ONLINE APPENDIX

Sales Taxes and Internet Commerce

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This online appendix contains the following three items. First, in Appendix A we provide evidence about eBay's market share and the extent to which its users are representative of the general population of internet shoppers. Second, in Appendix B we provide more details about the various calculations that are behind many of the numbers that are mentioned in the main text. Third, Appendix C contains some additional details about the derivations that are behind key equations in the paper. Finally, in addition to the appendix tables that are referred to from Appendix A, this document also contains several other figures and tables that are referred to in the main text.

Appendix A. Comparing eBay users to internet users

Our analysis is based on data from eBay. In this appendix we try to assess the extent to which eBay is representative of overall internet retail. We present two pieces of evidence that suggest that the consumer population in our data is reasonably representative of the broader set of internet users and specifically internet shoppers.

We first note that on its own eBay accounts for a fairly large share of internet commerce. Transactions on eBay account for roughly 11–13 percent of internet retail dollar revenues in the United States. The user population is also large: eBay is the sixth most-visited web site in the United States, ahead of Wikipedia and behind only Google, YouTube, Facebook, Yahoo! and Amazon.[1] Globally, eBay reports having 112 million active users. If the user share in the United States is proportional to the share of eBay transaction volume in the United States, that would mean over 40 million active users.

Second, we present statistics from two web tracking companies that compare the population of eBay users to the overall population of internet users and to users of other prominent internet retail web sites along various demographic characteristics. This statistics indicate that eBay's user population is quite similar to Amazon's and to the general population of internet users. Other top internet retail sites, such as Wal-mart, Staples, and Sears, appear to be more differentiated relative to the general internet population.

A rough estimate of eBay's "market share"

Here we describe how we arrive at eBay's share of overall e-commerce revenues in the United States. According to eBay's earnings report, Gross Merchandise Revenues (GMV) on the

[1] The traffic rank statistic is from Alexa. The user numbers and US share over overall eBay gross merchandise value are reported on eBay's webside. Both were accessed on January 30, 2013.

primary eBay.com platform (that is, excluding vehicles, which are sold via eBay Motors) for the United States in 2011 was $22.9 billion. If we subtract what is probably an overly large $1 billion in GMV for tickets and events, this leaves $21.9 billion.

Some uncertainty arises in determining the appropriate denominator. Census E-Stats reports a total online retail GMV of $194.3 billion. An alternative estimate of US online retail GMV for 2011 is provided by ComScore, who give a figure of $162 billion. These numbers both exclude goods sold by auction. To adjust for this, we assume that eBay accounts for essentially all of the auction e-commerce transactions. Auctions on eBay are roughly 37.5% of GMV, or $0.375 * \$21.9 = \$8.213$ billion.

This gives us two adjusted estimates of total e-commerce transactions equal to $202.5 billion and $170.3 billion.[2] These imply that eBay's share of overall e-commerce in the U.S. as of 2011 was on the order of $\$21.9/\$202.5 = 10.8\%$ or $\$21.9/\$170.2 = 12.9\%$

A rough estimate of Amazon's "market share"

A similar exercise with Amazon could be informative. Based on Amazon's annual report for 2011, worldwide net product sales were $42 billion and net service sales were $6.077 billion, so the share of net sales represented by products was 0.875. Assuming this ratio holds for North America as well, which had a reported net sales of $26.705 billion, and assuming the US share of North American sales is 0.9, we get an estimated US net product sales of $21.03 billion.

Amazon marketplace facilitates third-party sales as well as sales by Amazon itself.[3] Amazon reports that third party sales represented 36% of units sold in 2011. Let's assume this remains true when restricted to the US market. If the average price of third party units sold is the same as for Amazon products, then Amazon's total GMV for the U.S. would be around $32.8 billion, or 16-19% of overall e-commerce in the U.S. depending on the choice of denominator. If the average price of third party units sold on Amazon was only half that of Amazon products, this number would be smaller, in the 13-16% range.

eBay's audience relative to that of other prominent e-commerce web sites

To investigate the extent to which eBay's audience is similar (or not) to that of other prominent web sites, we obtained data from two of the leading companies who specialize in web tracking analysis, Alexa and Quantcast. Each of these web sites provides a breakdown of the demographic characteristics of web sites' user population. The data from Alexa is reported in the six panels of Figure A2. Alexa reports each number as a deviation from a baseline, with the baseline representing the "general internet population" (as defined by Alexa). We report these deviations for a range of demographic characteristics (age, income, education, gender and children dummy variables, race, and the primary location of internet use) for the

[2] The Census number already includes eBay's commissions on auction sales, but making a further adjustment so as not to double-count this does not affect the calculation by very much.

[3] Amazon's reported net sales do include Amazon's commission on third party sales. We ignore this in our calculations, but making an adjustment so that these commissions are not double counted has only a small effect on the numbers below.

top 5 internet retail sites: eBay, Amazon, Wal-mart, Staples, and Sears. The key pattern that emerges is that eBay's audience seems to track Amazon's audience quite closely, and that eBay and Amazon audiences seem to be more representative of the overall internet user population, relative to the other three sites. We should note that these other sites (Wal-mart, Staples, and Sears) are all operated by "brick and click" retailers (retailers who operate both online and offline), so a plausible hypothesis is that eBay is more representative of "internet only" retail web sites, such as Amazon.

The second set of figures—the five panels of Figure A3—represents similar evidence from Quantcast, a different web tracking company. In the context of Quantcast, we could only obtain data for eBay and Amazon. However, in contrast to the Alexa data, the data show the actual distribution of demographic characteristics, as well as that of the general internet population, making it somewhat easier to interpret. Again, the same pattern emerges: eBay and Amazon appear quite similar to each other, and quite similar to the general internet population.

Appendix B. More details about derivations and sources for numbers that appear in the text

The main text mentions many numbers that are based on our estimation results or derived from results reported in other articles. In this appendix we follow the order in which the numbers appear in the main text, and provide more details about the way the estimation results map to each number.

B.0. Abstract

1. "increases online purchases by state residents by almost 2%" corresponds to our preferred estimate from Table 6 (see B.3.9 below).

2. "decreases their online purchases from state retailers by 3–4%" is our preferred estimate for the combined offline-online and inter-state effect, which takes into account both cross-state substitution and the effect on overall online purchase volume (see B.3.15 below).

B.1. Introduction

1. "well over a hundred billion dollars annually" is based on the "E-Stats Report" of the US Census Bureau (2011), which gives figures for 2009.

2. "more than a thousand articles" is from the Google News search `http://www.google.com/search?tbm=nws&q=internet+OR+online+OR+e-commerce+%22sales+tax%22` for January 1, 2012–February 29, 2012, which returned "About 1,040 results".

3. "more than 30% of state tax revenues" is based on Maguire's report for the Congressional Research Service, which says: "State governments rely on general sales and use

taxes for just under one-third (30.8%) of their total tax revenue—approximately $241 billion in FY2008."

4. "$10 billion a year" comes from the same report by Maguire, which states "Researchers estimated in April 2009 that total state and local revenue loss from 'new e-commerce' in 2011 will be approximately $10.1 billion."

5. "... roughly 11–13 percent of internet retail commerce, or around $23 billion annually." These figures are discussed above in Appendix A.

6. "state sales taxes ranged from zero... to seven percent or more"; state sales tax rates (as of January 2010) are listed in Table A6.

7. "on average, the application of a 10% sales tax reduces purchases by 15% among buyers who have clicked on an item." See B.2.9 below.

8. "an increase of just under two percent in online purchasing" corresponds to our preferred estimate from Table 6 (see B.3.9 below).

9. "a 3–4 percent decrease in the volume of online purchases from home-state sellers" is our preferred estimate for the combined effect, which takes into account both the cross-state substitution and the effect on overall online volume (see B.3.15 below).

10. "24 percent" is Goolsbee's primary estimate, reported also in the abstract of his paper.

11. "a fourth as large" is based on Alm and Melnik (2005), who state (page 185): "In our preferred model, the elasticity of the probability of online purchases with respect to the tax price of online purchases is only 0.52, or roughly one-fourth the size of Goolsbee's."

12. Ellison and Ellison (2009) state that their discrete choice model for 128MB PC100 RAM gives a price elasticity estimate of -35 (page 66). Their estimated coefficients are given in Table 5 (page 67). The computed own-price elasticity roughly corresponds to one minus the mean purchase probability times the coefficient estimate times the average price; the purchase probabilities and average prices are given in their Table 4 (page 66). For the 128MB PC100 estimates, this yields $(1 - 0.007) \times -0.56 \times 66.24 = -36.8$, which roughly matches -35. The other three models yield estimated own-price elasticities of $(1 - 0.006) \times -0.81 \times 73.82 = -59.4$, $(1 - 0.002) \times -0.43 \times 130.77 = -56.1$, and $(1 - 0.004) \times -0.40 \times 146.52 = -58.4$. The average over the four own-price elasticity estimates is -52.7. Their corresponding estimated sales tax coefficients (salience parameters) are 0.05, 0.33, 0.06, and 0.95 (the average is 0.35); the elasticities with respect to sales tax rates can be computed by multiplying the own-price elasticity estimate by the corresponding tax coefficient. This gives estimated tax-price elasticities of -1.84, -19.60, -3.37, and -55.48. Using the average tax coefficient gives tax-price elasticities of -12.88, -20.79, -19.64, and -20.44 (the average is -18.44). Dropping the tax coefficient estimates of 0.05 and 0.95 gives a trimmed-mean tax coefficient of 0.195 and an average tax-price elasticity of -10.28.

