effect on either online (pre-tax) prices or on i's online price index P_i, and let's assume for simplicity that offline sellers fully pass through the tax to consumers.[19] Then we have

$$\frac{\partial \log Q_i}{\partial \log(1+\tau_i)} \approx \eta,^{20} \tag{9}$$

and, using the fact that $\partial \log w_i / \partial \log(1+\tau_i) \approx \eta$,

$$\frac{\partial \log q_{ij}}{\partial \log(1+\tau_i)} \approx -\sigma \mathbf{1}\{i=j\} + \eta. \tag{10}$$

So, if we consider a one percentage point decrease in state sales tax (such as occurred in California on July 1, 2011), our baseline estimates suggest roughly a 1.5-2% decrease in online purchases by state residents, and a corresponding decrease in cross-state online purchases, but a 3-4% increase in online purchases by state residents from home-state sellers.

A more sophisticated analysis might relax either the "small-share" assumption, or the "full pass-through" assumption. To see that the former is not particularly important, suppose we maintain the pass-through assumption, and let $x_{ii} = (p_{ii}q_{ii})/w_i$ denote the share of online expenditure that state i devotes to home-state purchases. With CES demand, $\partial \log P_i / \partial \log(1+\tau_i) = x_{ii}$, so if x_{ii} is not trivial, an increase in τ_i will affect online (post-tax) prices as well as offline prices. Instead of the expressions above, we have

[18] Note that for this connection to be tight, then as noted in footnote 16 above, we need to interpret Q_{it} in the overall online demand model as the CES aggregate of online consumption, not as a count of online purchases as we did in our empirical implementation.

[19] Note that more generally, if $p_{ij} = \left(1 + \tau_i \mathbf{1}_{\{i=j\}}\right) p_j$, and sellers do not change pre-tax prices in response to a change in τ_i, then under our CES specification $\partial \log P_i / \partial \log(1+\tau_i) = (p_{ii}q_{ii})/w_i = x_{ii}$. The assumption that $x_{ii} \approx 0$ is a reasonable approximation for most states. Using expenditure shares for eBay, the median state has $x_{ii} = 0.03$, and only two states (CA and NY) have $x_{ii} > 0.10$ (see Appendix Table A1, column (k)).

[20] Note that $\tau_i \approx \log(1+\tau_i)$ for low tax rates, so the semi-elasticity with respect to the tax rate $\partial \log Q_i / \partial \tau_i$ is approximately equivalent to $\partial \log Q_i / \partial \log(1+\tau_i)$, the elasticity with respect to the tax multiple $(1+\tau_i)$.

$\partial \log Q_i / \partial \log(1+\tau_i) = \eta\,(1 - x_{ii})$, and

$$\frac{\partial \log q_{ij}}{\partial \log(1+\tau_i)} = -\sigma \mathbf{1}\{i = j\} + \eta + (\sigma - \eta)\, x_{ii}. \tag{11}$$

To see that this makes little difference, note that for most states $x_{ii} < 5\%$ and even for California x_{ii} is only 0.21, so that $\partial \log Q_i / \partial \log(1+\tau_i)$ is still $1.8 \cdot 0.79 = 1.4$.

The pass-through assumption is potentially more relevant, particularly if one were to consider a large structural change such as imposing a requirement that sales tax be collected on all interstate online sales. While considerable caution should be placed on such a large extrapolation from the environment generating our estimates, a back-of-the-envelope calculation is interesting. As of January 1, 2010, the population-weighted average sales tax in the United States was about 7.3%. Taken literally, our estimates imply that if that tax rate were applied to all interstate online transactions, and online prices responded in the same way that offline prices do to the tax changes in our data, overall online purchasing would fall by about 12%.

To see why pass-through might be relevant, however, suppose that the (relatively small) sales tax changes in our data did not affect retail prices, but that in response to a major legislative shift, online sellers would adjust prices. If, for instance, prices fell so that retailers absorbed half of the 7.3% online tax increase, we would expect only a 6.2% fall in online purchases and a 3.65 percentage point fall in seller margins. If current margins are 30%, online seller profits would fall by about 18%, so such a change could have a considerable impact on online retailers.

3.5 Reconciling the Individual and Aggregate Estimates

Our individual-level estimates of tax sensitivity in Section 2, and our aggregate estimates in Section 3 are based on somewhat different data samples and research designs, but more importantly they focus on conceptually distinct consumer responses to sales taxes. In this section, we clarify the distinction and show how one can link the estimates in Section 2 and 3 by considering the relationship between sales taxes and page views.

Some simple accounting is useful here. Let K_j denote the set of items available in location

j, and (with some notational abuse) let q_{ik} denote the number of purchases of item k by location i buyers. Now, suppose we decompose each q_{ik} into the number of page views by location i buyers and the conversion rate on these views, so that $q_{ik} \equiv v_{ik} \cdot z_{ik}$.

It follows that the total purchases of location j items by location i buyers can be written as:

$$q_{ij} = \sum_{k \in K_j} q_{ik} = \sum_{k \in K_j} (v_{ik} \cdot z_{ik}), \tag{12}$$

and the purchase elasticity with respect to the location i sales tax is

$$\frac{\partial \log q_{ij}}{\partial \log (1 + \tau_i)} = \sum_{k \in K_j} \frac{v_{ik} z_{ik}}{q_{ij}} \frac{\partial \log v_{ik}}{\partial \log (1 + \tau_i)} + \sum_{k \in K_j} \frac{v_{ik} z_{ik}}{q_{ij}} \frac{\partial \log z_{ik}}{\partial \log (1 + \tau_i)}. \tag{13}$$

Thus, the purchase elasticity is equal to the sum of a (weighted) views elasticity and a (weighted) conversion elasticity. To the extent that sales taxes affect consumer searching and browsing patterns, we should expect the effects of sales taxes on conversion rates to be different from the effects on aggregate purchasing.

To take this one step further, we collected data on user search, focusing on searches for which eBay's default search parameters and sort order were used; these represent all but a small minority of searches. For each search, we extract the buyer's location and the locations of items appearing on the first page of the search results. Under these default settings, eBay does not select or sort resulting items by location or effective tax rate. While, as noted earlier, eBay does not surface information on item location in its search results display (Figure 3(a)), one may expect buyers to vary in the eBay searches they do as a result of underlying differences in tastes and incentives. For instance, a user in Montana could be more likely to search for snowshoes and a user in California more likely to search for sandals, than vice versa. Furthermore, a consumer in Montana may search for and purchase a laptop at her local big box retailer, paying no sales tax, while a similar consumer in California would choose to search for laptops on eBay.

Using these data, we estimate the aggregate specification from Table 5, column (b), where the dependent variable is a count of the number of times an item from state j appeared in a search by a user in state i. Despite eliminating the possibility for the buyer or eBay's algorithm to artificially impose location constraints, there is a significant effect of distance; the estimated distance elasticity is -0.067 (standard error 0.006). That is, as may be expected, there is positive sorting within the same state toward local sellers because of a geographic match between product demand and product supply; California sellers are more likely to list sandals whereas Montana sellers are more likely to list snowshoes.[21]

In addition, using the same specification we also find a significant tax effect associated with search results, with an estimated tax-price elasticity of -3.58 (standard error 1.59). Searches by buyers in high-tax states are more likely to show items listed in other states, relative to searches by buyers in low-tax states. This estimated tax effect, combined with the micro-level estimated conversion elasticity of about -2, yields an overall tax-price elasticity of about -5.6, similar to our baseline estimate of -5.9 (Table 5, column (b)).

