cesifo WORKING PAPERS

8924 2021

March 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 8924*

The Internet as a Tax Haven?

Abstract

If online transactions are tax-free, increased online shopping may lower tax rates as jurisdictions seek to reduce tax avoidance; but, if online firms remit taxes, online sales may put upward pressure on tax rates because internet sales help enforce destination-based taxes. I find that higher internet penetration generally results in lower municipal tax rates, but raises tax rates in some jurisdictions. The latter effect emerges in states where many online vendors remit taxes. A one standard deviation increase in internet penetration lowers local sales taxes in large municipalities by 0.15 percentage points or 16% of the average rate.

JEL-Codes: H250, H710, H730, L810, R500.

Keywords: e-commerce, online shopping, sales tax, tax competition.

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The author is also an affiliate member of CESifo. I thank three anonymous referees and the editor, Daniel Silverman, along with Claudio Agostini, Spencer Banzhaf, Christopher Bollinger, JS Butler, Sebastien Bradley, Craig Brett, Leah Brooks, Donald Bruce, Raj Chetty, Anthony Creane, William Dougan, Sara Fisher Ellison, Dirk Foremny, Bill Fox, Elisabeth Gugl, Arnold Harberger, Andreas Hauer, Jeffrey Hoopes, William Hoyt, Carlos Lamarche, Olga Malkova, Giorgia Maffini, Mohammed Mardan, Doug Miller, Andreas Peichl, Steven Rosenberg, Tuukka Saarimaa, Georg Schaur, Ian Schmutte, Joel Slemrod, Sebastian Siegloch, Gregory Trandel, Christian Traxler, Ronald Warren, David Wildasin, Jonathan Williams, Aaron Yelowitz, and James Ziliak for helpful comments. Special thanks to Don Bruce, Bill Fox LeAnn Luna and Jeffrey Hoopes for sharing data with me. Seminar and conference participants at the Canadian Public Economics Meetings, the Centre for Business Taxation, Clemson University, DIW Berlin, the Federal Reserve Bank of Boston, Indiana University, the Institut d'Economia de Barcelona, the 70th Annual Congress of the International Institute of Public Finance, the Lincoln Institute of Land Policy, Ludwig Maximilian University of Munich, the NBER Universities Research Conference, Syracuse University, the Tax Accounting Workshop at UGA, Universität Mannheim, the University of British Columbia, the University of California at Davis, the University of Georgia, the University of Kentucky, the University of Tennessee, the Workshop on Federalism and Regional Policy at the Universität Siegen, and Zentrum für Europäische Wirtschaftsforschung (ZEW) improved the paper. Any remaining errors are my own.

Throughout history, major changes in the structure of commerce and industry have affected fiscal systems in complex and sometimes unforeseen ways. Technological changes create challenges and opportunities for fiscal authorities. Although the academic literature has studied the effect of technological innovations on consumer behavior and firm organization,[1] there is a dearth of research on the effects of these new transaction technologies on fiscal systems. I focus on the specific case of how technological change resulting from the rapid rise of e-commerce may prompt fiscal responses by local governments. Moreover, economists often argue that a tax's incidence and economic effects are invariant to who remits the tax to the government. Again using the case of e-commerce, I show that remittance rules for online shopping have an important effect on the level and spatial pattern of taxes.

In the case of e-commerce, technological change can, on the one hand, facilitate the mobility of the tax base from brick-and-mortar to online vendors, lowering statutory tax rates, but on the other hand, enforce taxes where they are legally due, raising tax rates. I refer to the former as the "tax haven effect" and to the latter as the "enforcement effect".[2] Well known, and widely recognized by policymakers and the press, is the idea that declines in the cost of online shopping may shift more transactions from brick-and-mortar retailers toward online vendors. If online sales are effectively tax free because of legal restrictions requiring consumers rather than vendors to remit taxes, increased mobility of the tax base could place downward pressure on tax rates. That is, jurisdictions will attempt to reduce statutory tax rates in order to mitigate the revenue leakage to the internet, which acts as a tax haven. Tax enforcement (Slemrod 2019) has garnered popular attention in the context of online commerce, even raising anxieties about the long-run viability of sales taxation. On the other hand, concerns about the demise of retail sales taxation may very well be overblown, as the rise of e-commerce may provide unique opportunities for governments to enforce taxes at the place of consumption via changes in remittance rules. Evolving business

[1] See Brown and Goolsbee (2002), Jin and Kato (2007), Lewis (2011), and Goldmanis et al. (2010).

[2] Tax havens can have both positive and negative effects (Slemrod and Wilson 2009; Johannesen 2010), although unlike this literature, the internet is not a strategic player.

practices, e-commerce technology, administrative simplifications, and legal requirements all promise to enhance sales tax collection and indeed have already done so. The *South Dakota v. Wayfair* Supreme Court decision allows states to require online vendors with sufficient economic activity in the state to remit taxes, even in the absence of physical presence.[3] The change of these remittance rules can have a profound effect on reducing tax evasion (Slemrod 2008). Nexus, by changing the remitting party, has important implications for equilibrium tax rates. The opportunities created by the internet enforcing destination-based taxes may place upward pressure on tax rates by expanding the tax base of jurisdictions that can now more readily monitor shopping patterns.

The rise of internet commerce is a conspicuous recent instance in which technological change has disrupted retail commerce, but other examples of technological change affecting fiscal systems spring readily to mind. In the past, innovations such as the refrigerator, the automobile, and changes in packaging have had major impacts on where and how frequently people go shopping, how goods are transported from suppliers to retailers, and the organization of upstream transactions ("supply chains"). Analogous to online shopping today, following these technological changes, the emergence of large chain stores led many policymakers to worry about threats to small businesses in the 1920s and 1930s. In response, many states passed "chain taxes" because large retailers were driving out "mom and pop" stores – policy responses that were ultimately triggered by underlying technological change.[4]

These mechanisms highlighted theoretically and identified empirically apply more generally beyond the retail sales tax discussed above. In particular, as is well documented in the literature, technological change and globalization will continue to facilitate declining transportation costs for capital, labor, and profits, which will place downward pressure on

[3]Remittance rules are an important part of the design of the tax system. See Kopczuk et al. (2016), Waseem (2020) and Bibler, Teltser and Tremblay (2020).

[4]Similarly, the "Walmart economy" – characterized by a large variety of relatively cheap goods, large retailers, and, of course, off-shoring of suppliers – has again changed traditional commerce (Holmes and Singer 2017). These economies arose because of technological changes and the invention of the barcode, which allows Walmart and other firms to more effectively streamline and consolidate shipments (Holmes 2001; Holmes 2011). This triggered policy responses and bidding by local governments.

capital, corporate income, and individual income tax rates (Egger, Nigai and Strecker 2019). In the case of corporate taxes, a literature on tax havens has emerged (Dharmapala and Hines 2009; Hines 2010). Perhaps less appreciated is the ability for government institutions to evolve in ways that use technological change to their advantage. Technological change allows tax administrators to exploit electronic banking, accounting records, or credit cards (Slemrod et al. 2017), IP addresses to identify the place of work or consumption, and computer technologies to easily match records. Indeed, many governments have already adopted reforms that begin utilizing this digital footprint and the OECD recommends the use of all information to levy VAT for digital services. To the extent that governments can harness technology as a tax enforcement improvement, this may place upward pressure on profit, income or capital tax rates in those jurisdictions for which this enforcement is beneficial.

Although a large literature focuses on how consumer behavior is affected by the internet,[5] the literature on *consumer behavior* provides only an indirect test of how *jurisdictions' tax rates* will respond to online shopping. The presence of the tax enforcement effect means that we cannot interpret the online tax avoidance literature as providing the correct direction on tax rates and tax competition. Absent the internet, a consumer in a small jurisdiction (town) in Kansas might drive thirty minutes to Topeka to shop at Walmart, which contributes to the tax revenue of Topeka rather than her hometown. However, with the internet, she can order from Walmart online and pay a similar sales tax, but the tax revenue accrues to the hometown. Topeka, on the other hand, sees its retail agglomerations erode as its tax base shrinks. Not just the magnitudes, but the *sign* of the effect of internet penetration may depend on factors such as municipality size, distance to the state border, distance to large shopping malls, and state tax rates. The U.S. setting of local sales taxes facilitates data collection in order to answer the more general question of the effect of remittance regimes and technology on tax rates. What is the effect of online shopping on local sales tax rates? Or more generally, how do remittance rules affect the tax rates that governments can set?

[5]See Goolsbee (2000), Ballard and Lee (2007), Ellison and Ellison (2009), Goolsbee, Lovenheim and Slemrod (2010), and Einav et al. (2014).

To answer these questions, I use panel data on every local (town, county and special district) sales tax rate in the country and combine these data with cross-sectional Federal Communications Commission (FCC) measures of internet *penetration* (number of providers in the town, speed, services) available at the municipal level. Penetration differences across municipalities likely result from exogenous historical differences in infrastructure. To identify a causal effect of internet penetration on tax rates, I also present cross-sectional regression results that instrument for internet penetration using historical development of cable and phone networks, lightning strikes, and proximity to the internet backbone. I then distinguish between the tax haven and enforcement effects using data from Bruce, Fox and Luna (2015) on the number of online firms in each state with nexus. Enforcement effects should be largest in states where more online vendors have a physical presence. Following Goolsbee, Lovenheim and Slemrod (2010), under various assumptions about the growth of internet penetration at the municipal level, I also regress tax changes on changes in internet penetration and instrument for it. In addition, I aggregate local sales tax rates to the state level, so that I can combine it with state-level panel data on internet subscriptions reported on the FCC Form 477. I show that the direction of the cross-sectional effects are the same as when exploiting the dramatic changes in internet penetration over the last decade.

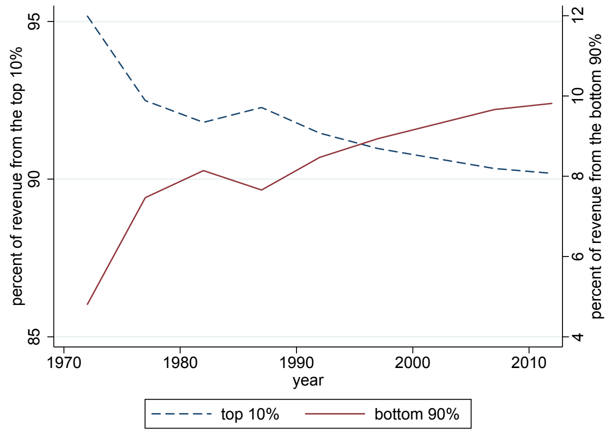
Regardless of the methods employed, the results are consistently robust in their signs. On average, higher internet penetration results in lower local sales tax rates, but this effect is most pronounced in large jurisdictions that likely see their tax base eroded by both their own residents who shop online and by reduced inflows of cross-border shoppers. The internet thus prevents large jurisdictions from tax exporting. In particular, a one standard deviation increase in penetration lowers local sales tax rates in the largest population quartile of jurisdictions by about 0.15 percentage points, or 16% of the average rate. Negative effects are also largest for border towns in low-tax states that were able to tax export in the pre-internet era when interstate cross-border shopping was the dominant mode of tax avoidance. However, although my data is from a period when Amazon was not collecting in a majority of states, I still identify positive effects of internet penetration in smaller jurisdictions and jurisdictions where many large online vendors remit taxes. The results in this paper suggest that technological change affects tax rates and redistributes revenues. I find that for the majority of towns in America, the internet constrains the growth of local sales taxes, but for towns in states with many online vendors with nexus, the internet may bolster municipal sales tax rates. The policy implications are stark. The conventional wisdom suggests that globalization puts downward pressure on transport costs, negatively affecting government's ability to collect tax revenue. Consistent with theoretical evidence in Agrawal and Wildasin (2020), this paper suggests that following appropriate changes to remittance rules, such as the recent *South Dakota v. Wayfair* ruling, (some) governments can exploit technological change to increase tax revenue. When technological change makes the tax base more readily monitored, appropriate policy changes facilitate tax collection. As in Slemrod (2019), tax remittance regimes influence tax evasion, but as demonstrated in this paper, this also has unintended consequences on the level of tax rates and the distribution of revenue.

1 Institutional Details

In the U.S., sales taxes are set at the state and local level. The majority of states allow counties and towns to levy additional sales tax rates on top of the state sales tax rate. While municipal tax rates average a bit under one percentage point, the importance of these taxes vary dramatically by state. Moreover, local shopping patterns are extremely "lumpy" – consumers buy a disproportionate share of consumption goods from large municipalities that have retail agglomerations or shopping malls. Given the median town in America is small, large jurisdictions accrue a disproportionate share of tax revenue and many small jurisdictions generate almost no sales tax revenue from brick-and-mortar retailers.[6] Figure 1 shows the spatial asymmetry of sales tax revenue. This figure shows that large cities – the

[6]Such a pattern would not be as pronounced if focusing on counties or states, as retail agglomerations have a more prominent role, the lower the level of government. Almost all counties in America have some physical retail operations – this is not true at the municipality level.