13. "about 6% more purchases" is also based on Ellison and Ellison (2009); see B.3.11 below.

14. "decreases same-state online purchases by 10% or more" is based on Hortaçsu, Martinez-Jerez, and Douglas (2009); see B.3.6 below.

B.2. Section I

1. "275,020 listed items posted by 10,347 different sellers" is given in the notes to Table 1.

2. "\$37" is the item-level average list price reported in Table 1 (\$36.95), rounded.

3. "just under 8%" describes the item-level average sales tax reported in Table 1 (0.0796).

4. "25 user page views" is the item-level average number of page views reported in Table 1 (24.7), rounded.

5. "6,796,691 page views" is given in the notes to Table 1.

6. "about one in five of these page views results in a purchase" refers to the item-level average purchase probability of $p = 0.215$ reported in Table 1.

7. "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." This is the elasticity at the margin for which the expected purchase probability is equal to the item-level average purchase probability for the sample (0.215; see B.2.6 above); the multiplier to translate coefficients to elasticities at this margin is simply $1 - 0.215 = 0.785$, which rounds up to 0.79.

8. "With that in mind, our preferred specification yields an approximate tax-price elasticity of -1.7." The preferred specification is column (b) of Table 2; the reported coefficient on $\log(1 + \text{effective tax})$ is -2.131. At the margin specified, the elasticity is $0.785 * -2.131 = -1.673$.

9. "A viewer charged a 5% sales tax is about 5% more likely to purchase than an equivalent viewer facing an 8% sales tax, and 8% less likely to purchase than one who is charged no sales tax." Here and later we compute predicted probabilities at the $p = 0.215$ margin (as above) by first using $\log(0.215/(1-0.215))$ to back out the right-hand-side value at that margin, then adding in the change term, using $p' = 1/(1+\exp(-RHS-change))$, and finally computing and reporting $p'/p - 1$.

$$\frac{1}{0.215}\left(1 + \exp\left(-\log\left(0.215/(1-0.215)\right) + 2.131 * \log(1.05/1.08)\right)\right)^{-1} - 1 = 0.048$$
$$\frac{1}{0.215}\left(1 + \exp\left(-\log\left(0.215/(1-0.215)\right) + 2.131 * \log(1.05)\right)\right)^{-1} - 1 = -0.079$$

A 10% sales tax reduces purchases by

$$\frac{1}{0.215}\left(1+\exp\left(-\log\left(0.215/(1-0.215)\right)+2.131*\log(1.10)\right)\right)^{-1}-1=-0.150$$

or about 15%, as stated in B.1.7 above.

10. "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." The calculation used here is

$$\frac{1}{0.215}\left(1+\exp\left(-\log\left(0.215/(1-0.215)\right)-0.028*\log(1000/250)\right)\right)^{-1}-1=-0.030$$

11. "a small fraction of the items (just under 15%)" refers to the approximate item-level average of the calculated shipping indicator for our data (0.146, not reported in any of the tables).

12. "increases by around \$0.56 for every doubling in distance" This number came from unreported regressions of the calculated rate shipping fee paid on the logarithm of the shipping distance for a sample of fixed-price items (not our sample for the tax regressions).

13. "reduces the probability of purchase by around 1.4%" is the result of the following calculation:

$$\frac{1}{0.215}\left(1+\exp\left(-\log\left(0.215/(1-0.215)\right)+0.026*\log(2)\right)\right)^{-1}-1=-0.014$$

14. "priced at \$43" The shipping-inclusive price of \$43 is constructed from the item-level average list price for the sample (\$36.95) plus the average calculated-rate shipping fee for items under \$100 in the shipping rate data (\$7.25).

15. "a price elasticity of about -1.1" is based on the following calculation: The log-price change at \$43 from doubling distance (and incurring an additional \$0.56 in shipping fee) is $\log(43.56/43) = 0.013$. The effect of doubling distance is $-0.026 * \log(2) = -0.018$. The ratio of the two is $-0.018/0.013 = -1.393$, which we translate into an elasticity at our usual margin by multiplying by one minus the purchase probability: $(1 - 0.215) * -1.393 = -1.093$.

16. "about 7% more likely" uses the following calculation:

$$\frac{1}{0.215}\left(1+\exp\left(-\log\left(0.215/(1-0.215)\right)-0.081\right)\right)^{-1}-1=0.065$$

17. "from -0.79 to -2.59": taken directly from Table 1 of Hoch et al. (1995).

18. “six largest product categories in our sample.” The six largest categories in our sample by number of items, in descending order, are Computers & Networking, Cell Phones & PDAs, Home & Garden, Electronics, Clothing, and Sporting Goods. In descending order by views, they are Home & Garden, Electronics, Computers & Networking, Cell Phones & PDAs, Clothing, and Sporting Goods. The item and view counts are reported in Table 3(a). They represent 67% of the sample items and 62% of the sample page views.

19. “We estimate the largest elasticity for electronics (-4.3), followed by sporting goods (-3.3).” These come from columns (a) and (f) of Table 3(a); the elasticities are computed at the margin corresponding to the categories' item-level average purchase probabilities:

$$\begin{aligned} \text{Electronics:} \quad & (1 - 0.200) \times -5.325 = -4.260 \\ \text{Sporting Goods:} \quad & (1 - 0.144) \times -3.864 = -3.308 \end{aligned}$$

20. “Three other categories (cell phones, computers, and clothing) are estimated to have a tax-price elasticity of about -2.” These come from columns (b), (c), and (d) of Table 3(a). The computations are:

$$\begin{aligned} \text{Cell Phones:} \quad & (1 - 0.274) \times -2.792 = -2.027 \\ \text{Computers:} \quad & (1 - 0.292) \times -2.733 = -1.935 \\ \text{Clothing:} \quad & (1 - 0.132) \times -1.647 = -1.430 \end{aligned}$$

21. “The ‘home and garden’ category is an exception, as we estimate essentially no tax sensitivity.” The coefficient estimate (in column (e) of Table 3(a)) is positive 0.273 with standard error 1.707. This corresponds to a positive elasticity estimate of $(1 - 0.166) * 0.273 = 0.228$.

22. “a coefficient of 0.53 with a standard error of 2.19” These numbers are reported in the second row of estimates, labeled “log(1 + effective tax) (clothing-exempt)”, in column (d) of Table A2.

23. “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 cheaper items (selling for less than 6 dollars, or for 6-12 dollars) to be between -0.6 and -1.1, compared to an elasticity of -2.1 to -2.5 for more expensive items.” The estimates are reported in Table 3(b). As before, the elasticities are computed at

the margin corresponding to the price bins' item-level average purchase probabilities:

$$\begin{aligned} <\$6&: \quad (1-0.265)*-1.502=-1.104 \\ \$6\text{–}12&: \quad (1-0.243)*-0.809=-0.612 \\ \$12\text{–}24&: \quad (1-0.204)*-2.740=-2.181 \\ >\$24&: \quad (1-0.160)*-2.979=-2.502 \end{aligned}$$

B.3. Section II

1. "ranging from -4.2 to -5.9 ... roughly 5%" The estimates are reported in Table 5; they are -5.556, -5.878 (our preferred specification), -4.234, and -4.743 (identified off changes over time). Their average across specifications is -5.10. Under the small state assumption, these are the elasticity estimates holding online expenditures fixed. Relaxing the small state assumption gives elasticity estimates equal to $-\sigma$ times one minus the in-state online expenditure share. Evaluating for the median state (which has in-state online expenditure share equal to 0.03) gives very similar elasticities of -5.39, -5.70, -4.11, and -4.60 (the average is -4.95).

2. "standard error is 2.3, and the 95% confidence interval is -1.3 to -10.4." From column (b) of Table 5, the standard error is 2.327. The radius of the 95% confidence interval is thus $2.327 * 1.960 = 4.561$, yielding interval endpoints $-5.878 + 4.561 = -1.317$ and $-5.878 - 4.561 = -10.439$.

3. "state i's purchases fall by roughly 7%" is computed from the distance coefficients in Table 5. The coefficient estimates for columns (a)-(c) are -0.104, -0.104 (preferred specification), and -0.105. The estimated effect of doubling distance is computed as

$$\exp\left(-0.104\log(2)\right) - 1 = -0.0696$$

4. "intrastate trade is about 75% higher" is based on the estimated coefficient from our preferred specification (Table 5, column (b)), which is 0.560. The estimated effect is $\exp(0.560) - 1 = 0.751$.

5. "Hortaçsu 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%." Their reported coefficient on the logarithm of distance is -0.07 and their estimated same-state coefficient is 0.56. The corresponding effect sizes are $\exp(-0.07\log(2)) - 1 = -.0474$ and $\exp(0.56) - 1 = 0.751$.

6. "As noted in the introduction, [Hortaçsu et al.] 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 include indicators for integer state tax levels and do not account for local taxes, and interact tax with distance. To first approximation, their estimated tax effect is rather larger than ours, at least -10, and perhaps -20." Their

estimates, from Table 7 (page 68), are for dummies indicating levels of state sales tax rates (rounded up):

state tax rate	coefficient estimate (Model II)	coefficient estimate (Model III)
6%	0.40	0.04
5%	0.44	0.40
4%	0.44	0.40
3%	0.84	0.63
0%	1.14	1.11

A least-squares regression of the dummy coefficients on $\log(1+\tau)$ gives an estimated coefficient of -13.87 for Model II and -17.25 for Model III. These are likely to be overestimates, as they neglect county and local sales tax rates.