We should note that the specifications of columns (a), (b), and (c) of Table 5 partially rely on cross-sectional variation in the in-state purchasing propensity across buyers from the lower and higher sales tax rates. Unobserved heterogeneity across buyers from different states could confound these estimates. The specifications in columns (d) and (e) of Table 5, which solely rely on within-state variation in tax rates over time, address this concern. In these specifications the estimated tax-price elasticities of -4.7 (yearly data) and -3.6 (monthly data) are smaller than the baseline estimate of -5.9 but larger than the conversion elasticity of -2 estimated from our micro-data. Relying on these estimates, this suggests that the behavioral effect of sales taxes on the demand side through buyer search behavior and the supply side through seller listing behavior yields a tax-price elasticity of around -2, similar in magnitude to the effect on conversions. This exercise is consistent with the hypothesis that online buyers respond to taxes by changing both their browsing behavior and their purchasing decisions, and helps explain why we obtain somewhat lower tax responsiveness in our estimates of conversion rates than in our estimates of overall purchasing.

[21] Both the distance and tax effect are driven entirely by what buyers search for and what items are available. for example, looking within searches that have the same search query (e.g., "iphone 4") we estimate no distance or tax effects, confirming that eBay's algorithms are not responsible for the patterns we see.

3.6 Retailer Locations and Tax Sensitivity

Our analysis has focused largely on consumer behavior, but an interesting avenue for future research is to explore how sales tax treatment affects online sellers' decisions about where to locate. Amazon, for instance, has assiduously avoided establishing tax presence in California and other large states.[22] More generally, the current structure of sales taxes creates a trade-off. Locating close to demand reduces transportation costs and may boost demand if buyers prefer nearby or "home-state" sellers, but it also means collecting more sales tax.

To see how this plays out based on our estimates, imagine a seller moving across the border from Oregon into California in 2010. Our results in Table 5 model (b) imply a roughly 40% decrease in California sales due to sales taxes, but a large and offsetting increase in demand (75%) due to the "home-state" effect, netting an overall increase of about 5%. This takes the estimated same-state effect at face value in computing the counterfactual; if the same-state effect partly reflects a less specific "nearness" preference, the tax effect might be the important one, at least for sellers located near state borders. Figure 6 provides some preliminary evidence on this. It shows the number of sellers located at different distances from borders between states with large tax differentials (of at least 5 percentage points). Consistent with retailer tax sensitivity, seller density is greater on the "low tax" side of the border.

4 Conclusions

Internet sales taxes have been the subject of considerable attention since the beginning of internet commerce. This paper has used detailed data from eBay to offer some new evidence on how sales taxes affect online browsing and purchasing behavior. Using a research design based on individual-level "tax surprises", we found that purchases by interested buyers fall by roughly two percent for every one percentage point increase in the sales tax charged by the seller. To the extent that consumers pay less attention to taxes than to base prices, this estimate also can be interpreted as providing an informative lower bound on the average

[22] As we were writing this paper, Amazon agreed to collect sales taxes on California sales starting in September, 2012, and appears to be reaching similar deals with other states.

price elasticity for interested buyers.

As a second and complementary approach, we have investigated the relationship between aggregate online trade flows (on eBay) and sales taxes. Using the considerable cross-state variation in sales tax rates as a source of identification, we estimated that, holding fixed the overall online spending of state residents, a one percentage point increase in a state's sales tax leads to a 3-6 percent decrease in online purchasing from home-state sellers. We also used changes in state and local sales taxes over time to estimate the overall effect of sales taxes on online purchasing. We find an elasticity of online purchasing with respect to sales tax of around 1.8, a substantial sensitivity but only about half the magnitude reported by Goolsbee (2000a). Combining these estimates, a one percentage point increase in a state's sales tax leads to an increase of just under 2 percent in online purchasing from other states, and a 3-4 percent decrease in online purchasing from home-state sellers.

Our results are subject to some important caveats, particularly if one hopes to extrapolate to counterfactual regimes suggested in current policy debates surrounding internet taxation. One caveat is that the estimates come from a single online platform, which may not be fully representative of all of online retail trade. Some of the major policy changes being considered also could have considerable effects on seller pricing and location decisions, which we have discussed to some extent but are mostly outside the scope of this analysis.