Figure 1: Percent of Sales Tax Revenue Raised by the Large/Small Jurisdictions



The figure shows the fraction of municipal sales tax revenue in the United States raised by the largest and smallest jurisdictions in the country. The figure shows the percent of revenue raised by the largest (by population) 10% of jurisdictions in the United States. The top 10% largest jurisdictions generally have more than 15,000 inhabitants.

largest 10 percent by population – accounted for 95% of all municipal sales tax revenues in the 1970s. This share has declined gradually to about 90% of all such revenues by 2010.

Prior law, under *Quill Corp. v. North Dakota*, only allowed states to require firms with a physical presence in the consumer's state to remit the retail sales tax. Under *Quill*, however, once a firm established physical presence in the state, the vendor was required to remit sales taxes on online purchases for *every* town in the state based on the buyer's residence, regardless of whether the firm had a physical presence in the buyer's town (Agrawal and Fox 2016; Goolsbee 2001). Taxes on sales from firms without nexus were effectively tax free because the obligation to remit the tax fell on the consumer, which the tax authority could not easily enforce. Despite this physical presence rule, evolving business practices and the desire of consumers to receive products quickly, led some online vendors to establish physical presence in many states. These changing business practices coupled with state reforms, gradually shifted the remitting party from the consumer to the vendor, from which the tax authority could more readily enforce destination-based consumption taxes. More recently, the United States Supreme Court ruled that states may now require online vendors to remit taxes if they have an economic presence – or sufficient amount of sales – in the state.

Given this paper will use data prior to 2012, the question is: how many online firms were remitting retail sales taxes in this period? Bruce, Fox and Luna (2015) study approximately 175 of the largest *online* vendors in 2011.[7] The authors omit firms, such as Walmart.com, that have a physical presence in every state so that they underestimate the true counts. They construct two measures of tax collection. The first is a simple count of the number of firms. Second, recognizing that online companies are heterogeneous, an alternative nexus measure is the share of total online sales by firms that remit taxes on online purchases by residents of the state. Even in 2011, the average state had 62 firms collecting sales taxes, which represented 51% of total sales by firms in their sample. Thus, even with Amazon collecting in less than ten states, the enforcement channel may still represent an important mechanism. The importance of the enforcement channel has likely grown since the period studied here.

2 Technological Change and Fiscal Systems

Technological change, and the the internet more specifically, may have unforeseen effects on fiscal systems. I focus on the tax haven and the enforcement effect in the context of tax competition, specifically over commodity taxes (Kanbur and Keen 1993; Nielsen 2001).[8]

I start with a general model of tax competition, where two governments ($i = 1, 2$) maximize a welfare function W_i by setting tax rates τ_i in a Nash game. The general setup will allow the reader to make inference about how technological change may affect tax rates other than those on commodities. Firms or individuals may engage in tax avoidance or shopping arbitrage at some cost $E = e + \phi(x)$ where e is a fixed costs and $\phi(x)$ is a variable cost that depends on a factor, x. In the case of online shopping, e may represent the cost of an internet subscription or Amazon prime membership, while $\phi(x)$ may be a shipping cost that increases in distance from the warehouse or in the quantity of online purchases. As I will use data on internet penetration, which arguably changes the fixed cost e, but not the variable cost, I will conduct a comparative static analysis with respect to e. I follow Caputo (1996)

[7] By 2011, Einav et al. (2014) estimate Amazon's share of online sales to be between 13% to 19%.

[8] For other types of tax competition, see Eugster and Parchet (2019), Mast (2019), and Parchet (2019).

to derive a general formula for the total effect of a change in the fixed cost of buying online on equilibrium tax rates τ_i^*:

$$\frac{d\tau_1^*}{de} = \frac{1}{\Theta}\left(\underbrace{\frac{\partial\tau_1}{\partial e}}_{(a)} + \underbrace{\frac{\partial\tau_1}{\partial\tau_2}\frac{\partial\tau_2}{\partial e}}_{(b)}\right) \quad \text{and} \quad \frac{d\tau_2^*}{de} = \frac{1}{\Theta}\left(\underbrace{\frac{\partial\tau_2}{\partial e}}_{(c)} + \underbrace{\frac{\partial\tau_2}{\partial\tau_1}\frac{\partial\tau_1}{\partial e}}_{(d)}\right), \tag{1}$$

where values of τ_i without a star denote the best-response functions of a town and $\Theta = 1 - \frac{\partial\tau_1}{\partial\tau_2}\frac{\partial\tau_2}{\partial\tau_1} > 0$ by the stability condition. By the implicit function theorem, $\frac{\partial\tau_i}{\partial e} = -\frac{\partial^2 W_i/\partial\tau_i\partial e}{\partial^2 W_i/\partial\tau_i^2}$. Because the second order condition has to be negative for a maximum, it is straightforward that sign $\left(\frac{\partial\tau_i}{\partial e}\right)$ = sign $\left(\frac{\partial^2 W_i}{\partial\tau_i\partial e}\right)$. Equation (1) shows that a shock to the parameter e can be broken up into two effects: (term a/c) a nonstrategic effect, which measures the direct effect of a change in e on player i's reaction function holding fixed the other town at its Nash equilibrium value, and (term b/d) a strategic effect which measures the indirect change that e has on player i's reaction function via the other player's response to the shock. In this general model, technological change can have either positive or negative effects.

For intuition, assume as is common in commodity tax competition models, that governments maximize tax revenue $W_i = \tau_i B_i(\tau_i, \tau_j, e)$, where B_i is the tax base. Then, tax rates are strategic complements $\left(0 < \frac{\partial\tau_i}{\partial\tau_j} < 1\right)$ and $\frac{\partial^2 W_i}{\partial\tau_i\partial e} = \frac{\partial B_i}{\partial e} + \tau_i\frac{\partial B_i}{\partial\tau_i\partial e}$. The sign of this expression depends upon the effect of e on the tax base and the rate of change of the base. In general, this expression cannot be signed if the sign of these two terms are opposite. However, reasonable assumptions found in the tax competition literature provide useful examples. Following Devereux, Lockwood and Redoano (2007), assume that the consumer utility function is quasi-linear. Then, e will not affect individual demand because there are no price effects, as e is independent of the quantity purchased. Further, there are no income effects on demand, as e is paid in the numéraire good, and utility is linear in that good. However, e will affect the number of shoppers buying online versus brick-and-mortar. As e

is a fixed cost, and only variable costs change $\frac{\partial B_i}{\partial \tau_i}$,[9] then sign $\left(\frac{\partial \tau_i}{\partial e}\right) = \text{sign}\left(\frac{\partial B_i}{\partial e}\right)$.

2.1 The Effect of Online Shopping with Tax-free Sales

Consider first the case where online shopping is (effectively) tax free. How does a decline in e affect tax policy? Recall that with revenue maximization, tax rates are strategic complements. A decline in e will imply that more consumers switch purchases from brick-and-mortar to online, shrinking the tax base and making $\frac{\partial \tau_i}{\partial e} < 0$. If all towns are symmetric, then a *decline* in e will lower tax rates in all jurisdictions by the same magnitude because for a given tax rate in jurisdiction j, jurisdiction i always wants to set a lower tax rate. If, however, jurisdictions are asymmetric and the internet erodes towns' bases differently, then a decline in e will have the largest effect on the place were the *direct* effect (term a or c) is largest because the indirect effects (terms b and d) are dampened by tax competition.

Consider an extreme case where, some goods can be purchased everywhere (perishables, gasoline, etc.) and some goods are only available at a large shopping mall in town 1. Then, if only the latter goods are purchased online, as e *declines,* online sales erode *only* the base of the town with the retail shopping center. Thus, terms (a) and (d) are negative, but terms (b) and (c) are zero because online shopping does not *directly* affect town 2. However, although the small town is not directly affected, its tax rate will still fall via indirect effects from tax competition (term d). As the direct shock to town 1 is muted by $\frac{\partial \tau_2}{\partial \tau_1}$ in term (d), the change in τ_1^* will be larger in absolute value that the change in τ_2^*. Intuitively, a decrease in the cost of shopping online will disproportionately lower tax rates in places that previously benefited from brick-and-mortar purchases of goods now available online. A change in e could have different effects with welfare maximizing governments, but as long as tax rates remain strategic complements and public services are sufficiently valued, the results are robust to a more general objective.

[9] The tax base is the number of individuals shopping in the town times individual demand. The number of shoppers paying taxes depends on how many buy online versus brick-and-mortar, which depends on the total cost of purchasing by each method. Then, because e is a fixed cost and does not affect individual demand, any determinant for who purchases online will depend on e independently of taxes.

Online shopping facilitates the mobility of the tax base away from in-store sales, toward purchases from the "rest of the world" and these purchases escape taxation. Large towns with retail agglomerations lose taxable sales and tax revenue to a "tax haven" and, therefore, lower their tax rates; towns with fewer retail shops decrease their tax rates to a lesser extent, and primarily because they are responding to the tax cuts of towns with shopping malls. This story is not specific to commodity tax competition. An increase of globalization that reduces transaction costs can place downward pressure on income tax rates, where the strongest effects arise in countries housing many corporations or high-income individuals.

2.2 The Effect of Online Shopping with Destination-based Taxes

Online vendors will remit taxes if they have nexus. To clarify the implications of nexus, assume *all* online sales are taxed at destination.[10] This case is discussed in Agrawal and Wildasin (2020), so I summarize it briefly. Continue to assume that town 1 has a shopping mall, which sells goods that consumers may also buy online, but when purchasing online consumers pay the tax of their home municipality. Then, a *decline* in the cost of online shopping implies tax rates fall in large towns, but rise in smaller towns. Intuitively, the internet erodes the tax base of the city, $\frac{\partial \tau_1}{\partial e} < 0$. If online taxes are destination-based, the city obtains revenue from its residents regardless of if they shop online or in store, but some cross-border shoppers from other nearby towns switch to online shopping rather than driving to the shopping mall. The switch to online shopping increases the tax base of these towns that previously did not obtain revenue on the transaction, $\frac{\partial \tau_2}{\partial e} > 0$. The internet "redistributes" the large town's tax base to the smaller town. The newfound windfall gain of tax revenue from the enforcement of destination-based taxes places upward pressure in the smaller community. But the city, which sees its tax base erode, lowers its tax rate to mitigate e-commerce.

[10] In doing this, I assume that consumers are not able to circumvent destination based taxation by shipping to another address such as a work address or PO box. If consumers are able to do this, then online shopping will increase the tax base of those towns rather than their home community.

Then, if terms (a) and (c) are equal in magnitude, but opposite in sign such that one town's loss is the other town's gain, the overall sign of (1) is given by the direct effects (a) and (c) because the slopes of the reaction functions mute terms (b) and (d). Of course, if towns were symmetric and both contained shopping malls, then destination based taxation would eliminate competition for online shoppers, allowing both towns to raise their tax rates. The results extend to corporate or income taxes. If technological change shifts the tax base to a more readily monitored source, that technological change may increase revenues of some at the expense of others, depending on the initial spatial distribution of economic activity.

Other mechanisms that raise tax rates may exist. For example, if governments have a fixed amount of spending that must be provided, then revenue leakages due to a shrinking tax base may be offset by higher tax rates. Unlike the model presented above, taxes would rise in large agglomerated towns and not in small towns. If many online firms have nexus, the increased base of smaller towns may allow them to lower their tax rates to maintain a fixed spending level. Thus, heterogeneity may provide an empirical test of the mechanisms.

2.3 Extensions

In the period studied empirically, the market for online sales was characterized by imperfect enforcement: some online sales were effectively tax-free, but others were subject to destination-based taxation because some online vendors had nexus in some states. Using (1), it is clear that if the fraction of sales subject to destination taxation is sufficiently large, the comparative statics will be qualitatively unaffected to those in section 2.2, while if they are sufficiently small, they will be closer to the downward pressure of tax-free online sales in section 2.1. Thus, for a decline in e to place upward pressure on tax rates in small towns without shopping malls requires a significant number of firms to have nexus elsewhere in the state (and therefore, remitting retail sales taxes).

Another source of heterogeneity that may influence the comparative statics, is whether towns are located in high-tax or low-tax states, as in Agrawal (2015). Pro-business policies often result in clustering of economic activity on the low-tax side of the state border (Holmes, 1998). Thus, towns located just over the border in low-tax states have (prior to the internet) more retail shopping centers than towns in high-tax states. If this clustering on the low-tax side of the state border relates to goods that have a high-propensity to be purchased online, then a decline in online shopping costs in the presence of destination-based taxes may have similar asymmetric effects across border towns in different states.

Of course, I have selected examples to illustrate important mechanisms at work. However, the beauty of (1) is its generality to various tax instruments, objective functions, assumptions on transaction costs, types of avoidance and the ease of extension to multiple towns. At its best, this equation makes it clear that towns may respond to technology shocks in unforeseen ways that may vary depending on the town's initial conditions. For this reason, empirical analysis is critical to understand the effects of technology on public finances.