7. "we drop about a fifth of the counties, which border lower-tax counties on the other side of a state boundary." The counties dropped number 571 out of a total of 3,054; they represent 18.7% of counties in our sample.

8. "our estimated elasticities in the bottom panel are higher, by about 25%." Here, we're comparing the coefficient estimates for "log(1 + effective tax)" in Table 6 Panel B, taking the ratio of those for the bottom sample to those for the top sample. Using either the average of the estimate ratios or the ratio of the average estimates for across columns (a)–(f) yields the same value to three decimal places, 1.257.

9. "our preferred estimate of η is around 1.8, meaning that a one percentage point increase in sales tax increases online purchasing by 1.8%" This is from Table 6 Panel B; our baseline specification is column (a), which has coefficient estimate of 1.82. The coefficient estimate more properly translates to an elasticity estimate by multiplying by one minus the expenditure share of home state goods. Thus, it is at least $(1-0.21)*1.82 = 1.44$ (California has the greatest intrastate expenditure share and therefore the lowest elasticity). The median state has an intrastate expenditure share of 3%, giving an elasticity estimate of $(1-0.03)*1.82 = 1.77$, which is "around 1.8".

10. "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." Goolsbee (2000a) states the following: "The results show that the sales tax has a significant impact on the decision to buy online of the predicted sign. The magnitude suggests that raising the sales tax by .01 increases the mean probability of buying online by .005. Since the mean probability of purchase is approximately .20, the estimated elasticity of online buying with respect to the tax price (one plus the tax rate) is 2.3." This corresponds to the regression in column (1) of his Table II; column (2) reports estimates for a sample restricted to states having a uniform sales tax rate, with an estimated elasticity of 4.3. Column (3) reports estimates from comparisons within metro areas across state boundaries and gives an estimated elasticity of 3.4.

11. "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." Their estimates from state-level regressions (in Table 2, page 60) are 5.96, 6.33, 6.14, and 7.21.

12. "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." The calculation is $\exp(1.82 \log(1.07)) - 1 = 0.131$.

13. "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 A6, column (k))." The expenditure shares are computed using our state-level summary statistics; California's expenditure share is the highest at 20.55%, which we round to 21%.

14. "So if we consider a one percentage point decrease in state sales tax (such as occurred in California on July 1, 2011), our estimates suggest roughly a 1.5-2% decrease in online purchases by state residents, and a corresponding decrease in cross-state online purchases..." The elasticity estimate for "overall online purchasing" is 1.82 (Table 6, Panel B, column (a)), giving $(1 - 0.03) * -1.82 = -1.77$ for the median state and $(1-0.21) * -1.82 = -1.44$ for California; see equation (20) below. The "corresponding decrease in cross-state online purchases" is greater for tax changes in states with large home-state online expenditure shares; for instance, the change in California has an estimated decrease in interstate purchases by California buyers of $-1.8 * (1 - 0.21) - 5.9 * (0.21) = -2.66$. See equation (25) below.

15. "...but a 3-4% increase in online purchases by state residents from home-state sellers." With $x_{ii} = 0$, the estimate is 4.1; for the median state, however, $x_{ii} = 0.03$, giving estimated elasticity $(1 - 0.03) * 4.1 = 3.98$. For California, $x_{ii} = 0.21$, giving estimated elasticity $(1 - 0.21) * 4.1 = 3.24$. See equation (25) below.

16. "To see that this makes little difference, note that for most states $x_{ii} < 0.05$, and even for California, x_{ii} is only 0.21, so that $\partial \log Q_i / \partial \log(1 + \tau_i)$ is still $1.8 \cdot 0.79 = 1.4$." Thirty-nine states have in-state expenditure shares of less than 5%; see Table A6 column (k).

17. "As of January 1, 2010, the population-weighted average sales tax in the United States was about 7.3%." This was computed using the state summary statistics; the populations and state-level population-weighted tax rates use 2000 Census figures.

18. "overall online purchasing would fall by about 12%." is simply $\exp(-1.82 * \log(1.073)) - 1 = -0.120$.

B.4. Conclusions

1. "4-6 percent" is based on equation (16) below. The smallest estimate of σ from our specifications (Table 5, column (c)) is 4.234; the elasticity estimate for a tiny state like

Wyoming is -4.23, and for the median state, the estimated elasticity is $-4.234 * (1 - 0.03) - 0.03 = -4.14$. The largest estimate of σ is 5.878, from our preferred specification (column (b)); the elasticity estimate for a tiny state like Wyoming is -5.85, and for the median state, the estimated elasticity is $-5.878 * (1 - 0.03) - 0.03 = -5.73$. For California, the smallest estimated elasticity is $-4.234 * (1 - 0.21) - 0.21 = -3.55$, and the largest estimated elasticity is $-5.878 * (1 - 0.21) - 0.21 = -4.85$.

2. "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)." See B.3.9 and B.3.10 above. Goolsbee's main estimate is that taxing internet sales could reduce online purchasers by around 24%; the mean tax rate for his sample is 6.6%, suggesting his headline elasticity estimate is 3.4 (from his within-metro, cross-border specification, column (3) of Table II). Using this, $1.8/3.4 = 0.53$.

3. "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." See B.3.14 and B.3.15 above.

Appendix C. More detailed derivations of the key equations in the paper

C.1. Preliminaries

With ad-valorem tax rate τ, the price net of tax is $(1+\tau)p$. We use the tax multiple $(1+\tau)$ and its logarithm extensively in our model specifications. Our estimated effects translate most readily to elasticities of demand with respect to the tax multiple (or, equivalently, elasticities with respect to the price net of tax, $(1+\tau)p$). Occasionally, we appeal to the small-τ approximation

$$\log(1+\tau) \approx \tau \tag{1}$$

and the small-τ approximation

$$\frac{\partial \log Q}{\partial \log(1+\tau)} = (1+\tau)\frac{\partial \log Q}{\partial \tau} \approx \frac{\partial \log Q}{\partial \tau} \tag{2}$$

which gives approximate equivalence of the elasticity with respect to the tax multiple $(1+\tau)$ and the semi-elasticity with respect to the tax rate τ.

Estimating effects under our specifications can be done (with a constant elasticity assumption, true for the upper-level but only approximately true for the lower level[4]) using

$$\frac{Q(\tau') - Q(\tau)}{Q(\tau)} \approx \exp\left(\left[\log\left(1+\tau'\right) - \log(1+\tau)\right]\frac{\partial \log Q}{\partial \log(1+\tau)}\right) - 1 \tag{3}$$

[4] The lower-level gravity model has near-constant elasticity, changing only with the expenditure share of the good whose price is changing. This effect is potentially quite small.

Using the approximate equivalences,

$$\frac{Q(\tau') - Q(\tau)}{Q(\tau)} \approx (\tau' - \tau) \frac{\partial \log Q}{\partial \log(1+\tau)} \tag{4}$$

The disagreement is particularly noticeable for changes leading to decreases in purchase quantities; for instance, with a constant demand elasticity of -5.9, applying a 10% tax to previously untaxed transactions leads to a 43% decrease in demand:

$$\frac{Q(1.10) - Q(1)}{Q(1)} = \exp\left(-5.9 \log(1.10)\right) - 1 = -0.43 \tag{5}$$

In contrast, using the approximation, the estimated change in demand is $-5.9 \times 0.1 = -0.59$, or a 59% decrease.

C.2. CES model of demand

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 buyers and j index goods. Equivalently, i indexes a buyer-state and j indexes a seller-state. Let q_{ij} denote the quantity purchased by state i from state j, and let p_{ij} denote the unit price net of any applicable sales tax.

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

$$\max_{q_{i1},\ldots,q_{iJ}} \left(\sum\nolimits_j \left(q_{ij}\zeta_{ij}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \qquad \text{s.t.} \qquad \sum\nolimits_j p_{ij}q_{ij} \leq w_i. \tag{6}$$

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

$$q_{ij} = \frac{p_{ij}^{-\sigma}\zeta_{ij}^{1-\sigma}}{P_i^{1-\sigma}} w_i, \tag{7}$$

where P_i is the CES price index for online goods:

$$P_i = \left(\sum\nolimits_j \left(\zeta_{ij}p_{ij}\right)^{1-\sigma}\right)^{1/(1-\sigma)} \tag{8}$$

Note the following property:

$$\frac{\partial \log P_i}{\partial \log p_{ij}} = \frac{\partial \log P_i}{\partial \log\left(1+\tau_{ij}\right)} = x_{ij}, \tag{9}$$

where $x_{ij} = p_{ij}q_{ij}/w_i$ is the expenditure share of location i consumers devoted to location j goods.