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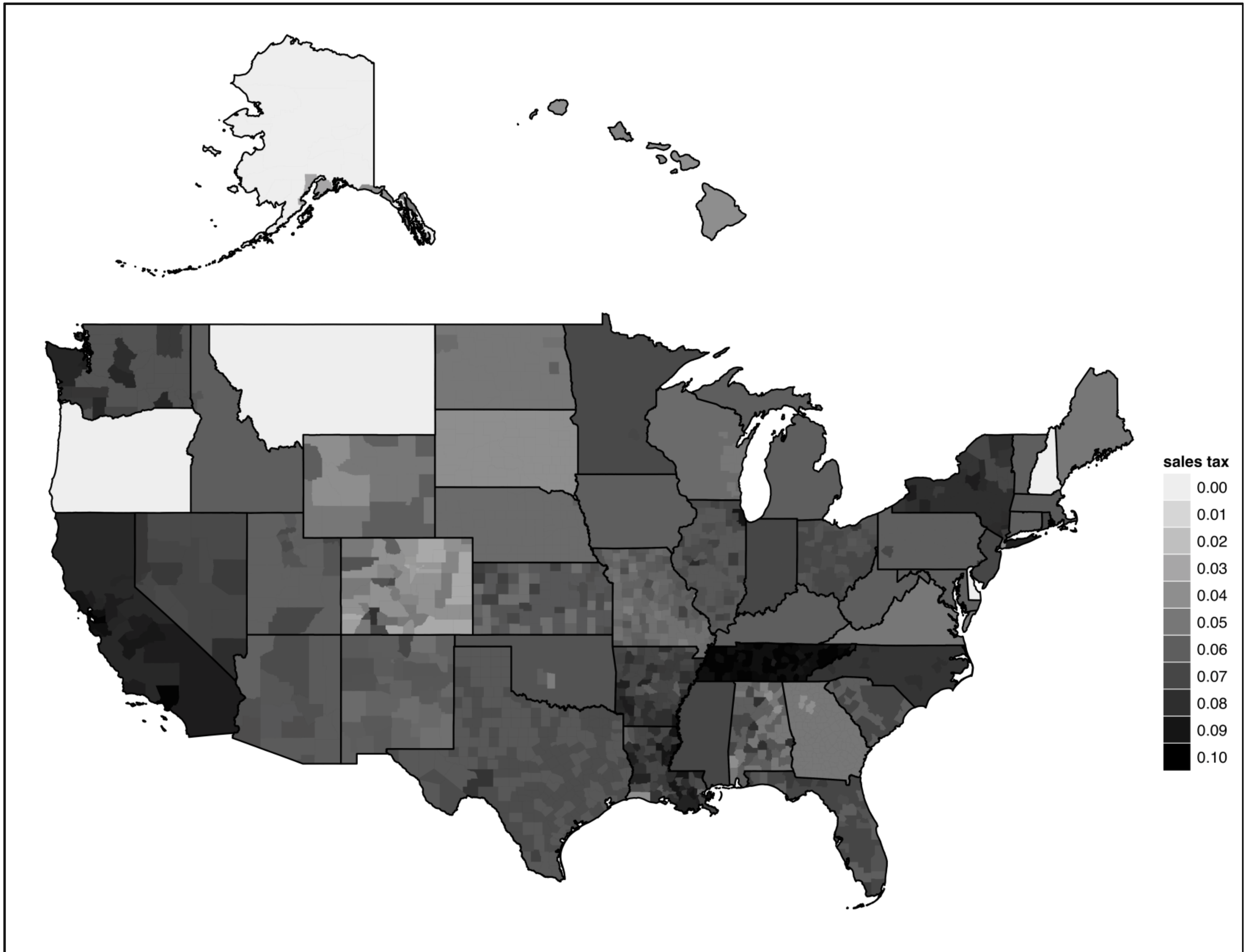
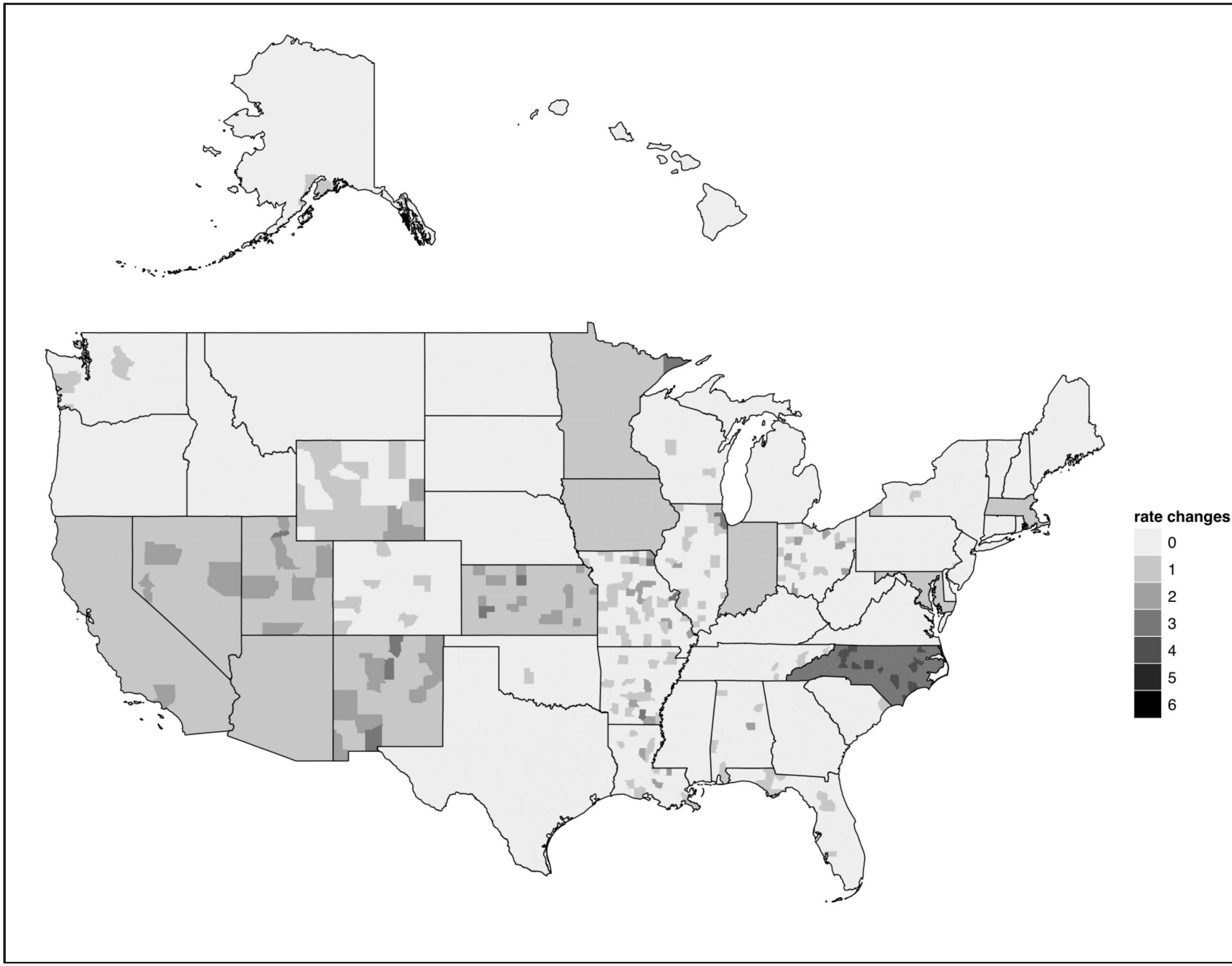
Figure 1: Cross Sectional Variation in Sales Tax Rates