3 Data

Studying the effect of the internet on tax rates is challenging because it requires having access to data on nexus rules, municipal tax rates, and consistent local data on internet penetration. Such a task might be even more daunting if one wanted to study the effect of technological change on international corporate or consumption tax rates. The online appendix describes the construction of the final data (Agrawal 2020) in further detail, along with all sources for specific datasets.

3.1 Data Used in the Analysis

Tax Data (Panel). I use data on sales tax rates for every town (municipality), county, state and sub-municipal district previously assembled in Agrawal (2014, 2015) and Agrawal and Mardan (2019). The tax data contain all local tax rates for September 2003 to December 2011 and have been harmonized to form a consistent panel.[11] States without local sales taxes

[11]Although the tax data are for towns as defined by state governments, these data are matched to Census place data in order to include demographic controls in the analysis. For state-specific discussions of local

are excluded from the analysis; towns that set a tax rate of zero are included in the analysis if they are in a state allowing for local taxes.

Distance Data (Cross-section). From Agrawal (2015), I use the minimum driving time from the population weighted centroid of each town to the nearest state border major road intersection. This driving time, in minutes, is calculated using the existing road network and speed limits. If the state tax rate in the nearest state is lower than the state tax rate in the municipality's own state, the municipality is in a "high-tax state." If the reverse is true, it is in a "low-tax state." Given states have many borders, some municipalities in a state are in a relatively high-tax state while others are in a relatively low-tax state.

Local Internet Data (Cross-section). I merge the tax data to data on internet penetration from the National Broadband Map, which is collected by the National Telecommunications and Information Administration (NTIA) in conjunction with the Federal Communication Commission (FCC). The data on internet penetration are available starting in July 2011.[12] The NTIA matches provider service maps to Census block maps. In doing so, they calculate the fraction of people within a place that have access to internet service providers. The NTIA data contain the percent of households with – access to various types of services including download speeds and the choice of multiple service providers.

State Internet Data (Panel). In 2000, the Federal Communications Commission (FCC) started collecting "broadband" subscription data. The FCC provides panel data on internet subscriptions at the *state* level in June and December of each year. These data are reported by internet service providers on FCC Form 477. Specifically, the FCC releases the number of households with a fixed residential broadband connection. The FCC then converts this number to a percentage of households by dividing by the number of households from the state-level Current Population Survey (CPS). To study the effect of internet subscription changes on taxes, I use the data on town, county, sub-municipal, and state sales tax data

sales taxes, please see Burge and Piper (2012), Sjoquist et al. (2007), and Luna, Bruce and Hawkins (2007).

[12]The Broadband map has now existed for several years, which potentially allows for the formation of panel data. However, at the *municipal* level, changes in the way the data have been collected prevents assembly of a true panel data set.

from 2003 to 2011 at the monthly frequency. To match these data to the state-level FCC data, I aggregate lower level tax rates up to their mean at the state level.

Nexus Data (Cross-section). Bruce, Fox and Luna (2015) visit the websites of 175 large e-tail firms and attempt to place a transaction from each state. A company is defined as having nexus in the state if sales taxes are due at checkout. Using their data, I know whether each state has an above average number of firms with nexus. I also know whether the fraction of sales volume from online firms with nexus in the state is above or below average. The data I use correspond to 2011; Bruce, Fox and Luna (2015) only have a panel over four years and the sample of firms are not consistent over time. In addition, I obtain the number of firms (with a retail NAICS code) that have their headquarters in a state from Compustat data. This variable is constructed using 2003 data.

3.2 Measures of Internet Penetration

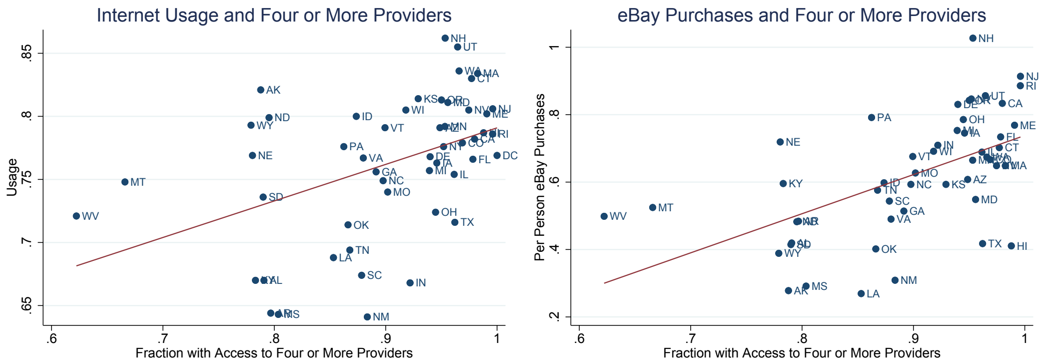
Let I_i^* denote the measure of internet usage in town i that policymakers know and set their taxes in response to. For example, a reasonable measure of I_i^* might be the fraction of people who *use* the internet or the share of online purchases. However, as discussed in the prior literature, such a measure is clearly endogenous to the local tax rate and is not available at the municipal level. Defining I_i as a measure of *penetration*, if

$$I_i^* = \lambda + \delta I_i + \nu_i \tag{2}$$

and $\delta > 0$ is significantly different from zero, then penetration can be a proxy variable.

The National Broadband Map has several potential candidates for I_i. For the baseline analysis, I select a proxy variable from the Broadband Map as the variable that maximizes the R^2 of a univariate regression (2). I assume that the variable that maximizes the R^2 at the state level would also do so in the cross-section of lower levels of governments. Table A.1 and figure 2 summarize the results. In my preferred specification, I_i^* is defined as state-level internet usage from the Consumer Population Survey (column 1). I alternatively define I_i^*

Figure 2: Relationship of Proxy Variable with Usage



The first graph shows the relationship between usage as measured by the CPS and the fraction of the population with access to four or more internet providers. The second graph shows the relationship between the average number of eBay purchases per person as released in Einav et al. (2014) and the fraction of the population with access to four or more providers.

as the per capita number of eBay purchases in each state (column 2) as created by Einav et al. (2014) or a binned measure of local usage (column 3) described in the appendix.

Column 1 indicates that the fraction of individuals with access to any type of internet service is not a strong proxy for internet usage; this variable has little variation, as almost all places in the country have access to one provider. The fraction of consumers with access to three or more providers starts to demonstrates a strong relationship between penetration and usage. This strong correlation is evident for the population with access to four or more providers and five or more providers. The fraction of people with access to four or more providers maximizes the R^2 and for this reason it is the preferred metric in the analysis.[13]

One explanation for this correlation is that more providers reduce prices, conditional on a given level of quality, which then provides a nice link to the fixed cost of online shopping discussed theoretically. The FCC conducted a survey of broadband service rates in urban areas in 2007. In its survey, the FCC released the prices in approximately one hundred cities and towns in urban areas. The survey contains both small and large towns. I match these prices to the municipal internet penetration data on the fraction of consumers with access to four or more providers. Table A.2 shows that a one standard deviation increase in the

[13]The importance of the fourth provider is summarized in the President's Community Based Broadband report: "...new entrants in wireless markets have a substantial impact on both prices and quality of service. Tellingly, ... this result occurred even when a market already had three participants – that is, the fourth entrant into a wireless market significantly improved costs and services."

fraction of people with access to four or more providers lowers internet service prices by 14% of the monthly price. This suggests that more people having access to multiple providers lowers prices, which provides the shock to e discussed theoretically.

3.3 Summary Statistics

The average town tax rate is 0.71 percentage points and the average town plus county tax rate is 1.59 percentage points, but with substantial heterogeneity across states. Within state variation differs substantially depending on the state, with average local tax rates greater than 3 percentage points in some states. With respect to the percent of residents with access to four or more providers, the average is 70% (standard deviation of 43).

4 Methods

Given the wide variety of data, but some limitations, I take four different approaches to studying the effect of technology on taxes: a cross-sectional design that comes with concerns of unobserved heterogeneity, a panel data design at the local level that relies on extrapolated penetration, an instrumental variable approach, and a panel data design at the state level. The panel data design reduces concerns of unobserved heterogeneity, while the IV design also reduces measurement error and endogeneity concerns.

4.1 Cross-sectional Model

A cross-sectional regression explaining the municipal tax rate, τ_i, in town i of state s is

$$\tau_i = \zeta_s + \beta I_i + g(y_i) + X_i\gamma + \epsilon_i, \tag{3}$$

where I_i is the town-level measure of internet penetration that was selected in section 3.2, ζ_s are state fixed effects, and X_i denotes the control variables. The tax rate used in the regression is the town tax rate or the total local tax rate (municipal plus county). Within the set of controls are county and town-level geographic, political, and demographic variables.

Spatial and state-level control variables y_i, such as driving time to the nearest border, state tax rates, and nexus may have heterogeneous effects on τ_i, and so $g(y_i)$ is a continuous function of these control variables. In particular, I include a polynomial in distance to the nearest state border.[14] Furthermore, given state-level control variables cannot be included as standalone variables but may have heterogeneous effects within a state, I then interact this polynomial in distance with an indicator for whether the town is on the high-tax side of the border, the state tax rate, the nearest neighboring state tax rate and an indicator for whether the state has an above average share of online sales from firms with nexus; the nexus metric is also interacted with the state tax rate and the distance polynomial.[15] In some specifications, to explore heterogeneity of the effect of declining costs of online shopping, I interact some of the elements of the function, $g(y_i)$, with internet penetration and include these interactions in the regression. State fixed effects account for differences in state sales tax bases that are common within a state and other state-specific institutions. All standard errors are clustered at the county level to allow for spatial correlation in taxes.

4.1.1 Identification Challenges

The model presented above may raise three endogeneity concerns: measurement error, omitted variable bias, and possible reverse causality.

Measurement error. If I_i^* is the true variable that policymakers respond to, then I_i acts as a proxy variable. Then, when estimating (3) by OLS, measurement error from using a single proxy variable is likely to attenuate the coefficient estimates. Thus, the estimated coefficient from the simple regression (3) will be biased towards zero. To reduce this bias, I will use the index creation procedure of Lubotsky and Wittenberg (2006). Alternatively, I will follow an IV approach utilizing instrumental variables that are arguably uncorrelated with the error in (2).

[14] This model assumes that towns are most directly influenced by the nearest state border. But, towns in small states or in the "corner" of a state may be close to multiple state borders. Given the results in Agrawal (2015) are not sensitive to controlling for distance to the second closest border, I maintain this assumption here.

[15] Nexus may be endogenous to state tax rates, but likely does not depend on individual local tax rates.

Omitted variables. In a cross-section, one may worry about unobserved characteristics of the municipality that are correlated with penetration and that directly impact taxes, such that $cov(I_i, \epsilon_i) \neq 0$. Unfortunately, in this setting, the sign any potential bias is indeterminate as it is unclear what precise variables are omitted. I will explore two different panel data approaches that will allow me to account for time-invariant characteristics of municipalities. Finally, the IV approach will address any omitted variable bias so long as the instruments are uncorrelated with the error term.

Simultaneity. Is internet penetration a function of sales taxes? Many providers make entry decisions based on historical factors such as the presence of prior cable or telephone lines in their network. This implies that providers may not enter into all parts of a town and may only service parts of it. Figure A.1 shows, for both small and large jurisdictions, substantial variation across Census blocks in the number of providers within a town and this variation cannot be explained by knowledge of internet usage for online shopping. This is the variation I exploit. If a provider were making the decision to enter a town because the town has substantial online shopping resulting from a low local sales tax in the community, I would expect the provider would enter the entire municipality. Given providers do not fully service all residents in a town, this suggests that the ability to enter a market contains a component outside the short-term control of the provider, likely do to the historical infrastructure network and the high fixed costs of expanding it. Of course, some providers, especially those with contracts with municipal governments, may enter an entire market. Even if this is true, it is likely that the service provider is responding to overall measures of consumer demand and not just demand for online shopping, which only represents a small fraction of household internet usage time. Nonetheless, lower sales taxes could possibly induce providers to enter, which I address via an instrumental variable approach.

If this added online shopping also influences provider entry decisions, then my measure of penetration is endogenous. In contrast to measurement error that attenuates my effects, this reverse causality biases my estimates upward. The literature on consumer tax avoidance indicates taxes are positively correlated with online shopping (Goolsbee 2000; Einav et al. 2014). Given this, even if there were no causal effect of penetration on sales taxes, then my regression would find a positive correlation between internet penetration and taxes. This implies that negative estimates would be biased toward zero and positive estimates would be biased away from zero.