Assuming that this general demand structure applies in each year t, and taking logs, we have:

$$\log q_{ijt} = -\sigma \log p_{ijt} + (1-\sigma)\log \zeta_{ijt} - (1-\sigma)\log P_{it} + \log w_{it}. \tag{10}$$

Prices are $p_{ijt} = (1+\tau_{ijt})\, p_{jt}$, where p_{jt} is the base price on goods sold from location j, and τ_{ijt} is the applicable sales tax rate. Suppose that in addition we can write the preference parameter ζ_{ijt} as

$$\zeta_{ijt} = \left(h^{\mathbf{1}\{i=j\}} d_{ij}^{\gamma}\right)^{1/(1-\sigma)} \zeta_{jt}, \tag{11}$$

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 (which accounts for the overall masses of sellers in various locations). With these assumptions, purchases by state i from state j in year t can be expressed as:

$$\log q_{ijt} = a_{it} + b_{jt} - \sigma \log(1+\tau_{ijt}) + \gamma \log(d_{ij}) + h\mathbf{1}\{i=j\}. \tag{12}$$

Note that P_{it} and w_{it} have been subsumed into the a_{it} term.

Considering w_{it} fixed, the elasticity of q_{ijt} with respect to the tax multiple $(1+\tau_{ijt})$ is given by

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{ijt})} = -\sigma - (1-\sigma)\frac{\partial \log P_{it}}{\partial \log(1+\tau_{ijt})} \tag{13}$$

From equation (9), $\partial \log P_{it}/\partial \log(1+\tau_{ijt}) = x_{ijt}$, so we have

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{ijt})} = -\sigma - (1-\sigma)x_{ijt} \tag{14}$$

Assuming that the state has an infinitesimal expenditure share gives the straightforward "small state approximation" $\partial \log q_{ijt}/\partial \log(1+\tau_{ijt}) \approx -\sigma$.

Taking taxes to be zero for interstate transactions, we have

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = -\sigma \mathbf{1}_{\{i=j\}} - (1-\sigma)x_{iit} \tag{15}$$

$$= \begin{cases} -\sigma(1-x_{iit}) - x_{iit} & \text{if } i=j \text{ (intrastate)} \\ -(1-\sigma)x_{iit} & \text{if } i\neq j \text{ (interstate)} \end{cases} \tag{16}$$

If, instead, we consider online expenditures w_{it} to vary with the local tax multiple $(1+\tau_{it})$, we have an additional term equal to the elasticity of online expenditure with respect to the local tax multiple:

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = -\sigma \mathbf{1}_{\{i=j\}} - (1-\sigma)x_{iit} + \frac{\partial \log w_{it}}{\partial \log(1+\tau_{it})} \tag{17}$$

In our baseline specification (column (b) of Table 5), we have $\hat{\sigma} = 5.9$. Thus, fixing total online expenditures and substituting the estimates into equation (16), our estimated elasticities are

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = \begin{cases} -5.9 + 4.9x_{iit} & \text{if } i = j \text{ (intrastate)} \\ 4.9x_{iit} & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{18}$$

At the upper-level, we use a simple log-log representation of consumer demand for online purchases,

$$\log Q_{it} = \xi_{it} - \eta \log\left(P_{it}/\overline{P}_{it}\right), \tag{19}$$

where Q_{it} are 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. 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}.

C.3. Combined effects of sales tax changes

We combine our upper-level model of overall online purchasing in equation (19) with our lower-level model of how online spending is distributed (equation (10)), noting that in the latter we can represent overall online expenditure w_i as P_iQ_i, where Q_i is the CES aggregate for online consumption and P_i is the corresponding CES online price index.

We maintain a complete pass-through assumption. Fixing total retail expenditures, a local sales tax increase primarily serves to increase local offline prices net of tax $\overline{P}_i$; however, it also increases the online price index (net of tax) P_i to the extent that online retail spending goes to local online sellers. As before, let $x_{ii} = p_{ii}q_{ii}/w_i$ denote the share of online expenditure that state i devotes to home-state purchases. In our lower-level CES demand, $\partial \log P_i/\partial \log(1+\tau_i) = x_{ii}$, so if x_{ii} is not trivial, an increase in state i's sales tax rate τ_i will increase online post-tax prices as well as offline post-tax prices.

We have

$$\frac{\partial \log Q_i}{\partial \log(1+\tau_i)} = \eta\,(1 - x_{ii})\,, \quad \frac{\partial \log P_i}{\partial \log(1+\tau_i)} = x_{ii}, \tag{20}$$

giving the elasticity of online expenditure with respect to the tax multiple as

$$\frac{\partial \log w_i}{\partial \log(1+\tau_i)} = \frac{\partial \log(Q_i)}{\partial \log(1+\tau_i)} + \frac{\partial \log(P_i)}{\partial \log(1+\tau_i)} = \eta\,(1-x_{ii}) + x_{ii} = \eta + (1-\eta)x_{ii}. \tag{21}$$

Thus, from equation (17), we have

$$\frac{\partial \log q_{ij}}{\partial \log(1+\tau_i)} = \left[-\sigma \mathbf{1}_{\{i=j\}} - (1-\sigma)x_{ii}\right] + \left[\eta + (1-\eta)x_{ii}\right] \tag{22}$$

$$= -\sigma \mathbf{1}_{\{i=j\}} + \eta + (\sigma - \eta)x_{ii} \tag{23}$$

$$= \begin{cases} \eta\,(1-x_{ii}) - \sigma\,(1-x_{ii}) & \text{if } i = j \text{ (intrastate)} \\ \eta\,(1-x_{ii}) + \sigma x_{ii} & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{24}$$

The first term is the online-offline substitution effect and the second term is the cross-state substitution effect.

Substituting into equation (24) from our estimated baseline specification for the upper-level (column (a) of Table 6, Panel C), which gives $\hat{\eta} = 1.8$, and our gravity model estimate from column (b) of Table 5, which gives $\hat{\sigma} = 5.9$, our estimated elasticities are

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = \begin{cases} -4.1(1 - x_{iit}) & \text{if } i = j \text{ (intrastate)} \\ 1.8(1 - x_{iit}) + 5.9x_{iit} & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{25}$$

C.4. Small state assumption

We continue to assume that offline sellers fully pass through the tax to consumers and consider the effect of an increase in state i's sales tax rate τ_i, which, under the current legal regime, will be applied to both local offline 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 change will have no pass-through effect on online (pre-tax) prices or direct effect on i's online price index P_i.

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 $x_{ii} > 0.10$ (California has an expenditure share of 20.55% and New York has an expenditure share of 10.98%; see Table A6 column (k)).

Using $x_{ii} \approx 0$, we have

$$\frac{\partial \log Q_i}{\partial \log(1+\tau_i)} \approx \eta, \tag{26}$$

and, using the fact that $\partial \log w_i / \partial \log(1+\tau_i) = (1 - x_{ii})\eta \approx \eta$,

$$\frac{\partial \log q_{ij}}{\partial \log(1+\tau_i)} \approx -\sigma \mathbf{1}_{\{i=j\}} + \eta \tag{27}$$

$$\approx \begin{cases} \eta - \sigma & \text{if } i = j \text{ (intrastate)} \\ \eta & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{28}$$

To see that the small state assumption ($x_{ii} = 0$) makes little difference, note that even for California, x_{ii} is only about 0.21. The estimated online purchasing elasticity for California without the small-state assumption is $\partial \log Q_i / \partial \log(1+\tau_i) = 1.8 \cdot 0.79 = 1.4$. Likewise, the estimated elasticities for intrastate and interstate online purchasing by California buyers without the small-state assumption are

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = \begin{cases} -3.2 & \text{if } i = j \text{ (intrastate)} \\ 2.7 & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{29}$$

With the small-state assumption, the online purchasing elasticity is 1.8, and the estimated elasticities for intrastate and interstate online purchasing are

$$\frac{\partial \log q_{ijt}}{\partial \log(1+\tau_{it})} = \begin{cases} -4.1 & \text{if } i = j \text{ (intrastate)} \\ 1.8 & \text{if } i \neq j \text{ (interstate)} \end{cases} \tag{30}$$

Figure A1: Visual Illustration of the Residuals Underlying the Item-Level Elasticities