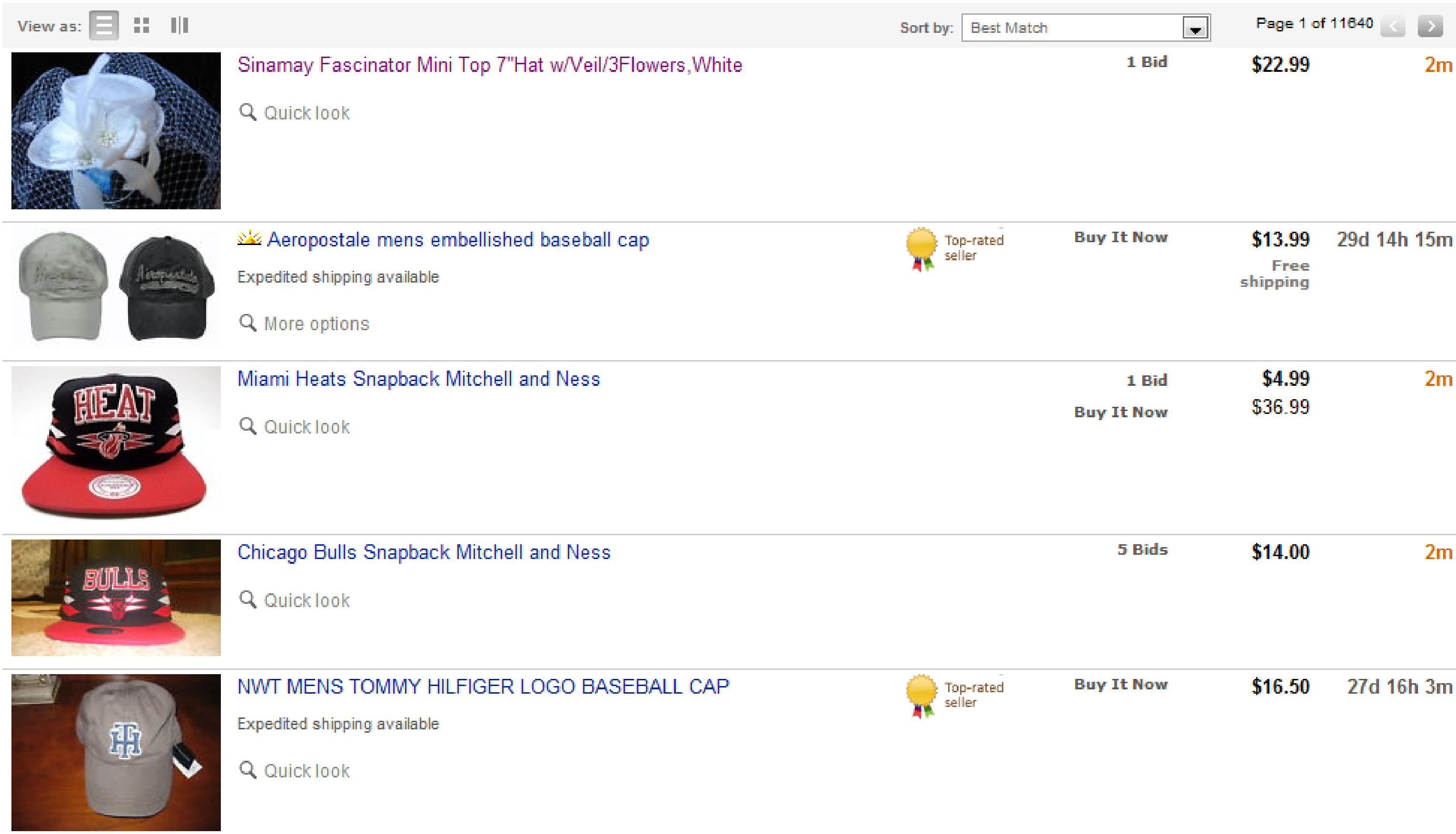
Map shows the sales tax rate in each county as of January 1, 2010 (in the middle of our observation period of 2008-2010). The (population weighted) average tax rate in the United States that day was 7.25% with a (population weighted) standard deviation of 1.74% (for population, we use the 2000 census).

Figure 2: Time Series Variation in Sales Tax Rates



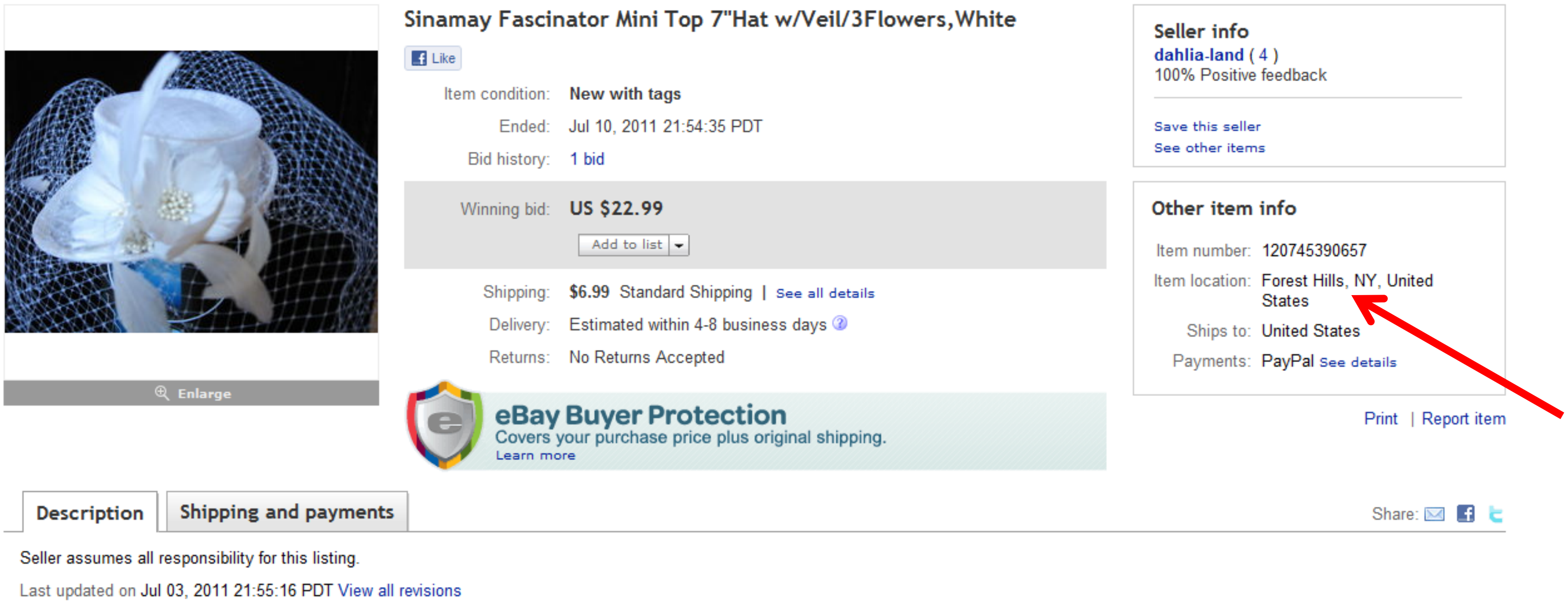
Map shows the number of changes in sales tax rate in each county during our observation period (2008-2010). During this period, 35.6% of the United States population has been exposed to at least one change in tax rate (31.6% to at least one tax rate increase; 4.1% to at least one tax rate decrease). Conditional on a change, the (population weighted) average change (in absolute values) was 0.73% with a (population weighted) standard deviation of 0.38% (for population, we use the 2000 census).

Figure 3(a): Screenshot of a typical eBay search result page



This is a screenshot of eBay search results (for a query that searched for “hat”). The key thing to notice is that the details about the seller, and especially about his location, are not provided on this page.

Figure 3(b): Screenshot of a particular item listing



This is a screenshot of the listing page (the first item from the list presented in Figure 3(a)). The seller location is now presented on the right.