4.2 Reducing Measurement Error: Index Creation

To address measurement error concerns, I use multiple proxy variables – the number of providers in a town, the fraction of the population with access to any number of providers, the fraction of the population with access to various types of service, and the fraction of the population with various download speeds – to reduce measurement error. Lubotsky and Wittenberg (2006) develop a procedure using multiple proxy variables, which in large samples, is superior to methods using only a single variable and will minimize measurement error. The technical details are in Appendix A.3, but to summarize, I have access to N proxy variables where I denote the n^{th} proxy as I_i^n. Lubotsky and Wittenberg (2006) show the researcher can estimate (3) including all of the "good" proxy variables rather than the single proxy variable, obtaining a coefficient β^n on each proxy variable. The regression with multiple proxies can then be used to construct an index I_i^ρ:

$$I_i^\rho = \frac{1}{\beta^\rho} \sum_{n=1}^{N} \beta^n I_i^n, \tag{4}$$

where $\beta^\rho = \sum_{n=1}^{N} \beta^n \frac{cov(\tau_i, I_i^n)}{cov(\tau_i, I_i^1)}$. I select the normalization, $cov(\tau_i,\, I_i^1)$, such that the results are comparable to regressions using the fraction of the population with access to four or more providers. Equation (3) can then be estimated using I_i^ρ as the independent variable to obtain a single coefficient of interest. Having the index variable allows for estimating an equation where I^ρ is also interacted with other covariates such as distance.

4.3 Accounting for Unobservables: Local Panel Data Approach

Given that in a cross-section it is likely that $cov(I_i, \epsilon_i) \neq 0$, a panel data approach would be a more convincing way to identify a causal effect because it would account for fixed characteristics of the municipality. However, internet penetration data at the local level dates back only to 2011, the last year of my tax data series. Under assumptions discussed subsequently, I estimate:

$$\triangle\tau_i = \beta\triangle I_i + g(\triangle y_i) + \triangle X_i\gamma + \triangle\epsilon_i, \tag{5}$$

where $\triangle$ denotes a long difference where for a given variable, $\triangle x_i = x_{i,2011} - x_{i,2003}$. Long differencing removes municipality fixed effects.[16]

Given I only observe I_i in 2011, I estimate its level in 2003 for each municipality. In the results reported in the text, I extrapolate my measure of internet penetration backwards using state time series data on the number of internet providers.[17] Using state time series data to calculate a growth rate of usage over the 2003-2011 time period, $\hat{g}$, and the 2011 local data on internet penetration, I can calculate penetration in 2003 as $\hat{I}_{i,2003} = I_{i,2011}e^{-8\hat{g}}$ where $I_{i,t}$ is internet penetration in town i in year t (measured by access to four or more providers), $\hat{g}$ is the growth rate estimated using state time series data on internet subscriptions from form 477, and $2003 - 2011 = -8$. This procedure raises additional measurement error concerns. As I discuss later, so long as the error in estimating $\hat{I}_{i,2003}$ is uncorrelated with my instruments, the long-difference combined with IV will allow me to identify causal effects under possibly weaker assumptions than in the cross-section.

[16]It also removes the standalone polynomial in distance in $g(\cdot)$, but not the interaction of the distance polynomial with the interaction of time-varying state characteristics such as the state tax rate.

[17]I also simply use the level of internet penetration in 2011 as $\triangle I_i$. This would be a reasonable metric if the fraction of households in a town with access to four or more providers was approximately zero in 2003. While I do not have data on penetration, national statistics indicate that less than 15% of households had a broadband subscription and the median zipcode had fewer than four providers in 2003.

4.4 IV Strategy

In addition to addressing measurement error concerns, I also utilize an IV strategy to address any concerns related to reverse causality. I summarize the instruments here.

Cable and Phone Infrastructure. Stevenson (2009) and Bellou (2015) suggest that state-level internet adoption follows patterns of adoption for household appliances and uses this as an instrument for usage. I use local data rather than state level data and modify the technologies used. In particular, I propose using the fraction of households in the county with a TV in 1960 and the fraction of households in the county with a telephone line in 1960 as instruments for current day internet penetration. Many internet connections run through cable or telephone lines. This means that the infrastructure development for these technologies in the early days of their adoption are important for the internet infrastructure today. Phones provide a clear link to the pattern of the wired phone infrastructure. The fraction of households with a TV in 1960 is indirectly linked to the cable infrastructure.[18] The basic idea is that the internet should diffuse in a manner similar to these other technologies because they rely on similar infrastructure. The exclusion restriction can be justified if historical infrastructure predicts current day internet infrastructure, but is not correlated with other unobservables.[19] Nonetheless, persistent factors may remain that explain these linkages. To strengthen the case for the exclusion restriction, I also control for the 1960 local usage of fridge freezers, washing machines, and air conditioning at home. These controls are designed to capture other possibly persistent factors related to technological adoption in a local area, but for technologies that do not help the internet disseminate. Further, estimating the model in long-differences requires a weaker assumption: the instrument may

[18]By 1960, 800 cable companies existed servicing just under 1 million households. Although many households still obtained TV signals via antenna signals, places with higher TV usage provide a natural point for cable expansions.

[19]In the cross-section, regressing cable and phone penetration on the level municipal covariates suggest that the instrument is correlated with observables. Thus, the identifying assumption is that the instrument is uncorrelated with unobservables that influence local taxes. However, regressing the instrument on the long-difference of municipal covariates yields few signficant correlations, strengthening the case for the instrument in equation (5).

co-vary with unobservable factors that explain local tax rates, so long as that covariance of the error term and the instrument is constant in 2003 and 2011.

Municipal Lightning Strikes. I also instrument for internet penetration at the local level using the flash density of lightning strikes, which are strictly exogenous. This approach follows Andersen et al. (2012) who show that lightning strikes are a powerful predictor of information technology (IT) usage at the *state* level during the period from 1996 to 2006. Andersen et al. (2012) argue the instrument is relevant because places with high lightning density experience more power disturbances. These power/frequency disturbances increase the cost of investing in IT for internet provider companies, which then lowers IT investment and internet usage in a given area. While Andersen et al. (2012) construct this using readily available state level data, I calculate this at the local level. I obtain grid level data on all lightning strikes from the 1986 to 2011 from the National Oceanic and Atmospheric Administration (NOAA). The data provide me the precise 4 km grid that the lightning strikes. I then aggregate from the grid level up to the municipal level. Then, the flash density of lightning is the average number of strikes in a year that hit a municipality i divided by the area of municipality i. I also have the same metrics at the state level.

Internet "Backbone". My final instrument relies on the computer science literature. A critical determinant of the level of service is the proximity to long-haul internet infrastructure (Durairajan and Barford 2016). Abstracting from connectivity via satellite technology, the physical (wired) internet network is critical. The physical internet consists of nodes (hosting facilities) and links or conduits (optical fiber connections between nodes). Durairajan et al. (2015) use public documents to reverse engineer the geographic locations of the long-haul fiber-optic internet links in the United States (of major ISPs and cable providers). These major links are essential for the deployment of new conduits. Durairajan et al. (2013) identify the buildings that house switching and routing commitments and the paths of conduits that connect them for more than 250 networks, including all tier-1 internet service providers. As discussed in Durairajan and Barford (2016), proximity to this physical infrastructure is an important cost determinant of expanding internet connectivity. Using the data maps constructed by these authors, I calculate the as-the-crow-flies distance from the population weighted centroid of each town to the nearest county containing this physical network. I use two different metrics: proximity to the long-haul fiber network and the broader metric constructed in Durairajan et al. (2013), but the baseline estimates in the text are for the former. To mitigate the perhaps non-random position of this infrastructure, I calculate the crow-flies distance rather than driving distance. This minimizes correlation of the instrument with unobservables that may be due to the internet backbone following the road network. Finally, I set this distance to be zero if the town's county has any part of the identified internet backbone in it. The compliers in the IV setting are towns outside of counties containing the internet backbone[20] so that I exploit the idiosyncratic position of towns that were not reasonably an alternative choice for the position of the network.

The exclusion restriction requires that the instrument, κ_i, satisfy $cov(\kappa_i, \epsilon_i) = 0$ when estimating (3). A concern, especially with TV and phone usage from 1960, may be that the instruments might be correlated with (fixed) unobservable municipal characteristics that also predict tax rates; distance to long haul routes might also be correlated with unobservable features. Estimating (5) using panel data may help to relax this assumption. If I observed internet penetration in both 2003 and 2011, then the exclusion restriction would require $cov(\kappa_i, \triangle\epsilon_i) = cov(\kappa_i, \epsilon_{i,2011}) - cov(\kappa_i, \epsilon_{i,2003}) = 0$. This is a weaker assumption because it could hold if $cov(\kappa_i, \epsilon_i) = 0$, $\forall t = 2003$, 2011 *or* if the instrument is correlated with unobservables in 2003 and 2011, so long as this covariance is the same in both years, i.e., $cov(\kappa_i, \epsilon_{i,2011}) = cov(\kappa_i, \epsilon_{i,2003}) \neq 0$. If historical factors, such as cultural and road infrastructure networks, persist and influence taxes, then the long difference will strengthen the credibility of the instrument. However, I do not observe internet penetration in 2003 and estimate it using state level penetration. Then, my estimated value $\hat{I}_{i,2003}$ equals the true value plus some error, η_i. Without any additional assumptions, the exclusion restriction

[20] Towns within the county where the internet backbone lies could have been chosen to be crossed by the backbone, but may not have been for unobservable reasons.

requires $cov(\kappa_i, \triangle\epsilon_i - \eta_i) = cov(\kappa_i, \epsilon_{i,2011}) - cov(\kappa_i, \epsilon_{i,2003}) - cov(\kappa_i, \eta_i) = 0$. If the instrument is uncorrelated with the measurement error in predicting 2003 internet penetration, $cov(\kappa_i, \eta_i) = 0$, then the prior discussion still applies.

4.5 An Alternative Identification Strategy: State Panel Data

Unlike the local level, panel data on internet penetration is available for the time period of my tax series. The goal of this final approach is to show that observed changes in internet usage are correlated with tax changes. I merge the state-aggregated panel data on local sales tax rates with the FCC's Form 477 data. I then estimate:

$$\tau_{s,t} = \beta z_{s,t} + X_{s,t}\gamma + \zeta_s + \theta_t + f_t(y_s) + u_{s,t} \tag{6}$$

where $\tau_{s,t}$ is the average local tax rate in state s of year t, $z_{s,t}$ is the fraction ofhouseholds with internet subscriptions from form 477, ζ_s are state fixed effects and θ_t are time fixed effects. I control for state level demographics, neighboring state taxes, and the share of municipalities near high-tax borders in the vector $X_{s,t}$. Because some variables y_s – such as nexus – are only available in a cross-section, they enter via $f_t(y_s)$ by interacting the variable with time dummies.

The FCC data on subscriptions is more likely to be endogenous to taxes than penetration. If internet subscription rates are higher in places with high taxes due to more online shopping, then endogeneity concerns arise due to reverse causality. To address this, first note that this endogeneity is most likely to be driven by state tax rates rather than local tax rates. Second, given that internet subscriptions are not subject to sales taxes in most states, any such reverse causality is likely to indicate a positive correlation between tax rates and internet usage (i.e., when taxes are high, people will do more online shopping and buy a subscription). Given that the coefficients I estimate are generally negative, my coefficients are biased toward zero. I address these endogeneity concerns using the same IV strategy as in the cross-section. I instrument for internet subscriptions with 1960 phone and TV usage in the state, the state flash density of lightning, and the average municipal distance to the internet backbone; because these instruments only vary cross-sectionally, I interact them with time dummies in order to use them as instruments. Standard errors are clustered at the state level.

5 Results

5.1 Cross-sectional Regressions

Table 1 presents the baseline cross-sectional estimates of (3) for total local tax rates and municipal tax rates. Given consumers care about total tax rates, the first four columns report the effect of internet penetration in a given town on county plus municipal tax rates. This specification allows counties to respond to municipal internet penetration, but such a response is unlikely if all municipalities in the county are small. In the second set of columns, I focus on municipal tax rates. The measure of internet penetration is standardized such that all reported coefficients are with respect to a one standard deviation increase in internet penetration. Recall that the measure of internet penetration has a mean of 70% and standard deviation of 43 percentage points. Panel A focuses on an average effect across the full sample of towns, while panels B and C focus on large towns (top 25% by population) and small towns (bottom 75%), respectively.[21] Population acts as a strong exogenous predictor of the presence of (large) retail stores. In addition to possible heterogeneity based on size as discussed theoretically, the top 25% of towns raise more than 90% of municipal sales tax revenue, so this split is also economically important. Each column adds controls starting with state fixed effects and municipal demographic/political characteristics; county characteristics; polynomials in distance to the border, state tax rates, and nexus status; and finally county fixed effects, which forces identification to come from within county variation.

Consistently, no noticeable effect across the full sample of towns is apparent. However, this might mask important heterogeneous effects discussed in the theoretical section. When allowing internet penetration to influence small and large jurisdictions differently, a one

[21] The population cutoff for this split is approximately 4700.