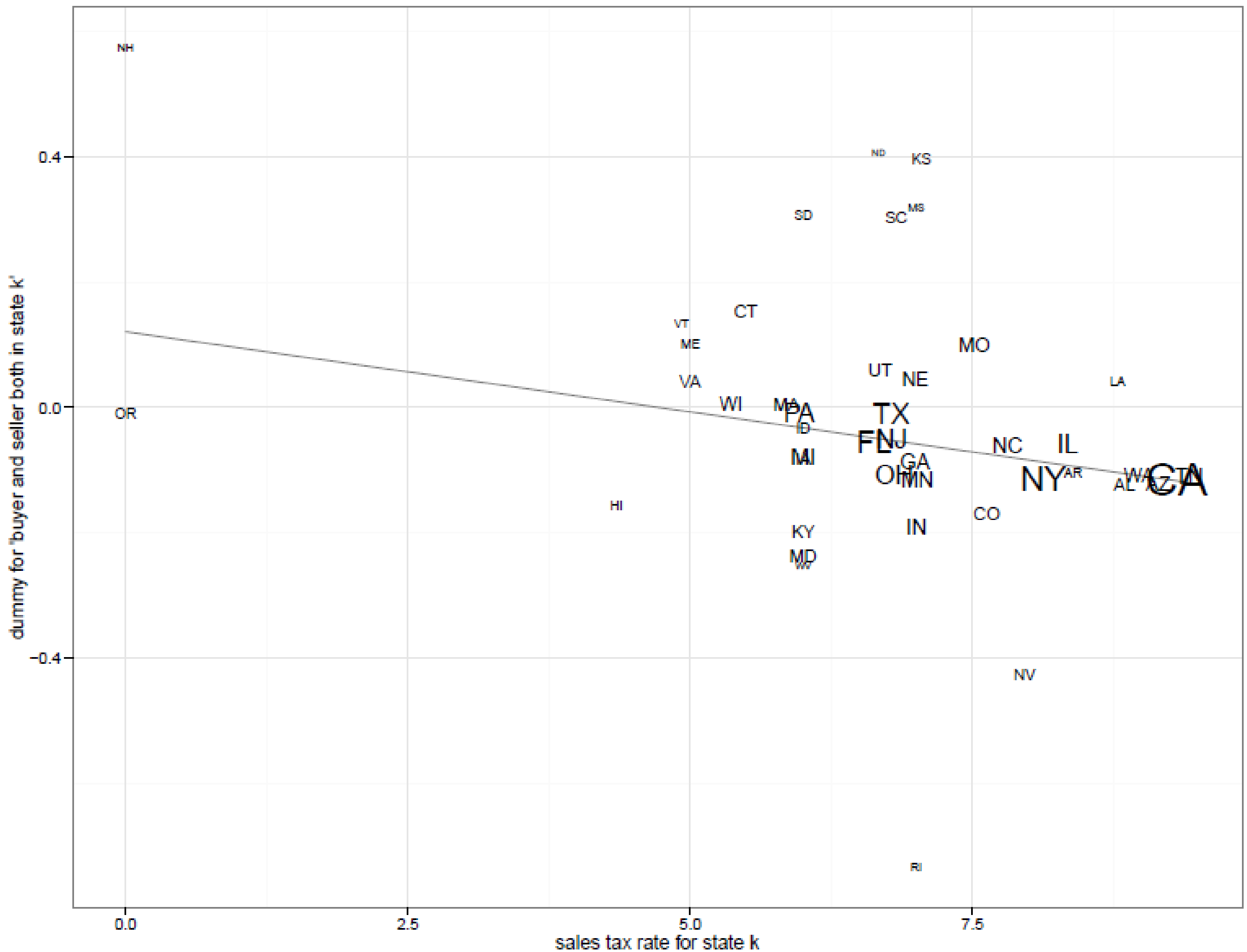

Figure uses the data used to generate Table 2, and plots each state's "same-state" effect against each state's effective tax rate. The same-state effects for each state are obtained by modifying the item-level regression model (equation (2)) to the following specification: $u_{ik} = \alpha_k + g(d_{ik}) + \delta_{state(i)} 1\{state(i)=k\}$, in which the δ's represent the "same-state" effect. In the figure, the size of each state label is proportional to the number of observation in the sample for each state, and the straight line is the (weighted) regression line.

Figure A2: User Demographics of Different Web Sites, based on Alexa.com

Figure A2(a)

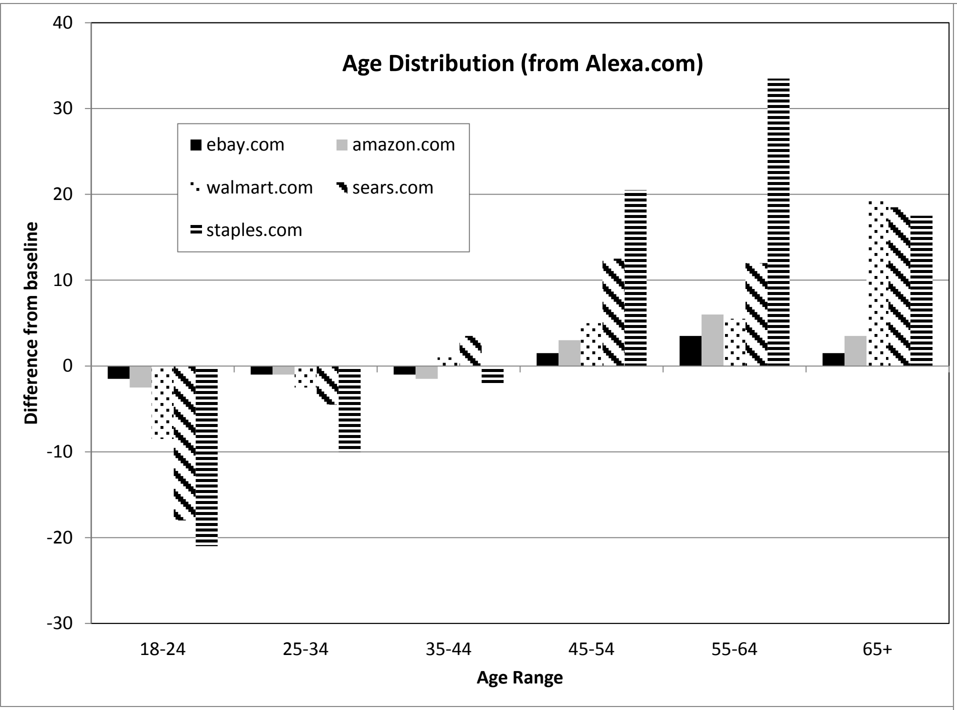

Figure A2(b)

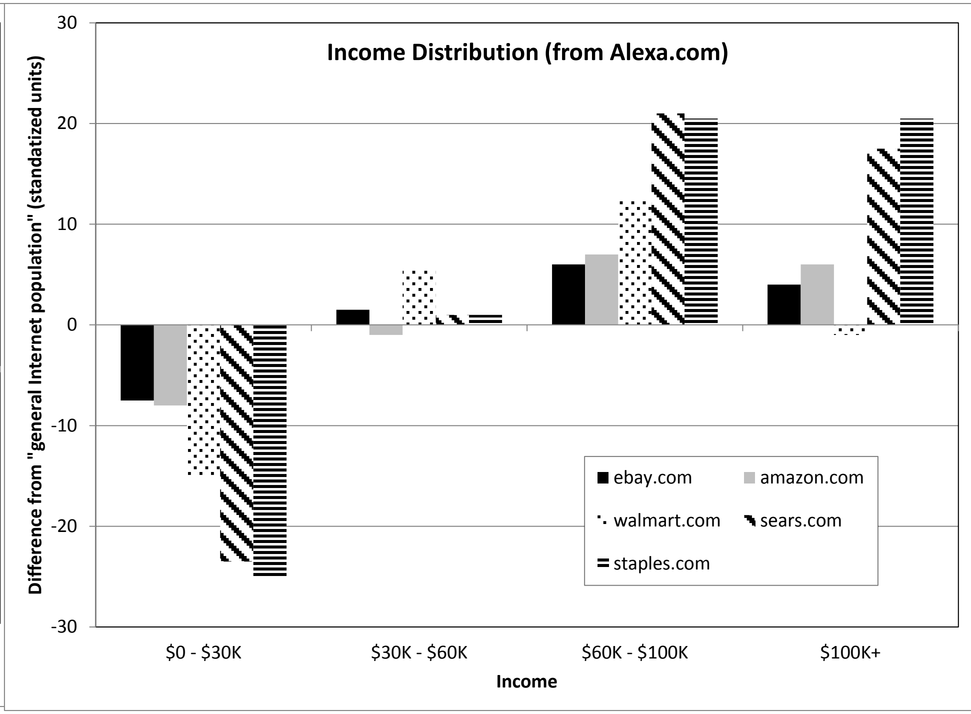

Figure A2: User Demographics of Different Web Sites, based on Alexa.com (cont.)

Figure A2(c)

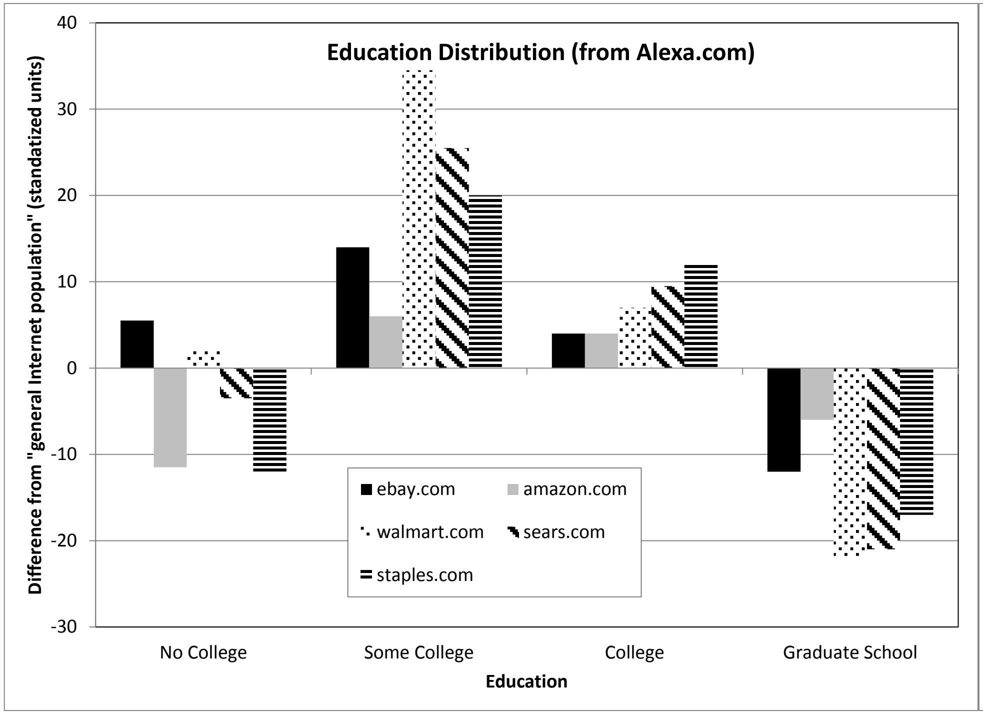

Figure A2(d)