Figure 4: The Relationship between In-State Purchasing and Sales Tax Rate

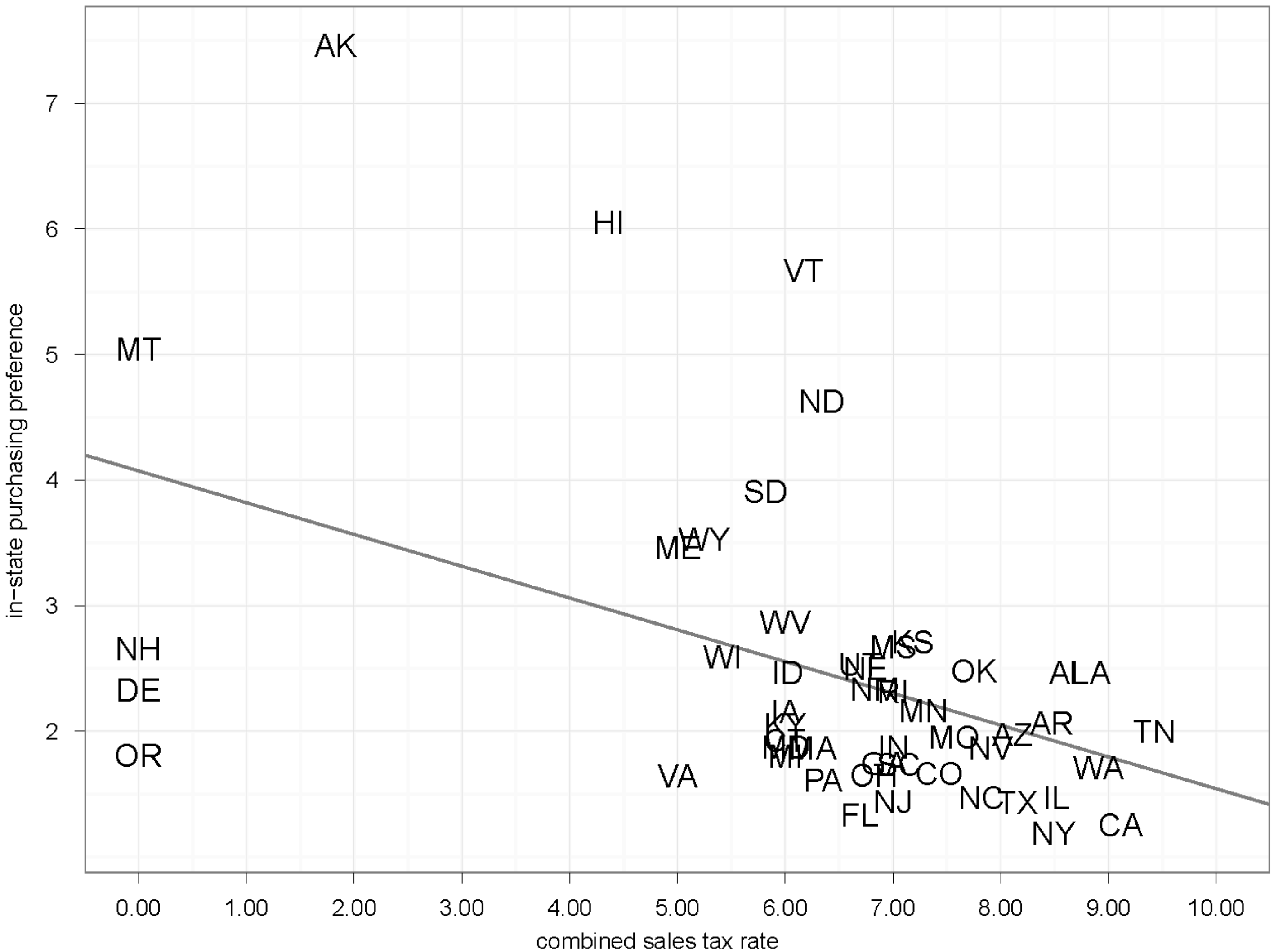


Figure presents the relationship between in-state purchasing rate and the state’s (population weighted) sales tax rate. The in-state purchasing rate is the ratio between the state’s purchasing share of the state’s sales to the state’s overall purchasing share. Purchasing and sales are computed as the number of transactions (not their value) on eBay during our observation period (2008-2010).

Figure 5: The Relationship between Per-Capita Online Purchases and Sales Tax Rate

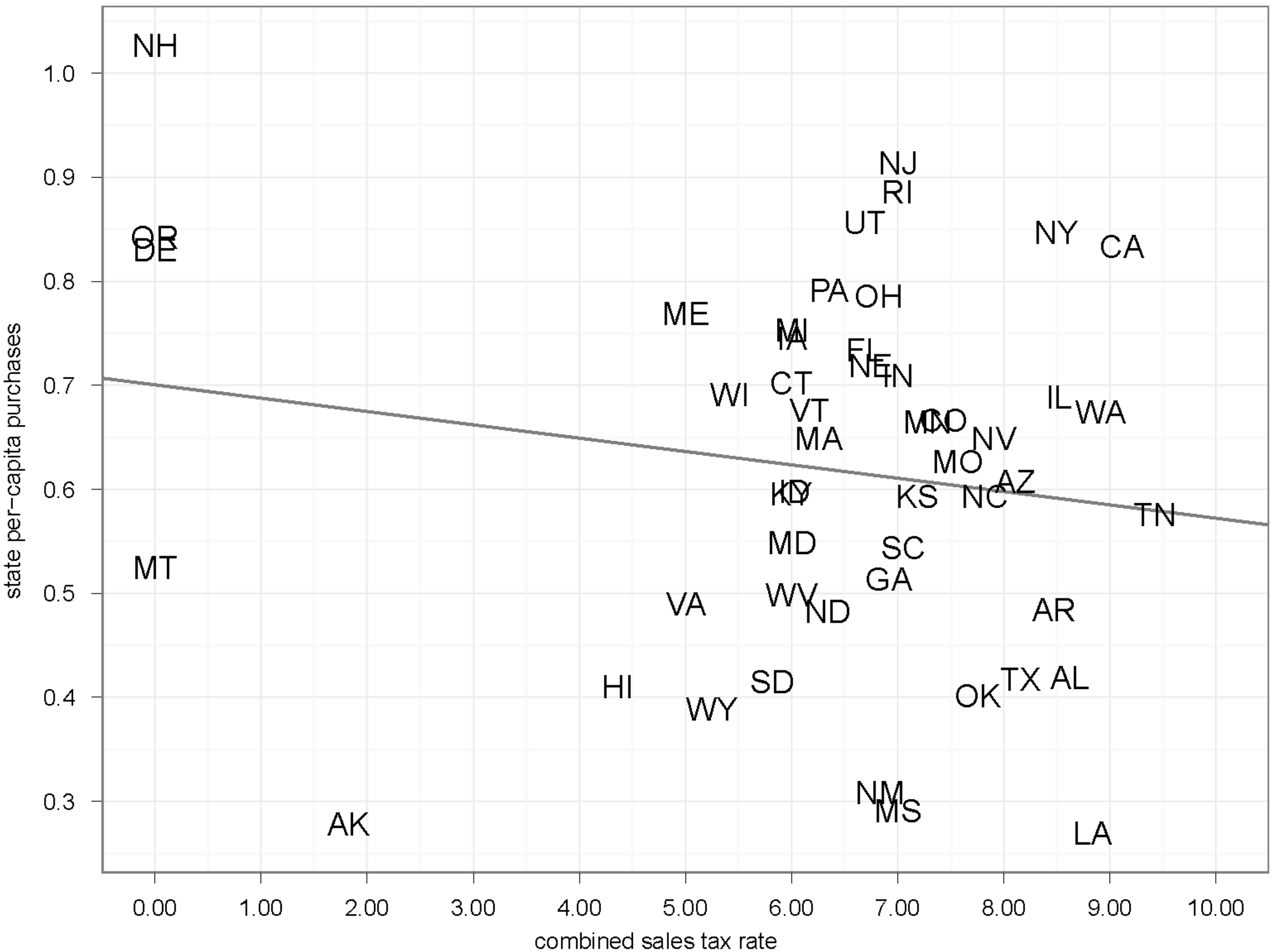


Figure presents the relationship between the state's per-capita number of purchases on eBay during our observation period (2008-2010) and the state's (population weighted) average sales tax rate.