Table 1: The Effect of the Internet on Tax Levels: Cross-Sectional Results

	(1')	(2')	(3')	(4')	(1)	(2)	(3)	(4)
		Total Local Tax Rate				Municipal Tax Rate		
A. ALL		Average rate = 1.590				Average rate = 0.712		
	-0.015*	-0.007	-0.012	0.010	-0.004	0.004	0.002	0.006
	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
B. LARGE		Average rate = 1.848				Average rate = 0.928		
	-0.157***	-0.144***	-0.145***	-0.118***	-0.164***	-0.143***	-0.139***	-0.130***
	(0.025)	(0.023)	(0.022)	(0.022)	(0.028)	(0.026)	(0.026)	(0.026)
C. SMALL			Average rate = 1.503				Average rate = 0.643	
	-0.009	-0.002	-0.007	0.012*	0.002	0.009	0.007	0.009
	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
State FE	Y	Y	Y		Y	Y	Y	
Local Controls	Y	Y	Y	Y	Y	Y	Y	Y
County Controls		Y	Y	Y		Y	Y	Y
$g(y_i)$			Y	Y			Y	Y
County FE				Y				Y

This table presents a cross-sectional regression where the unit of analysis is the town. In the first four columns, the dependent variable is the town plus county and district tax rate; in the last four columns the dependent variable is the town tax rate. The measure of internet penetration is the percent of the population with access to four or more providers in the town. This variable is standardized. Panel A focuses on the full sample of towns, while panels B and C partition towns based on their population size and estimate effects using an interaction model. All specifications include state fixed effects. Column (1) also includes municipal demographic control variables from the ACS, geographic variables and political variables. Column (2) adds the same demographic covariates at the county level. Column (3) adds a flexible functions of distance, state tax rates, high-tax/low-tax, and nexus measures all interacted with distance. Column (4) adds county fixed effects. Standard errors are clustered at the county level. ***99%, **95%, *90%

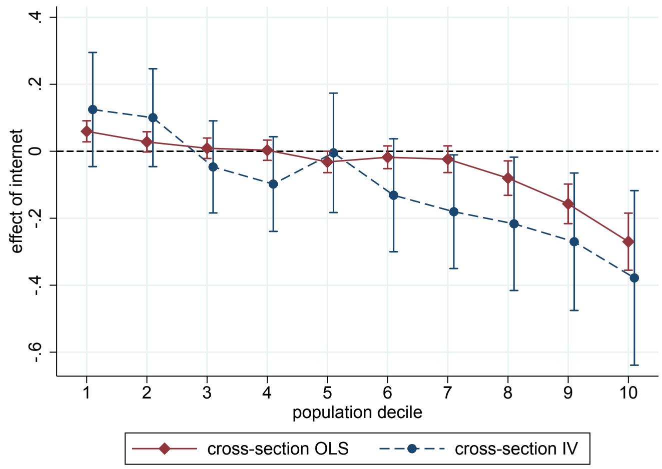
standard deviation increase lowers total local tax rates in large towns by 0.15 percentage points (or approximately 8% of the average total rate), but it has almost no effect on the tax rate of smaller jurisdictions. When focusing only on town tax rates, results are similar, lowering large town tax rates by 0.14 percentage points (15% of the average municipal rate). Most of the increase in *local* internet penetration affects the local tax rate and not the county tax rate. Large jurisdictions may respond to online shopping more intensely if it affects their tax base moreso than in small jurisdictions. This would be the case if consumers previously shopped in larger towns with retail agglomerations and switch these purchases online, but most of the purchases made in (the "general store" of) small towns, such as food or gasoline, are not amenable to online shopping in the period of my sample. In addition, the first set of columns with a prime provide suggestive evidence that *counties* do not respond to *municipal* internet penetration rates because the coefficients are similar to the last four columns. Given the similarity of the effect of internet penetration on total and local tax rates, and the fact that the breadth of heterogeneity is most likely to affect municipalities,[22] I focus subsequently on the municipal rates.

Given the stark differences by size, I group municipalities into deciles on the basis of population and allow internet penetration to flexibly affect tax rates via interactions with indicators for each decile rather than splitting based on the somewhat arbitrary definition of size in the prior table. The OLS results in figure 3 show a generally monotonic and increasingly negative effect of internet penetration on local taxes as jurisdiction size increases. The bottom two deciles, displaying a slightly positive relationship between internet and taxes, include towns with less than 300 inhabitants. Results become significantly negative in the top three deciles, which correspond to towns with more than approximately 3500 inhabitants. As noted previously, large towns may be most affected as their brick-and-mortar retailers lose shoppers from both their own residents and from surrounding smaller communities. If tax competition is at work, this might also lower local tax rates in very small nearby towns. However, the positive effects might be consistent with the enforcement channel. The results in figure 3 are robust to an IV strategy, discussed later.

Does the effect of online shopping depend on the state sales tax rate, and thus, opportunities for cross-border shopping? While consumers may cross-border shop across municipalities in the same state, the largest tax differentials and tax arbitrage opportunities exist at state borders. Thus, in addition to simply controlling for state tax differentials and proximity to the border via the function $g(y_i)$, I also interact internet penetration with a polynomial in distance to the border and the state sales tax rate differential at the border. I allow for different effects on the high-tax and low-tax side of the state border. Before doing this, one can see a differential effect in the raw data in figure 4. This figure splits the sample into towns that have below average and above average penetration rates. I then bin the data into 10 minute bins and calculate the average local tax rate in each bin, separately for

[22]While counties also differ in size and proximity to borders, these differences in size are less likely to affect counties within the same state because most counties have some relatively large retailers, while many municipalities do not. Moreover, splits based on size or distance at the local level might not be appropriate for the county level (e.g., very small towns in a large county).

Figure 3: Effects by Population Decile



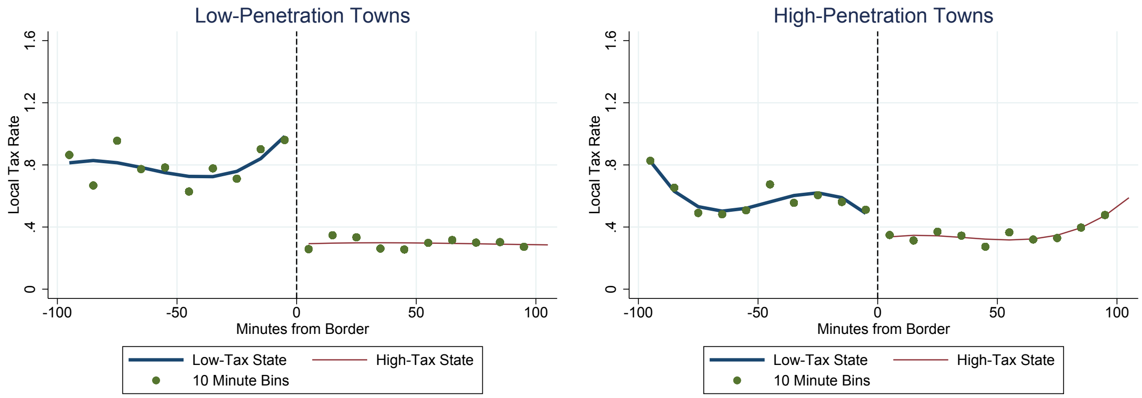
The figure shows how the marginal effect of internet penetration varies across population deciles. The largest jurisdictions are in decile 10 and the smallest jurisdictions are in decile 1. The dependent variable is the town tax rate. To construct this figure, internet penetration is interacted with indicators for each decile. The diamond line shows the results from the cross-sectional OLS regression with all covariates and state fixed effects. The circular dashed line shows the results from the cross-sectional IV using all four instruments discussed in the text. Bars indicate 95% confidence intervals.

the high- and low-tax side of the border.[23] I then fit a third degree polynomial, for each side of the border. The polynomial on the high-tax side of the border is similar for both low-penetration and high-penetration towns. However, on the low-tax side of the border, the polynomial shifts downward at all distances; this downward shift is most pronounced near the border. This visual evidence is in line with the more formal analysis to follow that will show strong downward shifts for border towns in low-tax states. Although a small level difference emerges in the -80 to -20 mile range, the difference may not be statistically significant and thus the main difference arises from the bins just to the left of the threshold. Thus the largest effects of online shopping lowering tax rates come from towns within twenty minutes of the border, likely because the internet is a substitute for cross-border shopping as a means of tax avoidance when the remitting party is the consumer rather than the firm.

More formally, the marginal effects of internet penetration at various distances and tax differentials are given by figure 5. To construct this figure, I interact penetration with a polynomial in distance, the tax differential at the border, and an indicator for the high-tax

[23] Approximately 8% of the sample is in the bin that is closest to the border.

Figure 4: Heterogeneity by Proximity to the State Border: Raw Data

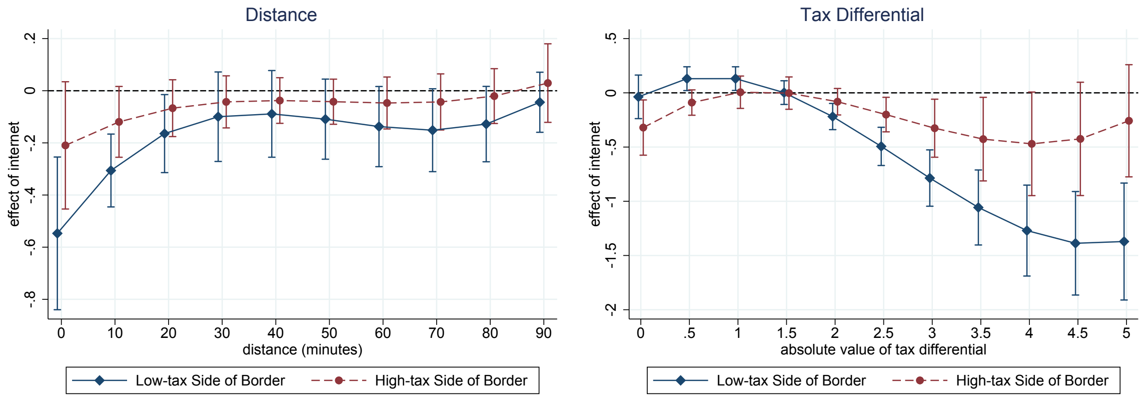


Each graph shows the average of the local tax rate in ten minute bins and then fits a third degree polynomial separately for towns on the low-tax side of the border and then for towns on the high-tax side of the border. The first figure does this for the sample of towns that have below-average internet penetration rates. The second figure does this for the sample of towns that have above-average internet penetration rates.

or low-tax side.[24] This allows me to flexibly estimate the effect of internet penetration. Focusing on large towns, with respect to distance, the left panel shows the largest negative effects are for towns near the border, especially on the low-tax side. Some negative effects on the high-tax side also emerge near the border, but generally the results are insignificant from zero in high-tax states. The difference relative to the plot of the raw data in figure 4 is driven by the fact that the prior figure uses all towns while figure 5 focuses on large towns. Why might the effects be most negative for border towns? One possibility is that online shopping is a substitute for tax avoidance via cross-border shopping. In the pre-internet era, localities in low-tax states were able to tax export and raise their tax rates due to inflows of cross-border shoppers. Bunching of firms on the low-tax side of border may have allowed these municipalities to extract agglomeration rents via higher taxes (Brülhart, Jametti and Schmidheiny 2012). But with online shopping, towns in low-tax states lose the tax base of their own residents and from shoppers in neighboring states who can avoid paying driving costs by online shopping, while also obtaining even larger tax savings via online shopping. On the high-tax side, the effect on cross-border shoppers is irrelevant if online sales are tax-free,

[24] The results may be sensitive to the parametric form of the polynomial (third degree). I verify the results are similar for higher and lower degree polynomials. The use of distance deciles could also be possible but would create many additional interactions.

Figure 5: Heterogeneity by Proximity to the State Border: Large Jurisdictions



The figure shows how the effect of internet penetration varies by distance to the border and the state tax differential at the border. I focus on large jurisdictions in this figure. The dependent variable is the town tax rate and this is a cross-sectional OLS regression. To construct the left figure, internet penetration is interacted with a third degree polynomial in distance to the border, a dummy variable for whether the town is on the high-tax side, the size of the tax differential at the border, along with interactions of those variables with the distance polynomial. State borders with no tax differentials are excluded. To construct the right figure, I interact internet penetration with a third degree polynomial in the state tax differential and its interaction with the high-tax side indicator. The right panel focuses on border towns, towns within thirty minutes from the state border. The circles/dashes show the effects on the high-tax side while the diamonds show the effects on the low-tax side. All specification include state fixed effects and control variables. Bars indicate 95% confidence intervals.