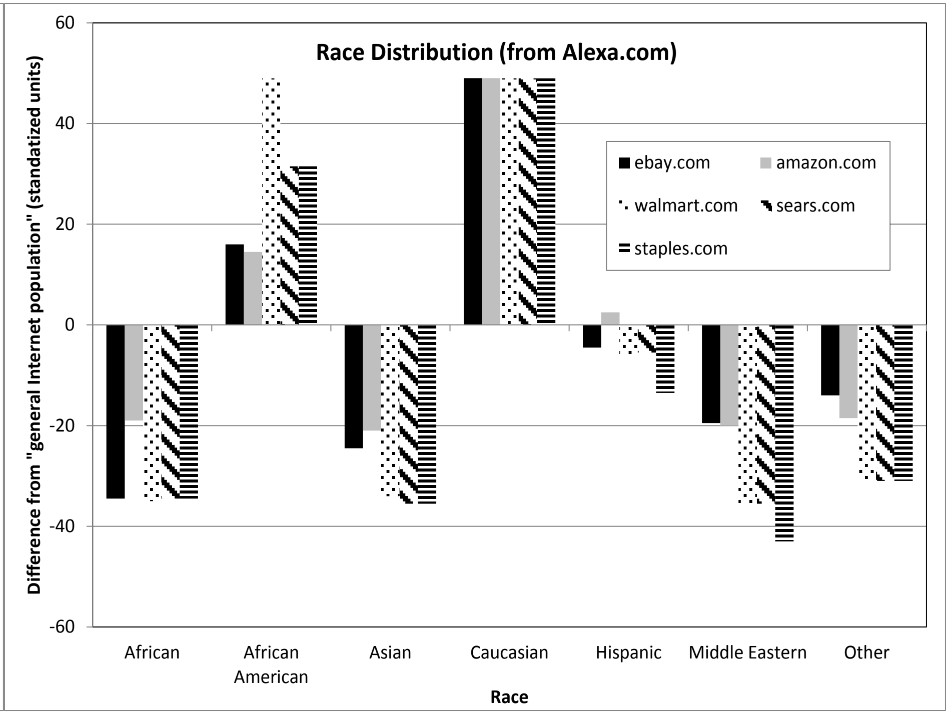

Figure A2: User Demographics of Different Web Sites, based on Alexa.com (cont.)

Figure A2(e)

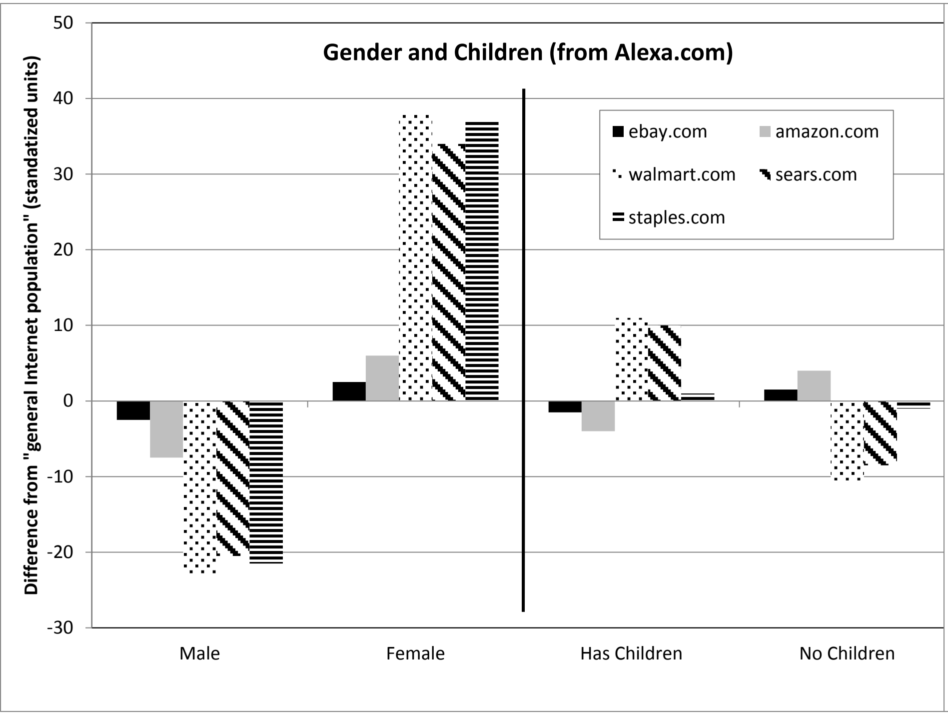

Figure A2(f)

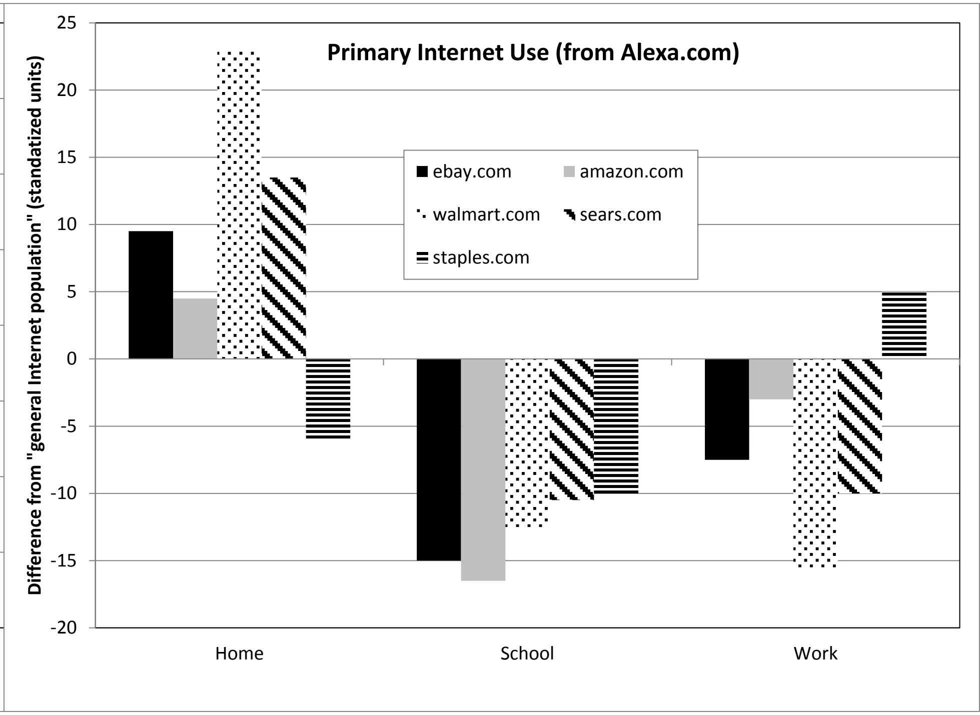

Figure A3: User Demographics of eBay and Amazon, based on Quantcast.com

Figure A3(a)

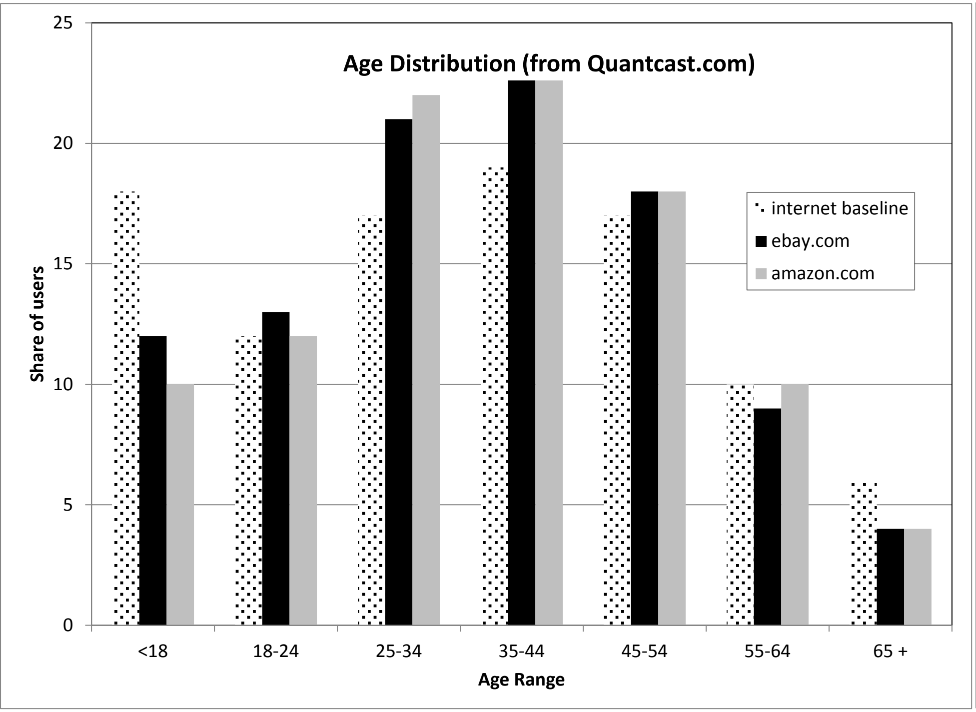

Figure A3(b)