Figure 6: Patterns of Seller Locations Near State Borders

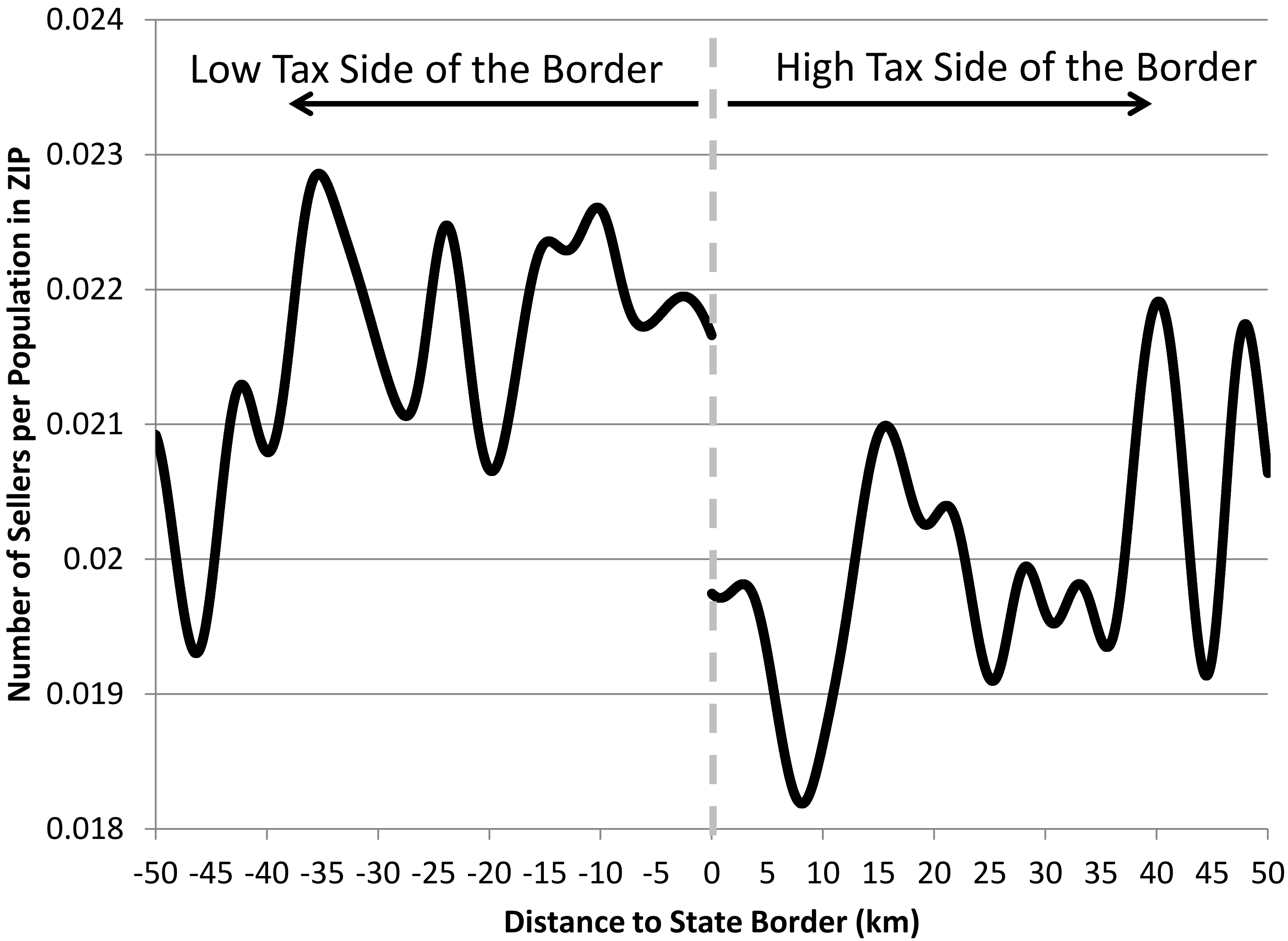


Figure presents kernel densities (Gaussian kernel, 5 km bandwidth) of the seller location on both sides of state borders. Data covers all users on eBay who sold at least one item in 2010. Y-axis is measured as the number of sellers in each 5-digit ZIP divided by the ZIP population in 2010. Distance from state border is measured (in km) between the ZIP centroid to the nearest point on the state border. Data used for the figure covers all border ZIP codes that are near borders that are associated with state sales tax difference of at least 5 percentage point (1,906 ZIPs around 14 state borders).

Table 1: Item-Level Data – Summary Statistics

	N	Mean	Std. Dev	p25	p50	p75
Item List Price ($)	275,020	36.95	164.98	6.22	12.99	29.99
Item Sales Tax[1]	275,020	7.96%	1.40%	7.00%	8.25%	8.88%
Logged-In Users Viewing Item	275,020	24.7	55.6	4	9	23
In-State Users Viewing Item	275,020	1.8	5.0	0	0	2
Purchase Rate (Purchases / Views)	275,020	0.21	0.17	0.08	0.17	0.33
Average Viewer Distance[2]	275,020	1,939	732	1,409	1,842	2,469

Table shows summary statistics for 275,020 items listed on eBay by 10,347 distinct sellers between January 1, 2010 and December 31, 2010. The data cover 6,796,691 page views, each by a different user.

[1] The item sales tax is the combined state and local tax in the seller's ZIP code as of April 1, 2010.

[2] Throughout, distances are measured as the great-circle distance between the centroids of the user ZIP code and the seller ZIP code, in kilometers.

Table 2: Item-Level Estimates of Tax Sensitivity

	Dependent variable: 1 if item purchased		
	All items (a)	All items (b)	By rate type[1] (c)
log(1+effective tax)	-1.160	-2.601	-2.277
	(0.093)	(0.501)	(0.504)
log(distance)	-0.028	-0.028	-0.025
	(0.002)	(0.002)	(0.002)
Same state Dummy		0.121	0.096
		(0.041)	(0.042)
log(distance)*Calc. rate Dummy			-0.026
			(0.004)
Fixed Effects	Item	Item	Item
No. of distinct items	275,020	275,020	275,020
No. of page views	6,796,691	6,796,691	6,796,691
Mean of Dep. Variable	0.215	0.215	0.215

Table shows coefficient estimates from a conditional logit regression where the dependent variable is equal to 1 if the viewing user purchased the item during the browsing session and zero otherwise. Each observation reflects a distinct page view by a distinct user. The mean purchase probability is shown at the last raw of the table, and the tax-price elasticity is the estimated coefficient (at the first row) multiplied by (1-purchase rate).

[1] Items can be listed as "flat shipping rate" or as "calculated shipping rate." In the latter case, the shipping cost of the item (paid by the buyer) is increasing in the shipping distance.