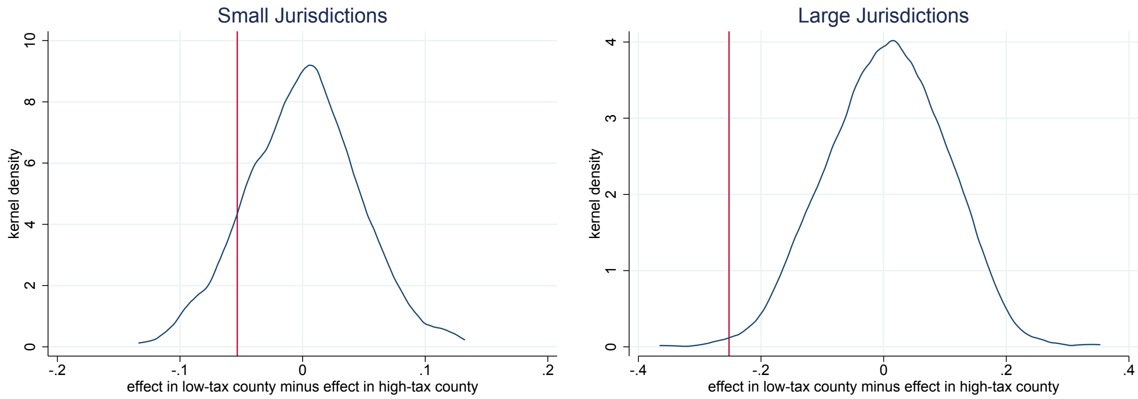
as regardless of the mode of purchase, the local tax authority gets no revenue. The negative effect on the high-tax side could be consistent with online shopping eroding the purchases of own-residents that previously purchased from home-town stores in their jurisdictions. But, if this were the case, we might reasonably expect the effects to be negative at all distances on the high-tax side. Given the effects are not always negative, the downward effect near the border in high-tax states could then be a result of tax competition. As municipalities in low-tax states lower their tax rates to reduce the incentive of their residents and non-residents to buy online, competitor towns in high-tax states will also lower their tax rates (if best responses are upward sloping) via the strategic effect discussed theoretically.

The right panel shows, for border towns, the results of interacting internet penetration with a polynomial in the tax differential at the nearest state border along with an indicator for the high-tax or low-tax side. The figure shows a monotonically declining relationship in low-tax states, and a generally flatter but slightly negative relationship in high-tax states. In the pre-internet era, cross-border shopping inflows were largest in very low-tax border towns, which gave them the largest incentives to raise their tax rates to tax export. The internet, by reducing incentives for cross-border shopping, constrains towns that previously were most likely to markup their tax rates. High-tax towns may then need to reduce their tax rates via tax competition.

Although effects differ in their economic magnitudes across both sides of the border, one might worry that this is a state border effect. Furthermore, when coding a side of the border as high-tax or low-tax, state tax rates are used rather than state plus county rates at the border crossing. The reason for this is that county tax rates *may* be endogenous to both local tax rates and the local internet penetration of any one municipality. In particular, counties may respond to the actions of one particular large city. Moreover, although counties may respond to one municipal tax rate, they may also not respond to the internet penetration rates of smaller cities, which means combining the city and county rate on the left side may not be appropriate for heterogeneous effects, especially for counties that are very large in area. Thus, I use the state rates as an exogenous partition. I verify that this designation based on the state tax rate corresponds to if I had used state plus county rates for the majority of border crossings in the U.S.

To further address this, for states that allow for both county and town sales taxes, the heterogeneous effects at borders should arise at county borders. County borders provide two checks. First, other confounding policies are less likely to change at county borders. Second, many county borders have the same county tax rates on both sides; these borders can be used as a placebo test. However, county tax rates that partition the sample into the high- and low-tax sides of the border may be endogenous. Using within-state county borders (that are not also state borders) with non-zero county tax differentials – shows the internet acts as a tax haven in low-tax counties but that enforcement effects emerge in high-tax counties. For large jurisdictions, similar in sign to state borders, the effect is -0.14 on the low tax side but is 0.11 on the high-tax side (both statistically significant). For small towns, results are basically zero on the low-tax side but 0.04 on the high-tax side. The results in high-tax counties show stronger positive effects than at state borders. Why might enforcement effects

Figure 6: County Borders Results and Placebo Test



The left panel focuses on small towns; the right panel focuses on large towns at county borders. I only use within-state county borders to construct this figure. The vertical line in the graph shows the effect of a one standard deviation increase in the internet for a town in a low-tax county minus the effect of a one standard deviation increase in the internet for a town in a high-tax county. These effects are estimated using the sample of borders where county tax rates are different. The pdf shows the distribution of the same difference of effects using only the set of county borders where county tax rates are the same at the border. The distribution is from 1000 random assignments, where one side of each boder pair with the same county tax rates is assigned to be high-tax.

begin to emerge in high-tax counties even though they do not generally arise in high-tax states? One possibility is that when county tax rates are different, states are more likely to give flexibility to local governments in setting their tax rates or, alternatively, that tax competition at county borders may be different than at state borders.

As a placebo exercise, I use the county borders that are not also state borders, where county tax rates are the same. I take this subset of same-tax borders and randomly assign one side of the border to be the "high-tax" side and the other side to be the "low-tax" side. I repeat this randomization 1000 times and estimate (3), including appropriate interactions with "high-tax" and distance, for each randomization. Figure 6 plots the distribution of the difference in the marginal effect of the internet on the placebo "low-tax" side of the border minus the effect on the "high-tax" side of the border. The distribution is centered on zero, which suggests that an increase in internet penetration has a similar effect on town tax rates for both sides of county borders where county tax rates are the same. When using borders where county tax rates differ, the effects are more negative on the low-tax side of borders; the difference calculated from using actual high-tax and low-tax borders (red vertical line) lies well to the left of the distribution from same-tax borders. The results indicate that for large towns, differential effects at the border are statistically meaningful and not due to a border effect.

5.2 Multiple Proxies and Instrumental Variables

As discussed, endogeneity concerns resulting from measurement error, simultaneity, or omitted variables may arise in a cross-sectional regression.

To mitigate the measurement error problem, I use the procedure of Lubotsky and Wittenberg (2006) from section 4.2. This approach should reduce any attenuation bias. Table 2 shows the result. Comparing the coefficients to the prior table, the use of the single proxy variable attenuates the coefficients toward zero for the set of small towns (and thus the full sample results). Coefficients for large towns are almost identical and only slightly larger in absolute value after using multiple proxies. This suggests that the proxy variable of four or more providers is a better predictor of usage in large jurisdictions than in small jurisdictions, where fewer providers or information on quality also appear to matter. However, adding multiple proxies comes with the caveat that these results might be less reliable if additional proxies are "bad" or endogenous to the model.

The "cross-sectional IV" rows in the table present the results using an instrumental variable strategy.[25] The instruments have a strong first stage. Although I suppress all the first stage regression coefficients, I briefly summarize them for column (3). Phone and TV usage in 1960 are positively correlated with internet penetration today, consistent with internet deployment following the technological diffusion of prior infrastructure (wire) development. Distance to the nearest long-haul internet cable is negatively correlated with penetration today, consistent with higher costs of providing access to places further away from the internet backbone. Finally, lightning strikes are negatively correlated with internet penetration, consistent with frequency/power disturbances raising the costs of providers, but this relationship is insignificant and much weaker than the state level relationship in Andersen et al.

[25] The IV estimates do not include county fixed effects because TV and phone usage only vary at the county level and the other instruments do not have sufficient strong variation within a county.

Table 2: Cross-Sectional Results with Lubotsky and Wittenberg (2006) or IV

	(1)	(2)	(3)	(4)
	Municipal Tax Rate			
A. All	Average rate = 0.712			
Lubotsky and Wittenberg (2006)	-0.076***	-0.072***	-0.072***	-0.072***
	(0.008)	(0.008)	(0.008)	(0.009)
Cross-sectional IV	-0.036	0.025	-0.015	-
	(0.048)	(0.111)	(0.106)	
B. Large	Average rate = 0.928			
Lubotsky and Wittenberg (2006)	-0.198***	-0.187***	-0.181***	-0.147***
	(0.023)	(0.025)	(0.026)	(0.018)
Cross-sectional IV	-0.224***	-0.142	-0.190*	-
	(0.063)	(0.113)	(0.110)	
C. Small	Average rate = 0.643			
Lubotsky and Wittenberg (2006)	-0.061***	-0.060***	-0.060***	-0.066***
	(0.008)	(0.008)	(0.008)	(0.009)
Cross-sectional IV	0.005	0.052	0.016	-
	(0.043)	(0.081)	(0.078)	
State Fixed Effects	Y	Y	Y	
Local Controls	Y	Y	Y	Y
County Controls		Y	Y	Y
$g(y_i)$			Y	Y
County Fixed Effects				Y
F-statistic	68.36	12.54	13.76	
Hansen J Test p-value	0.094	0.143	0.185	

This table presents a cross-section regression where the unit of analysis is the town and the dependent variable is the town tax rate. Panel A focuses on the full sample of towns, while panels B and C partition towns based on their population size and estimate effects using an interaction model. Each row corresponds to a different regression. The row marked "Lubotsky and Wittenberg (2006)" uses multiple proxy variable. The row marked "cross-sectional IV" uses the percent of the population with access to four or more providers in the town and instruments for this independent variable using 1960 phone and TV usage, the flash density of lightning strikes and the distance to the internet backbone. The independent variable measuring internet penetration is standardized. All specifications include state fixed effects. Column (1) also includes municipal demographic control variables from the ACS, geographic variables and political variables. Column (2) adds the same demographic covariates at the county level. Column (3) adds flexible functions of distance, state tax rates, high-tax/low-tax, and nexus measures all interacted with distance. F-statistic and Hansen J test p-values are for panel one. Standard errors are clustered at the county level. ***99%, **95%, *90%

(2012). Figure A.2 shows the relationship of each instrument with penetration.

Relative to the OLS results with a single proxy, coefficients increase in absolute value for both large and small towns, but are only statistically significant in large jurisdictions. The direction of the bias is consistent with the possible reverse causality story: IV should increase the coefficients in absolute value. In these specifications, a one standard deviation increase in internet penetration lowers municipal tax rates in large towns by 0.19 percentage points (or about 20% of the average rate). Instrumenting for the interaction of population deciles and internet penetration with the interaction of the decile indicator and the instruments, shows similar effects of the IV when analyzing heterogeneity in figure 3. As expected, standard errors become larger when instrumenting. While one might wish to utilize only lightning strikes, given it clearly satisfies the assumption of strict exogeneity, the instrument utilized by itself is weak.

5.3 Local Tax Changes

Table 3 shows the result for the long difference model estimated using OLS and IV. The results are reassuring: towns that saw increases in internet penetration see negative effects on local tax rates. This effect is more pronounced in large jurisdictions than small jurisdictions. The IV estimates suggest a one standard deviation increase in penetration lowers local sales tax rates by -0.21 percentage points in large jurisdictions. This estimate is slightly larger than the cross-sectional IV estimates. In small jurisdictions, a similar increase in internet penetration lowers local tax rates by only -0.06 percentage points. This is slightly different than the cross-sectional IV estimates, and now statistically significant. These results suggest that the effects are driven by local tax *changes*.

Up to now, the internet appears to act as a tax haven or to have no (or negligible) effects on tax rates in smaller jurisdictions. Could the latter result be due to offsetting enforcement and tax haven effects, given the enforcement channel is most likely to arise in jurisdictions without retail agglomerations? To get at this, I focus on the role of nexus using the measures in Bruce, Fox and Luna (2015). I define a jurisdiction as being a high-nexus state if the state has an above average share of online shopping by the largest (online) vendors that remit taxes on a destination basis. Results are robust to other measures in their paper, but are weaker when simply counting the number of firms. I then interact the indicator for whether the town is in a high-nexus state with indicators for whether the town is in a high-tax or low-tax state and an indicator for jurisdiction size (large versus small). The figure shows the results of (5) with instrumental variables, but the results estimating (3) with IV are qualitatively similar. Given nexus is cross-sectional, this variable enters in levels, as does the high-tax indicator, but using the status prior to the start of my sample.