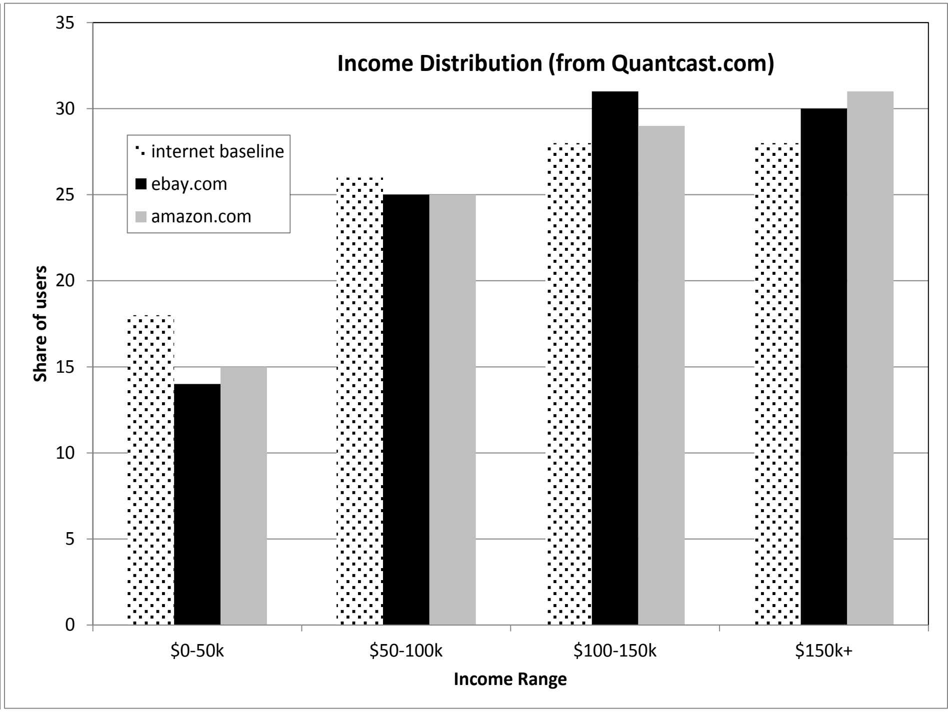

Figure A3: User Demographics of eBay and Amazon, based on Quantcast.com (cont.)

Figure A3(c)

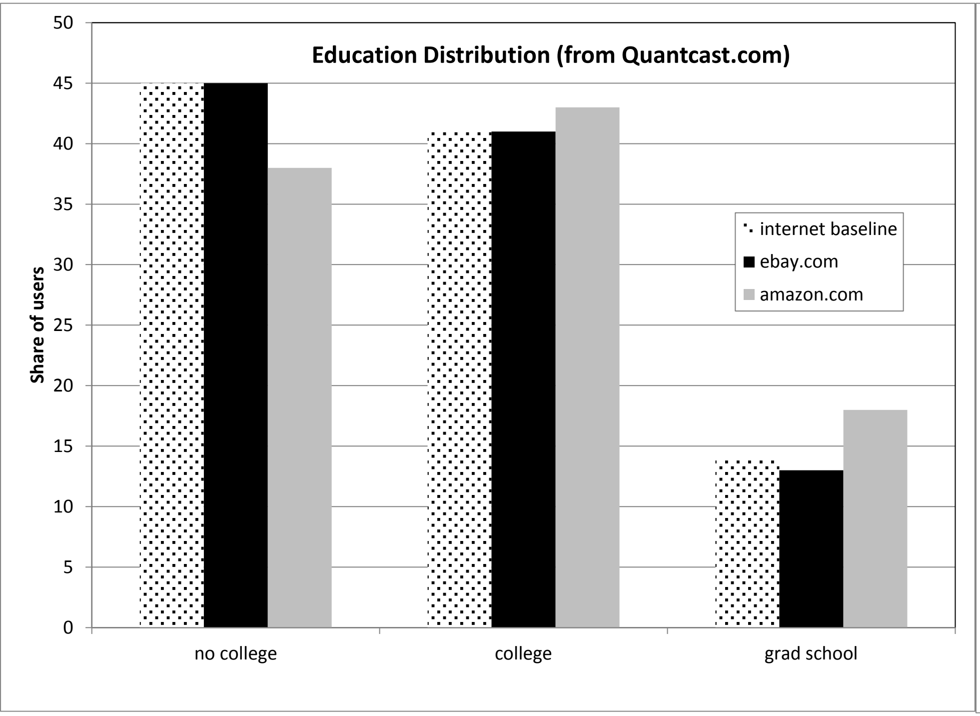

Figure A3(d)

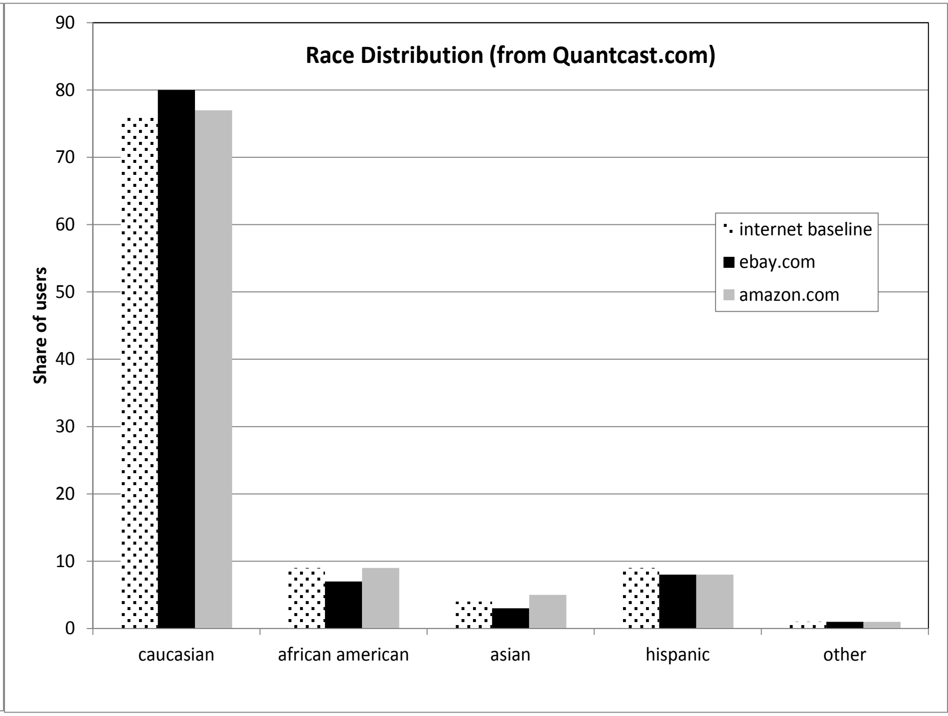

Figure A3: User Demographics of eBay and Amazon, based on Quantcast.com (cont.)

Figure A3(e)