Table 3(a): Item-Level Estimates of Tax Sensitivity by Category

	Dependent variable: 1 if item purchased					
	Electronics	Cell Phones	Computers	Clothing	Home & Garden	Sporting Goods
	(a)	(b)	(c)	(d)	(e)	(f)
log(1+effective tax)	-5.33	-2.79	-2.73	-2.19	0.27	-3.86
	(1.75)	(1.44)	(1.38)	(1.89)	(1.67)	(2.19)
log(distance)	-0.03	-0.03	-0.04	-0.02	-0.03	-0.03
	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)	(0.009)
Same state Dummy	0.31	0.13	0.11	0.13	-0.07	0.22
	(0.15)	(0.12)	(0.12)	(0.16)	(0.13)	(0.17)
Fixed Effects	Item	Item	Item	Item	Item	Item
No. of distinct items	24,013	42,188	45,640	16,489	28,034	12,263
No. of page views	733,753	701,155	707,973	677,031	929,767	468,955
Mean of Dep. Variable	0.200	0.274	0.292	0.132	0.166	0.144

As in Table 2, the table shows coefficient estimates from a conditional logit regression where the dependent variable is equal to 1 if the viewing user purchased the item during the browsing session and zero otherwise. Each observation reflects a distinct page view by a distinct user. The mean purchase probability is shown at the last raw of the table, and the tax-price elasticity is the estimated coefficient (at the first row) multiplied by (1-purchase rate).

Table 3(b): Item-Level Estimates of Tax Sensitivity by Price Level

	Dependent variable: 1 if item purchased			
	< $6	$6-12	$12-24	> $24
	(a)	(b)	(c)	(d)
log(1+effective tax)	-2.00	-2.15	-2.72	-3.25
	(1.04)	(1.06)	(1.02)	(0.91)
log(distance)	-0.03	-0.03	-0.02	-0.03
	(0.004)	(0.004)	(0.004)	(0.003)
Same state Dummy	0.07	0.09	0.15	0.16
	(0.09)	(0.09)	(0.08)	(0.08)
Fixed Effects	Item	Item	Item	Item
No. of distinct items	68,339	62,830	58,997	84,854
No. of page views	1,030,448	1,109,980	1,414,700	3,241,563
Mean of Dep. Variable	0.27	0.24	0.20	0.16

As in Table 2, the table shows coefficient estimates from a conditional logit regression where the dependent variable is equal to 1 if the viewing user purchased the item during the browsing session and zero otherwise. Each observation reflects a distinct page view by a distinct user. The mean purchase probability is shown at the last raw of the table, and the tax-price elasticity is the estimated coefficient (at the first row) multiplied by (1-purchase rate).

Table 4: Substitution Patterns

	Dependent variable: 1 if … during subsequent session				
	Bought any other item	Bought from a different seller	Bought from a diff. seller but in the same state	Bought from a diff. seller, in the same broad category	Bought from a diff. seller, in the same narrow category
	(a)	(b)	(c)	(d)	(e)
Panel A. Reduced form effects					
log(1+effective tax)	1.48	1.95	-3.28	1.86	1.59
	(0.42)	(0.45)	(1.22)	(0.50)	(0.63)
log(distance)	0.016	0.021	-0.017	0.024	0.024
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Same state Dummy	-0.103	-0.142	0.348	-0.124	-0.104
	(0.035)	(0.037)	(0.105)	(0.042)	(0.052)
Fixed Effects	Item	Item	Item	Item	Item
No. of distinct items (estimation sample)	205,314	192,435	54,821	168,638	121,789
No. of page views	6,348,623	6,217,586	2,831,003	5,834,658	4,830,520
Mean of Dep. Variable (in estimation sample)	0.228	0.211	0.114	0.190	0.165
Mean of Dep. Variable (in original sample)	0.178	0.153	0.023	0.120	0.075
Fraction bought the original item (in est. sample)	0.181	0.176	0.162	0.173	0.170
Panel B. Substitution estimates (linear prob. models)					
Original item was bought (OLS)	0.021	-0.005	-0.013	-0.032	-0.056
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Original item was bought (IV)	-0.692	-0.853	-0.072	-0.782	-0.579
	(0.091)	(0.094)	(0.064)	(0.083)	(0.073)

In Panel A we report conditional logit regressions similar to those in Table 2, except that the dependent variable reflects outcomes from the user's browsing session that follows the original page view that got him into the sample. All the right-hand-side variables apply to the original page view, as in Table 2. Note also that the estimation sample shrinks for some of the narrower outcomes that lead us to drop items for which subsequent outcomes do not vary (they are all zero).
In Panel B we use linear probability models to estimate the direct effect of whether the original item was bought or not on the same subsequent outcomes used in Panel A. We first report an OLS estimate (with item fixed effects), and then report an IV estimate, in which the regressors from Panel A are used as instruments (so that the results reported in Table 2 can be thought of as similar to the first stage).

Table 5: Estimates of Online State-to-State Flows

	Dependent variable: Number of state-to-state purchases				
	(a)	(b)	(c)	(d)	(e)
log(1+effective tax)	-5.556	-5.878	-4.234	-4.743	-3.642
	(1.932)	(2.327)	(2.237)	(3.377)	(1.795)
log(distance)	-0.104	-0.104	-0.105	--	--
	(0.008)	(0.007)	(0.006)		
Same state Dummy	0.537	0.560	0.988	--	--
	(0.146)	(0.149)	(0.367)		
log(distance) * Same state			-0.105		
			(0.085)		
Fixed Effects	Buyer State * Year, Seller State	Buyer State * Year, Seller State * Year	Buyer State * Year, Seller State * Year	Buyer State * Year, Seller State * Year, Buyer-Seller State Pair	Buyer State * Month, Seller State * Month, Buyer-Seller State Pair
N	7,500	7,500	7,500	7,500	90,000

Table shows results from a Poisson regression where the dependent variable is the number of sales from state i to state j, using a panel data of three years (2008-2010); data is aggregated to the yearly level for columns (a)-(d) and the monthly level for column (e). Standard errors are computed using a state-level block bootstrap with 50 replications. The distance variable is measured at the *(I,j)* state-pair level by computing the average distance over all transactions between a seller ZIP from state *i* and a buyer ZIP from state *j*.

Table 6: The Effect on Overall Online Purchasing

Panel A: Identification off cross-sectional variation

	Dependent variable: Number of purchases in county during 2010			
	(a)	(b)	(c)	(d)
log(1+effective tax)	-2.10	0.45	-5.14	-0.55
	(0.39)	(0.24)	(2.31)	(1.14)
Fixed Effects	None	None	State	State
Other controls	Population	All[1]	Population	All[1]
No. of Obs. (Counties)	3,050	3,037	3,050	3,037

Panel B: Identification off matched counties across state borders

	Dependent variable: Number of purchases in county during 2010			
	(a)	(b)	(c)	(d)
log(1+effective tax)	-0.045	0.416	-1.547	-0.681
	(0.575)	(0.550)	(7.775)	(3.283)
Fixed Effects	Border pairs[2]	Border pairs[2]	State, Border pairs[2]	State, Border pairs[2]
Other controls	Population	All[1]	Population	All[1]
No. of Obs. (Counties)	1,116	1,111	1,116	1,111

Panel C: Identification off within-locality changes in sales tax

	Dependent variable: Number of monthly purchases during 2010					
	County-level			ZIP-level		
	(a)	(b)	(c)	(d)	(e)	(f)
log(1+effective tax)	1.82	1.999	1.788	1.762	1.936	1.719
	(0.855)	(0.658)	(0.687)	(0.881)	(0.584)	(0.603)
Fixed Effects	County, Month	County, Month x Region	County, Month x Division	ZIP, Month	ZIP, Month x Region	ZIP, Month x Division
No. of Obs. (Locality-month)	109,872	109,872	109,872	1,386,828	1,386,828	1,386,828

Table shows results from a Poisson regression where the dependent variable is total of eBay purchases in the county over 2010 (Panels A and B) or every month (Panel C). Panel C uses data from January 2008 to December 2010. Standard errors are computed by a county-level block bootstrap with 50 replications.