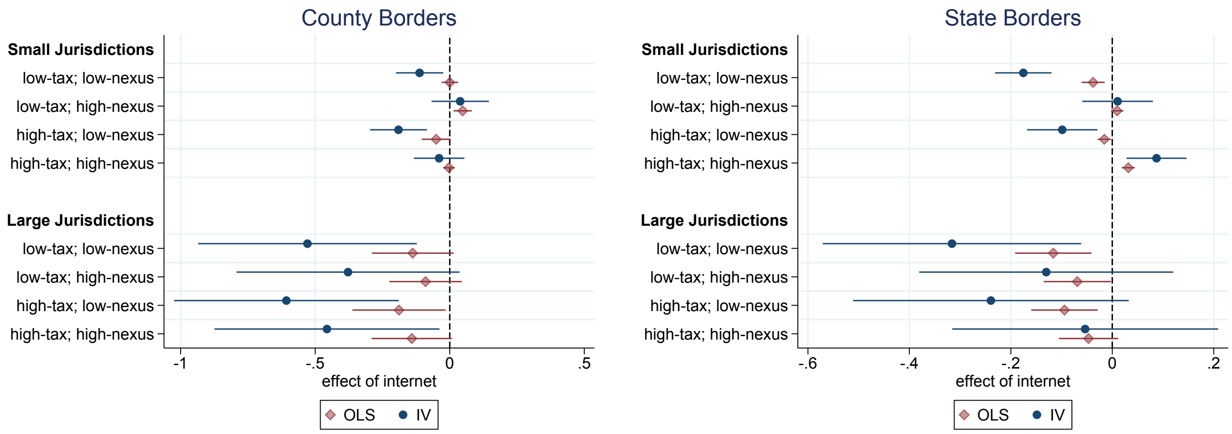
Table 3: The Effect of the Internet on Tax Changes: Long Differences with IV

	(1)	(2)	(3)
		Municipal Tax Rate	
A. All		Average rate = 0.715	
Long Difference	-0.015***	-0.006	-0.004
	(0.005)	(0.004)	(0.004)
Long Difference IV	-0.075***	-0.074***	-0.075***
	(0.017)	(0.021)	(0.022)
B. Large		Average rate = 0.930	
Long Difference	-0.064**	-0.052*	-0.053*
	(0.028)	(0.028)	(0.028)
Long Difference IV	-0.179	-0.155	-0.212*
	(0.112)	(0.119)	(0.120)
C. Small		Average rate = 0.646	
Long Difference	-0.012***	-0.004	-0.002
	(0.004)	(0.004)	(0.004)
Long Difference IV	-0.065***	-0.062***	-0.062***
	(0.014)	(0.017)	(0.018)
Local Controls	Y	Y	Y
County Controls		Y	Y
$g(y_i)$			Y
F-statistic	121.4	69.55	65.16
Hansen J Test p-value	0.965	0.965	0.206

This table presents long-difference regressions where the unit of analysis is the town and the dependent variable is the change in the town tax rate. Panel A focuses on the full sample of towns, while panels B and C partition towns based on their population size and estimate effects using an interaction model. Each row corresponds to a different regression. The row marked "long difference" uses the change in internet penetration; penetration in 2003 is extrapolated using state growth rates from broadband data. The row marked "long difference IV" instruments for internet penetration using 1960 phone and TV usage, the flash density of lightning strikes and the distance to the internet backbone. The internet penetration measure is standardized. State and county fixed effects difference out. Column (1) also includes municipal demographic control variables from the ACS, geographic variables and political variables. Column (2) adds the same demographic covariates at the county level. Column (3) adds flexible functions of distance, state tax rates, high-tax/low-tax, and nexus measures all interacted with distance. F-statistic and Hansen J test p-values are for panel one. The samples of towns – and thus the means – are slightly different than the prior tables do to missing data over time. Standard errors are clustered at the county level. ***99%, **95%, *90%

Figure 7 shows the results for both county borders and at state borders. Here I focus on the case of state borders. Critically, the effects in high-nexus states are always larger or less negative – though generally not statistically different – than the effects in low-nexus states. This is consistent with the tax enforcement effect muting the negative tax haven effects. The only place that significant positive effects arise are in high-nexus states and the effect is much more pronounced on the high-tax side. Why might nexus interact with being on the high-tax side of a state border? For these jurisdictions, the convenience of online shopping may switch residents away from cross-border shopping large purchases into the neighboring state; given these towns were likely to have the largest proportion of residents cross-border shopping, they may also realize the largest gains from online vendors remitting

Figure 7: Interaction with the Nexus Status and Border Tax Differentials

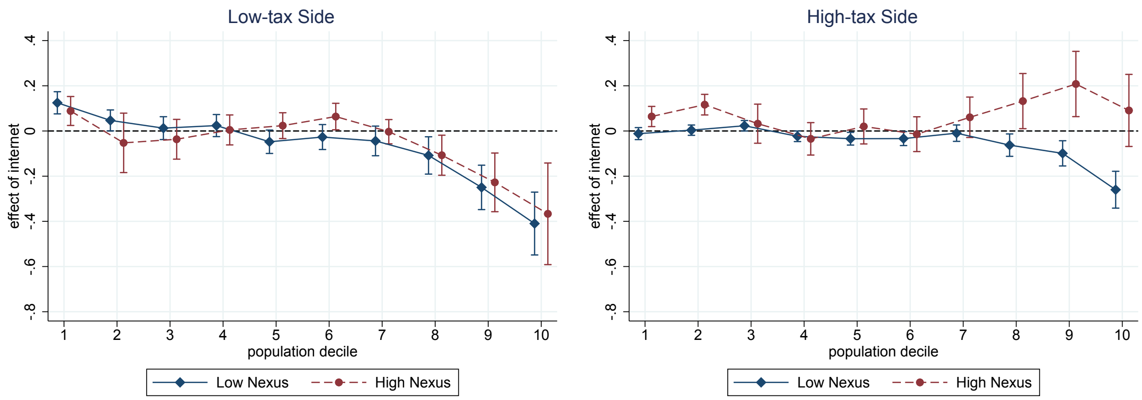


The figure shows how the effect of internet penetration varies by jurisdiction size, nexus status and tax differentials at the border. The dependent variable is the long difference of the tax rates. To construct the figure, internet penetration is interacted with dummy variables for jurisdiction size, nexus status of the state and whether the town is in a state that is high-tax relative to the nearest neighbor. Large jurisdictions are those in the top 25% based on population, high nexus states have an above average share of online sales from vendors with nexus, and a town is high-tax if the nearest neighboring state (county) sets a lower tax rate. Borders with no tax differential are excluded. The left figure utilizes within-state county borders and the right figure uses state borders. The circles show the effects using IV while the diamonds show the effects using a simple difference model. All specifications include the full set of control variables. Bars indicate 95% confidence intervals.

taxes on a destination basis. Given my sample includes the period where Amazon was still only collecting in a handful of states, the tax enforcement channel may not be fully realized by jurisdictions, so finding an effect in even a sub-sample of jurisdictions in this period would suggest even larger effects post-*Wayfair*. Moreover, the fact that nexus raises all negative coefficients towards zero is consistent with the enforcement channel muting revenue leakages to the tax haven.

To further explore this issue, I allow nexus and internet penetration to interact flexibly with jurisdiction size. I divide my sample of jurisdictions into ten deciles based on population. I then interact the internet penetration variable with indicators of the high-tax variable, the high-nexus variable, and the series of dummy variables for each decile. This allows me to flexibly estimate the effect of a one standard deviation increase in internet penetration across the population distribution and across high-nexus and low-nexus states. However, the number of interactions makes an IV strategy untractable. The marginal effect of internet penetration is displayed in figure 8. In both high-tax and low-tax states, the effect of internet penetration is more negative in low-nexus states. Generally, small jurisdictions have slightly

Figure 8: Interaction with Nexus and Population Deciles by State Taxes



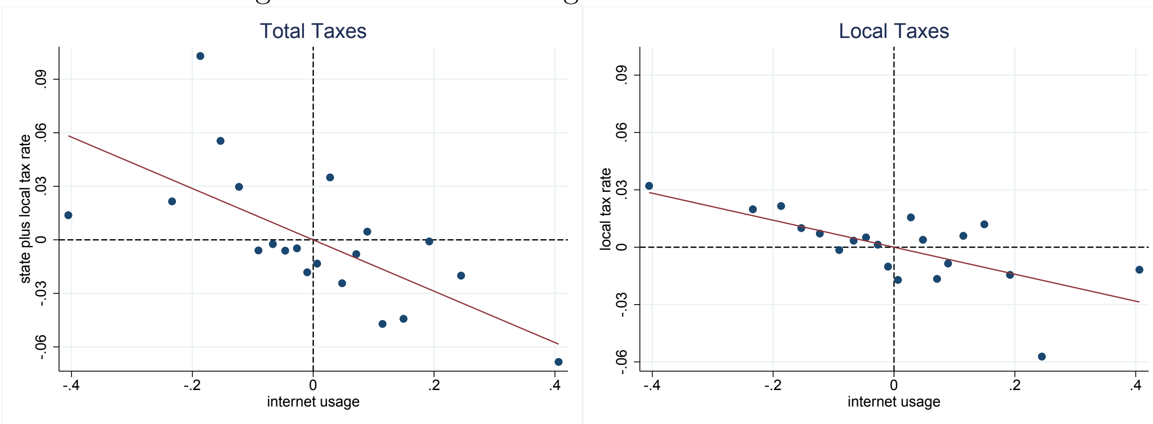
The left figure shows how the effect of internet penetration varies across population deciles on the low-tax side of the border where the effects in low nexus states are given by the diamond line and the effects in high nexus states are given by the circle-dashed lines. The right figure shows how the marginal effect of internet penetration varies across population deciles on the high-tax side of the border where the effects in low nexus states are given by the diamond line and the effects in high nexus states are given by the circular-dashed lines. The dependent variable is the local tax rate. To construct the figure, internet penetration is interacted with dummy variables for jurisdiction size based on deciles of the population distribution, nexus status of the state and whether the town is in a high-tax state. Large jurisdictions are those in the top 25% based on population, high nexus states have an above average share of online sales from vendors with nexus, and a town is high-tax if the nearest neighboring state sets a lower tax rate. Borders with no tax differentials are excluded. All specifications include the full set of control variables. Bars indicate 95% confidence intervals.

positive effects, but this is most pronounced on the high-tax side of the state border – indeed, even some large towns have positive effects in these states. Overall, this suggests that the enforcement effects are largest in places that have more firms with nexus and that it benefits both small and large towns. Even though positive effects of internet penetration may not consistently emerge, the figures make it clear that having more firms with nexus mutes the negative effects of the internet on tax rates, so much so that for many jurisdictions the internet does not have a noticeable haven effect. This suggests that enforcement effects resulting from the switch of the remittance regime are an important policy consideration that is yet to be discussed in the empirical literature.

5.4 State Panel Data Approach

Given internet penetration is only observed in the cross-section and the long difference requires some assumptions on the growth of penetration, I now supplement the municipality analysis with a simple state-level panel data analysis to see if the results are consistent. The model is estimated in first differences and I weight by the size of the state to give more

Figure 9: Panel Data Regressions: Plot of Residuals



To construct this figure, I regress the tax rate on fixed effects. Then I regress internet penetration on the same fixed effects. After each regression I predict the residuals. The residuals are then binned into twenty equally sized bins and the averages within the bins are plotted. This approach provides a non-parametric way of visualizing the panel data regressions. The left panel uses the state plus average local tax rate while the right panel uses only the average local tax rate from the state.

weight to bigger states, as in the cross-sectional regressions. I aggregate total local tax rates to the state level and then regress the average local tax rate in the state on a time varying measure of the fraction of households with internet subscriptions in the state from FCC form 477. I standardize this variable so that the magnitudes can be compared to the local regressions. Although it could be argued that state level measures of internet subscriptions are exogenous to the average local rate, I instrument for this variable with state level lightning strikes, the average municipality distance to the internet backbone, and state TV and phone subscriptions in 1960. As all of these variables are time invariant, I interact each of them with time dummies and use those interacted variables as my instruments. Finally, to get at heterogeneity, when aggregating the local tax rates, I separately do so for large and small jurisdictions as well as jurisdictions on the low-tax and high-tax side of borders.[26]

Figure 9 presents the results of simple panel data regressions. Using the panel of the 48 contiguous states and data from 2003 to 2011, I regress tax rates on state fixed effects and year dummies; then I do the same thing for internet subscriptions. I bin the residuals and plot them along with the line of best fit that corresponds to the coefficient from the panel data regression. Both figures show a negative relationship for state plus local taxes and local

[26]To hold the sample fixed, I use population in 2000 and state tax differentials prior to the start of my panel data to construct these groups.

Table 4: Panel Data Regressions with IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. Baseline Estimates			B. Heterogeneity			
Sample		All Towns		Small	Large	Low-tax	High-tax
Internet Subscriptions	-0.052**	-0.051**	-0.050**	-0.034	-0.085**	-0.190**	-0.041
	(0.025)	(0.025)	(0.025)	(0.024)	(0.041)	(0.081)	(0.041)
Controls	Y	Y	Y	Y	Y	Y	Y
State Tax Variables		Y	Y	Y	Y	Y	Y
Nexus Variables, $f_t(y_s)$			Y	Y	Y	Y	Y

This table presents a state level panel data regression estimated in first-differences where the dependent variable is the average town tax rate in the state. The independent variable is the percent of households in the state with an internet subscription, which is standardized to be comparable to the cross-sectional results. Panel A focuses on all towns in the state, while Panel B uses the average local tax rate for various sub-samples. All specifications instrument for internet subscriptions using 1960 phone and TV usage, the flash density of lightning strikes and the distance to the internet backbone, each interacted with time dummies for temporal variation. All specifications include time fixed effects; state fixed effects difference out. Column (1) adds state level demographic control variables from the ACS. Column (2) adds the state tax rate and the fraction of towns near high-tax borders. Column (3) adds a 2003 measure of nexus interacted with year dummies. Turning to the heterogeneity analysis, columns (4) and (5) calculate the average local rate over small and large towns respectively. Columns (6) and (7) calculate the averages over towns on the low-tax and high-tax side of state borders in 2003. All regressions are weighted by the size of the state. Standard errors are clustered at the state level. ***99%, **95%, *90%

taxes alone. The slope of the latter graph is flatter, as local tax rates are lower than state tax rates. Given the goal of this analysis is to verify the prior local results in a formal panel data setting, I subsequently focus on local tax rates only.