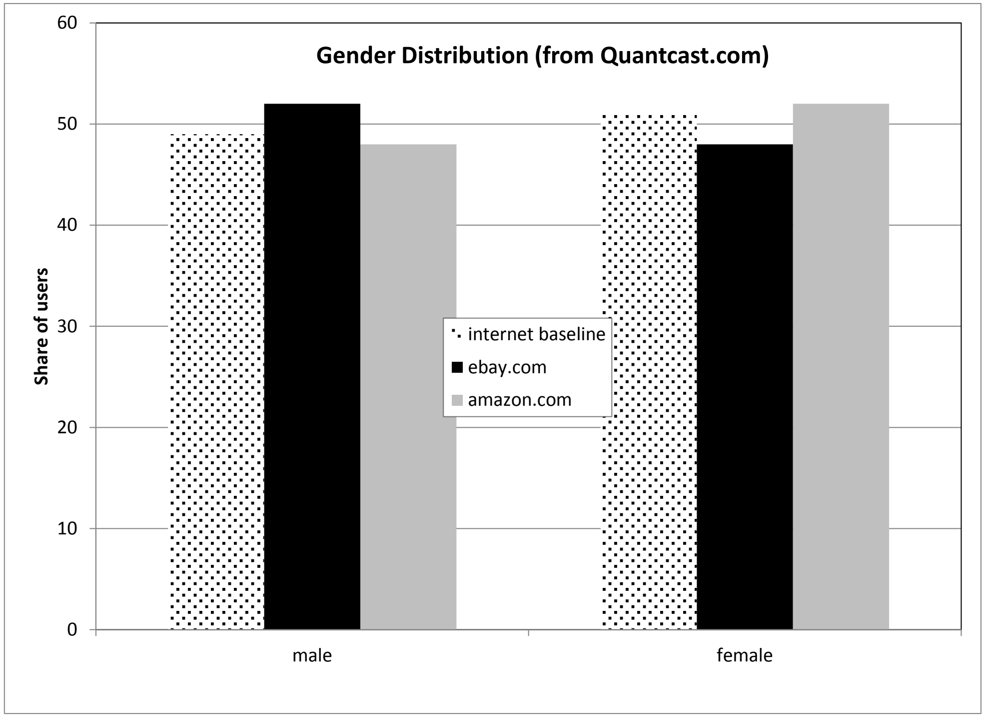

Table A1: Item-Level Estimates of Tax Sensitivity, Census Regions and Divisions

	Dependent variable: 1 if item purchased						
	All items		All items			By rate type	
	(a)	----------(b)	----------	----------	----------(c)	----------	----------
log(1+effective tax)	-1.182 (0.104)	-2.131 (0.406)	-1.600 (0.488)	-1.502 (0.502)	-1.897 (0.408)	-1.464 (0.487)	-1.378 (0.501)
log(distance)	-0.029 (0.002)	-0.028 (0.002)	-0.028 (0.002)	-0.028 (0.002)	-0.025 (0.003)	-0.025 (0.003)	-0.025 (0.003)
log(distance)*Calc. rate dummy					-0.026 (0.005)	-0.025 (0.005)	-0.025 (0.005)
Same state:							
National		0.081 (0.033)			0.063 (0.033)		
[R1] Northeast			0.043 (0.039)			0.035 (0.038)	
[D1] New England				0.180 (0.069)			0.169 (0.070)
[D2] Middle Atlantic				0.031 (0.040)			0.024 (0.040)
[R2] Midwest			0.038 (0.039)			0.021 (0.040)	
[D3] East North Central				0.015 (0.042)			-0.001 (0.042)
[D4] West North Central				0.098 (0.052)			0.076 (0.052)
[R3] South			0.070 (0.037)			0.058 (0.037)	
[D5] South Atlantic				0.043 (0.040)			0.032 (0.040)
[D6] East South Central				0.000 (0.064)			-0.013 (0.064)
[D7] West South Central				0.103 (0.041)			0.090 (0.041)
[R4] West			0.027 (0.045)			0.020 (0.044)	
[D8] Mountain				0.019 (0.068)			0.004 (0.068)
[D9] Pacific				0.019 (0.046)			0.012 (0.046)
Implied Tax-Price Elasticity	-0.928 (0.082)	-1.673 (0.319)	-1.256 (0.383)	-1.179 (0.394)	-1.489 (0.320)	-1.149 (0.382)	-1.082 (0.393)
Same state Estimates	None	National	Regional	Divisional	National	Regional	Divisional
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 row of the table, and the tax-price elasticity is the estimated coefficient (at the first row) multiplied by (1-purchase rate). If present (models (b) and (c)), the 'Same state' coefficient estimate is constrained to be equal nationally (first sub-column for each model), within Census regions (second sub-column), or within Census divisions (third sub-column); the first sub-column estimates are identical to those reported in Table 2.

Table A2: "Placebo" Estimates using States with Tax Exemption for Clothing Items

	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)	-5.891	-2.349	-1.629	-1.249	0.395	-4.116
(non-exempt)	(1.780)	(1.564)	(1.635)	(1.946)	(1.677)	(2.223)
log(1+effective tax)	-6.692	-1.988	-0.971	0.526	0.837	-4.698
(clothing-exempt)	(1.976)	(1.782)	(1.964)	(2.190)	(1.805)	(2.580)
log(distance)	-0.029	-0.031	-0.042	-0.016	-0.025	-0.031
	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)	(0.009)
Same state Dummy	0.366	0.089	0.008	0.022	-0.095	0.247
	(0.151)	(0.135)	(0.144)	(0.163)	(0.132)	(0.175)
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
Implied Tax-Price Elasticity	-4.713	-1.705	-1.153	-1.084	0.329	-3.523
(non-exempt)	(1.424)	(1.135)	(1.158)	(1.689)	(1.399)	(1.903)
Implied Tax-Price Elasticity	-5.354	-1.443	-0.687	0.457	0.698	-4.021
(clothing-exempt)	(1.581)	(1.294)	(1.391)	(1.901)	(1.505)	(2.208)

Table replicates Table 3(a) in the paper, but allows the tax coefficient to be different for the nine states in which clothing items are exempt from sales tax. A priori, the tax coefficient should be affected (and become zero) only in column (d).

Table A3: Heterogeneity in Response to Tax across Buyer Types

	Dependent variable: 1 if item purchased			
	Estimate	Std. Err.	Elasticity	Std. Err.
Segment A log(1+effective tax)	-2.530	(0.591)	-1.934	(0.452)
Segment B log(1+effective tax)	-2.305	(0.502)	-1.827	(0.398)
Segment C log(1+effective tax)	-2.082	(0.467)	-1.693	(0.380)
Segment D log(1+effective tax)	-2.047	(0.468)	-1.695	(0.388)
Segment E log(1+effective tax)	-1.940	(0.564)	-1.537	(0.447)
Segment A Dummy	0.161	(0.015)		
Segment B Dummy	-0.004	(0.013)		
Segment C Dummy	-0.134	(0.012)		
Segment D Dummy	-0.235	(0.011)		
log(distance)	-0.029	(0.002)		
Same state Dummy	0.081	(0.037)		
Fixed Effects	Item			
No. of distinct sellers	10,000			
No. of distinct items	241,493			
No. of page views	5,476,927			
Mean of Dep. Variable	0.208			

Table replicates column (b) of Table 2, but allows different buyer segments to have different responses to taxes (as well as different segment-specific baseline purchase rates). eBay classifies buyers into five categories based on their purchasing volume (in dollars) over the previous twelve months. "A" buyers (165,198 distinct users) represent the highest-volume buyers and are in the top percentile of purchasing volume. "B" buyers (611,724 distinct users) represent the second highest category, and are between the 1st and 5th percentile. "C" buyers (2,481,707 users) are between the 5th and 30th percentile, and "D" buyers (2,009,086 users) are all other active buyers. "E" buyers (209,212 users) are those who were not active over the previous twelve months.

Table A4: State-to-State Trade Flows in Dollar Value (Rather than Transaction Count)

	Dependent variable: GMV of state-to-state purchases				
	(a)	(b)	(c)	(d)	(e)
log(1+effective tax)	-9.897	-10.114	-7.351	-10.636	-7.691
	(4.395)	(4.570)	(4.123)	(14.941)	(5.022)
log(distance)	-0.127	-0.127	-0.128	--	--
	(0.013)	(0.013)	(0.012)		
Same state Dummy	0.876	0.892	1.574	--	--
	(0.297)	(0.310)	(0.622)		
log(distance) * Same state			-0.170		
			(0.120)		
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
No. of Obs.	7,500	7,500	7,500	7,500	90,000

Table replicates Table 5 in the paper, with the only difference being that state-to-state flows are measured by the Gross Merchandise Value (GMV) in dollars rather than by the count of transactions.

Table A5: Estimates of Online State-to-State Flows, Census Regions and Divisions

	Dependent variable: Number of state-to-state purchases								
	(a)			(b)			(c)		
log(1+effective tax)	-5.556 (1.932)	-3.728 (1.607)	-4.977 (1.500)	-5.878 (2.327)	-4.123 (1.786)	-5.435 (1.695)	-4.234 (2.237)	-3.129 (2.026)	-5.022 (1.744)
log(distance)	-0.104 (0.008)	-0.108 (0.004)	-0.109 (0.006)	-0.104 (0.007)	-0.108 (0.004)	-0.109 (0.006)	-0.105 (0.006)	-0.198 (0.075)	-0.182 (0.094)
log(distance) * Same state							-0.105 (0.085)	-0.108 (0.005)	-0.108 (0.006)
Same state:									
National	0.537 (0.146)			0.560 (0.149)			0.988 (0.367)		
[R1] Northeast		0.388 (0.119)			0.416 (0.129)			0.785 (0.300)	
[D1] New England			0.503 (0.094)			0.527 (0.100)			0.804 (0.405)
[D2] Middle Atlantic			0.472 (0.114)			0.505 (0.126)			0.837 (0.500)
[R2] Midwest		0.513 (0.125)			0.539 (0.136)			0.921 (0.338)	
[D3] East North Central			0.568 (0.100)			0.599 (0.119)			0.933 (0.492)
[D4] West North Central			0.736 (0.125)			0.767 (0.138)			1.103 (0.512)
[R3] South		0.414 (0.128)			0.442 (0.139)			0.856 (0.316)	
[D5] South Atlantic			0.411 (0.086)			0.441 (0.111)			0.794 (0.473)
[D6] East South Central			0.869 (0.135)			0.905 (0.160)			1.246 (0.535)
[D7] West South Central			0.569 (0.198)			0.604 (0.204)			0.986 (0.480)
[R4] West		0.322 (0.139)			0.354 (0.147)			0.774 (0.352)	
[D8] Mountain			0.597 (0.152)			0.630 (0.153)			0.947 (0.496)
[D9] Pacific			0.406 (0.258)			0.443 (0.248)			0.818 (0.605)
Same state Estimates	National	Regional	Divisional	National	Regional	Divisional	National	Regional	Divisional
Fixed Effects	Buyer State * Year, Seller State			Buyer State * Year, Seller State * Year			Buyer State * Year, Seller State * Year		
No. of Obs.	7,500			7,500			7,500		

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 of three years (2008-2010); data is aggregated to the yearly level. 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.* The 'Same state' coefficient estimate is constrained to be equal nationally (first sub-column for each model), within Census regions (second sub-column), or within Census divisions (third sub-column); the first sub-column estimates are identical to those reported in Table 5.

Table A6: 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 the 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).