[1] County-level controls include population, average income, gender (% female), race (% white, black, Asian), education (% high school, some college, college, graduate degree), age (% 0-9. 10-17, 18-29, 30-49, 50-69), and variables associated with internet connectivity (residential broadband connections, % living in college housing, % working in info industry, % institutionalized).

[2] Border pairs fixed effects use matched pairs of adjacent counties on each side of a state border.

Table A1: Summary Statistics for State-Level Data

State	Population ('000)	State Tax Rate	Combined Tax Rate	Per-Capita Purchases	Per-Capita Sales	Purchase to Sales Ratio	Share of State Sales Made to State Residents	Share of National Sales Made to State Residents	In-State Preference	In-State Expenditure Share
(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)
AK	710	0.00	1.82	278.0	871.4	0.32	0.72%	0.10%	7.46	0.77%
AL	4,780	4.00	8.62	419.3	595.1	0.70	2.42%	0.98%	2.47	3.64%
AR	2,916	6.00	8.47	484.0	620.2	0.78	1.42%	0.69%	2.07	1.49%
AZ	6,392	5.60	8.10	607.8	601.5	1.01	3.74%	1.90%	1.97	3.84%
CA	37,254	8.25	9.11	833.6	668.8	1.25	19.00%	15.17%	1.25	20.55%
CO	5,029	2.90	7.43	666.8	664.1	1.00	2.72%	1.64%	1.66	3.29%
CT	3,574	6.00	6.00	702.2	703.6	1.00	2.36%	1.23%	1.92	2.88%
DE	898	0.00	0.00	830.4	674.5	1.23	0.85%	0.36%	2.33	1.33%
FL	18,801	6.00	6.69	734.0	667.7	1.10	8.97%	6.74%	1.33	9.83%
GA	9,688	4.00	6.91	514.0	560.0	0.92	4.24%	2.43%	1.74	5.75%
HI	1,360	4.00	4.36	410.7	719.5	0.57	1.65%	0.27%	6.05	1.80%
IA	3,046	6.00	6.00	745.4	741.5	1.01	2.39%	1.11%	2.15	2.49%
ID	1,568	6.00	6.02	598.0	680.9	0.88	1.13%	0.46%	2.47	1.14%
IL	12,831	6.25	8.52	689.0	684.8	1.01	6.36%	4.32%	1.47	7.42%
IN	6,484	7.00	7.00	709.4	723.5	0.98	4.21%	2.25%	1.87	4.61%
KS	2,853	5.30	7.19	593.2	737.5	0.80	2.24%	0.83%	2.71	2.38%
KY	4,339	6.00	6.00	595.7	725.4	0.82	2.59%	1.26%	2.05	2.98%
LA	4,533	4.00	8.83	269.2	521.5	0.52	1.47%	0.60%	2.47	2.10%
MA	6,548	6.25	6.25	648.5	674.5	0.96	3.88%	2.07%	1.87	4.70%
MD	5,774	6.00	6.00	548.4	698.4	0.79	2.90%	1.55%	1.88	4.15%
ME	1,328	5.00	5.00	768.7	810.6	0.95	1.73%	0.50%	3.46	1.51%
MI	9,884	6.00	6.00	753.1	666.8	1.13	6.55%	3.64%	1.80	6.62%
MN	5,304	6.88	7.28	664.8	689.0	0.96	3.73%	1.72%	2.17	4.05%
MO	5,989	4.23	7.56	627.0	695.0	0.90	3.58%	1.83%	1.95	3.92%
MS	2,967	7.00	7.00	291.4	485.4	0.60	1.13%	0.42%	2.67	1.28%
MT	989	0.00	0.00	524.7	794.7	0.66	1.28%	0.25%	5.04	1.21%
NC	9,535	5.75	7.82	593.2	612.6	0.97	4.06%	2.76%	1.47	4.15%
ND	673	5.00	6.34	482.4	803.2	0.60	0.73%	0.16%	4.63	0.88%
NE	1,826	5.50	6.74	719.1	718.6	1.00	1.60%	0.64%	2.50	2.34%
NH	1,316	0.00	0.00	1027.0	774.4	1.33	1.75%	0.66%	2.66	1.87%
NJ	8,792	7.00	7.00	913.8	660.0	1.38	5.65%	3.92%	1.44	6.14%
NM	2,059	5.00	6.83	308.8	592.2	0.52	0.73%	0.31%	2.34	1.02%
NV	2,701	6.50	7.90	648.6	634.7	1.02	1.60%	0.86%	1.87	1.67%
NY	19,378	4.00	8.49	846.6	665.7	1.27	9.50%	8.01%	1.19	10.98%
OH	11,537	5.50	6.82	785.5	701.4	1.12	7.29%	4.43%	1.65	8.17%
OK	3,751	4.50	7.75	401.7	644.5	0.62	1.82%	0.74%	2.48	2.57%
OR	3,831	0.00	0.00	842.4	759.4	1.11	2.85%	1.58%	1.81	3.01%
PA	12,702	6.00	6.35	791.6	755.4	1.05	7.91%	4.91%	1.61	8.18%
RI	1,053	7.00	7.00	885.9	669.9	1.32	1.05%	0.46%	2.31	1.06%
SC	4,625	6.00	7.05	543.7	583.0	0.93	2.13%	1.23%	1.73	2.33%
SD	814	4.00	5.82	414.7	707.3	0.59	0.65%	0.16%	3.91	0.72%
TN	6,346	7.00	9.42	575.9	688.2	0.84	3.57%	1.78%	2.00	3.88%
TX	25,146	6.25	8.16	417.5	549.1	0.76	7.34%	5.13%	1.43	9.11%
UT	2,764	4.70	6.69	856.3	617.3	1.39	2.93%	1.16%	2.53	3.52%
VA	8,001	4.00	5.00	490.1	704.9	0.70	3.15%	1.92%	1.65	3.59%
VT	626	6.00	6.17	675.9	841.3	0.80	1.17%	0.21%	5.67	0.88%
WA	6,725	6.50	8.91	674.1	805.7	0.84	3.79%	2.21%	1.71	3.89%
WI	5,687	5.00	5.42	691.4	703.9	0.98	4.98%	1.92%	2.59	5.85%
WV	1,853	6.00	6.00	498.5	789.0	0.63	1.30%	0.45%	2.87	1.58%
WY	564	4.00	5.25	388.7	837.8	0.46	0.38%	0.11%	3.53	0.39%

Population is based on 2000 census. Tax rates are as of January 1, 2010. Per-capita purchases and sales are multiplied by an undisclosed factor. In-state preference (column (j)) is the ratio of column (h) to column (i).