Table 4 shows the results. Given the model is estimated in first differences, the first column contains time dummies and the same demographic controls included in the local analysis. Then, the next column adds the (time varying) state tax rate and a (time varying) variable indicating the fraction of towns on the high-tax side of state borders, which may change if the state tax rate increases relative to the neighboring state. Finally, column (3) attempts to control for state's nexus status. Although the Bruce, Fox and Luna (2015) measure of nexus is available for four years, the authors did not maintain a consistent sample to control for nexus over time and, furthermore, one would want to use metrics prior to the start of the sample to reduce endogeneity concerns. Thus, I use Compustat data to count the number of firms that list their headquarters (and thus have a physical presence) in each state in 2003 and are classified by a NAICS corresponding to the retail sector. I then control for nexus by interacting this variable with time indicators. The F-statistic on the instruments is strong, ranging between 14 and 35 depending on the specification, and the first stage coefficients are of the expected sign.

Overall, the results indicate that a one standard deviation (adjusted to be comparable to the cross-sectional analysis) increase in internet subscriptions lowers local tax rates by 0.05 percentage points or approximately 5% of the municipal rate in the average state. Then, focusing on the sample of large and small towns, the effects indicate substantial heterogeneity. Internet subscriptions appear to be uncorrelated (or slightly negatively) correlated with the average rates of small towns, but have a significant negative effect in large towns. A one standard deviation increase in subscription rates, lowers local taxes by 0.09 percentage points in large towns. Towns on the low-tax side of state borders also have much larger effects than towns on the high-tax side of state borders, consistent with the prior results. I also study heterogeneous effects by static measures of the nexus status of the state, but I do not detect any heterogeneous effects. This is likely due to the fact that nexus was a dynamic process over this time period; online supply chains, business models, and state laws were rapidly evolving. Moreover, enforcement effects may not emerge until later in the panel as more firms start to establish nexus.

The panel data aggregate analysis generally yields similar signs as the cross-sectional regressions, but the magnitudes are slightly different, which could be a result of using the subscription rate of the state to predict the changes in average local tax rates, rather than the variation in internet penetration within the state. Nonetheless, the robustness to using actual data on changes in tax rates and internet usage is reassuring.

6 Conclusion

Numerous studies (Goolsbee 2000; Ballard and Lee 2007; Ellison and Ellison 2009; Einav et al. 2014; Baugh, Ben-David and Park 2018) show that consumers are responsive to tax differentials from online shopping. Other studies show that firms change their business models and supply chains in response to sales taxes (Houde, Newberry and Seim 2019). Because the internet influences the elasticity of demand for goods and because the elasticity is an important determinant of optimal tax rates, the natural step taken in this paper is to determine how differences in internet penetration distort tax rates.

Although the analysis focuses on the example of local sales taxes, the implications of this paper are broader. First, technological change and globalization are often argued to place downward pressure on tax rates. I show that this is generally true, but it is not a hard rule, given that technology can improve the government's ability to enforce taxes. Second, online commerce provides a unique opportunity to study the effect of the remitting party on equilibrium tax rates. Although the public finance literature often argues that who remits a tax does not matter for the economic implications of taxation, I show that it matters not only for reducing evasion, but also for the optimal tax rates set by governments. In this paper, by switching to a remitting party that can be more readily monitored (firms versus individuals), tax havens become less relevant – allowing governments to raise taxes. Neither of these lessons are specific to sales taxes and they apply more broadly to personal income, corporate income, and wealth taxes along with withholding and information reporting rules.

The effects in this paper have important policy implications for sales taxes as well. First, local government policies designed to encourage competition in broadband markets may have unanticipated consequences on sales tax revenues and rates. In very large towns, this effect might reduce tax revenues. Reducing the digital divide in smaller towns might allow for sales tax collections, especially if taxes can be enforced at destination – if states adopt an economic presence standard following *South Dakota v. Wayfair*. This relates to the second policy impact: absent a state adopting economic presence, increased internet availability lowers local sales tax rates and thus results in an equilibrium where some jurisdictions are setting lower taxes due to the existence of tax evasion. A policymaker seeking to reduce these tax-setting inefficiencies might try to find ways to better enforce destination based taxation, which has the potential to reduce tax competition resulting from tax evasion due to online shopping. Indeed, the case for taxation at destination remains strong (Keen and Wildasin 2004). To put this differently: by enforcing destination-based taxes, remittance rules are an important part of tax systems – and not just for reducing evasion, but also for the equilibrium pattern of tax rates and revenues that we observe. Following *South Dakota v. Wayfair*, sales tax rates may increase in some jurisdictions for two reasons: first, the tax haven effects identified in this paper are no longer present and, second, because the new remittance rules facilitate tax collection for some jurisdictions. Technological innovation, while making businesses and shopping patterns more footloose and traditionally argued to result in declining tax rates, has the potential to create opportunities for tax authorities.

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Online Appendix for "The Internet as a Tax Haven?"

David R. Agrawal

A Appendix (For Online Publication)

This online appendix provides information on data sources, data construction, and supplementary material / results mentioned in the text of the paper.

A.1 Baseline Data

A.1.1 Taxes

The raw sales tax data were acquired from Pro Sales Tax (2003-2011) and assembled in Agrawal (2015) and Agrawal (2014). To summarize that assembly procedure, Agrawal (2015) merges a cross-section of the tax data to Census data. Thus, Agrawal (2015) restricts the sample to municipalities that are identified Census Places.[27] When doing this, Agrawal (2015) name merges data provided by the American Community Survey (ACS) to the tax data. These cross-sectional data are extended to a panel data setting in a later paper, Agrawal (2014). These data have complete coverage of all local sales taxes in the United States at the monthly frequency from 2003 to 2011. The sales tax data used in this paper and the data merging procedure are described in detail in these two prior papers.

A.1.2 Driving Distances

Using the geo-spatial network data in Agrawal (2015), which modifies Lovenheim (2008) to calculate distance to the border, I also data on the driving time to the nearest state border major road crossing. Distance to the border is the time (in minutes) that minimizes the driving time from the population weighted centroid of a town to the closest state border and a major road intersection. By using minutes rather than miles, these data are able to capture the true cost of driving to the border. Agrawal (2015) then identifies a town as being in a high-tax state if its state has a higher state sales tax rate than the nearest neighboring state; a town is in a low-tax state if its state sales tax rate is lower in the own state than

[27]A Census Place is generally an incorporated place with an active government and definite geographic boundaries such as a city, town, or village. In some western states, a Census Place may be an unincorporated place that has no definite boundaries or government. Census Places contain some locations that may not have legal authority or jurisdiction to set sales taxes.

the nearest neighboring state. The driving data assembled in Agrawal (2015) were merged to the panel data in Agrawal (2014) by Agrawal and Mardan (2019).

A.1.3 Primary Internet Data from Broadband Map

Data on local internet penetration comes from the July 2011 version of the National Broadband Map, which is collected by the National Telecommunications and Information Administration (NTIA) in conjunction with the Federal Communication Commission (National Broadband Map 2011). These data are supplemented with state level data from Form 477 (FCC 2003-2011) and pricing data from the FCC Reference Book (FCC 2008).

A.1.4 Internet Usage at the Local Level

Unlike the *penetration* data in the Broadband Map (which is available at the town level), internet *usage* is not available at the town level. For every Census tract, the FCC releases binned data on the percentage of households with a fixed internet connection (FCC 2008-2011), ι such that:

$$\iota = \begin{cases} 0 & \text{if } I^* = 0 \\ 1 & \text{if } 0 < I^* \leqslant .20 \\ 2 & \text{if } .20 < I^* \leqslant .40 \\ 3 & \text{if } .40 < I^* \leqslant .60 \\ 4 & \text{if } .60 < I^* \leqslant .80 \\ 5 & \text{if } .80 < I^* \leqslant 1 \end{cases} \tag{A.1}$$

where I^* is the true fraction of households with an internet subscription. Because these are tract level data and tracts can cross town lines, I aggregate up to the town level by assuming that the value of ι is uniformly distributed within the tract. I calculate the fraction of the town area in any Census tract using ArcGIS software and Census mapfiles. I then calculate the municipal-level value of ι by aggregating up using the percent of area in the Census tract as weights. This yields a continuous value of internet usage between zero and five. I then assume that each integer value of ι is the mid-point between its bin's extreme values. Given the town level measures constructed using area weights are not necessarily integers, I calculate a value of internet usage based on how far the decimal is from each of the two nearest integers. This gives me a continuous measure of internet usage between zero and 0.90. Note that this variable contains measurement error because: (1) ι contain error and the midpoint assumption also introduces error, and (2) for towns that are smaller than a Census tract, the value in the FCC data may be substantially off if the distribution is not uniform within a tract.

A.1.5 Computer and Internet Usage at the State / National Level

Measures of computer and internet usage come from the Current Population Survey. Aggregate state information is from CPS (2003-2011a) and micro information is from CPS (2003-2011b). I supplement this with information on online shopping from Census (1998-2012).

A.1.6 Nexus Data

Bruce, Fox and Luna (2015) construct nexus data by hand. Bruce, Fox and Luna (2015) visit the websites of the largest e-tail firms and attempt to make a retail purchase from each state. They code the firm as having nexus if retail sales taxes are levied on that transaction. These authors provide me with summary data as to whether the state has an above average nexus variable along the with the quartiles in the nexus distribution for each state.

Finally, I ask someone with access to Compustat data to count of the number of firms in traditional retail sectors that are headquartered within a state. This measure does not directly get at nexus as in Bruce, Fox and Luna (2015); rather, it is designed to proxy for nexus by state. The underlying assumption is that states with more retail firms headquartered in the state are more likely to have more firms with nexus. To construct this, I classify firms by their NAICS codes as "retail firms" – firms traditionally remitting retail sales taxes on most purchases. The count is the total number of retail firms headquartered in a state as listed in the Compustat database. This variable is used in the state level panel data regression.

A.1.7 Controls and Revenue Data

All baseline controls come from the 2000 Census (Census 2000) or various American Community Surveys (Census 2005-2011). Political controls are downloaded from a database at MIT (MIT Election Data and Science Lab 2018). Sales tax revenue data comes from the Census of Governments (Census 1967-2012).

A.1.8 Summary Statistics

Figure A.1 shows examples of areas serviced by four or more broadband providers (2011) in a large metro area and in smaller towns. The providers often elect to service areas that do not start or end at municipal borders. As is clear, providers make decisions to enter particular parts of a municipality, likely based on historical infrastructure.

A.2 Theoretical / Policy Justification for Proxy Variable

Why does the fraction of households with access to four or more providers a good proxy for internet access? The existing industrial organization literature provides some theoretical and empirical evidence that increased competition by broadband companies will increase take-up of the internet. For example, Faulhaber and Hogendorn (2000) shows that "the subgame equilibrium capacity and price strategies depend only on the number of networks to which a household has access." Thus, the number of providers serving an area (the outcome of the first stage) is, from a theoretical perspective, the most important determinant of price in this industry. Second, as shown in Distaso, Lupi and Manenti (2006) and verified empirically, inter-platform competition such as DSL versus cable technologies (rather than intra-platform competition), increase internet usage. If individuals have more types of choices – and they will in places with more providers – then they are more likely to adopt a particular technology. Prieger and Hu (2008) also show empirically that competition in broadband markets is an important contributing factor of the Digital Divide that exists across races even though prices do not vary substantially across various markets; the authors provide evidence that suggests more intense competition increases internet usage because companies compete more intensely on installation, service fees, and other charges.

All of this evidence taken together suggests that markets with more intense competition will have higher internet usage rates and that penetration is also correlated with online purchases, which should then feedback into the tax setting behavior of the jurisdictions. The economics literature is also complemented by the views of the NTIA, who write in the National Broadband Map, "The primary factors that people consider when deciding what type of broadband internet service to subscribe to include service availability, connection speed, technology and price." The United States National Broadband Plan studies some of the data on competition and notes that competition in residential broadband markets "provides consumers the benefits of choice, better service and lower prices."

A.3 Implementation of Lubotsky and Wittenberg (2006)

As noted in the text, I can aggregate up to a single coefficient of interest using:

$$\beta^{\rho} = \sum_{n=1}^{N} \beta^{n} \frac{cov(\tau_i,\, I_i^n)}{cov(\tau_i,\, I_i^1)}. \tag{A.2}$$

The expression is normalized by $cov(\tau_i,\, I_i^1)$. This means that the procedure is an interpretation procedure where the coefficient is scaled such that a one unit increase corresponds to a one unit increase in I_i^1. In order to be able to compare this procedure to my other results, I select this normalization such that the results are comparable to the fraction of the population with access to four or more providers. Lubotsky and Wittenberg (2006) show that attenuation bias will be most reduced when estimating β^{ρ} and Bollinger and Minier (2015) show that including all proxy variables in the regression minimizes the bias on other coefficients in the regression as well.

To implement this, I use variables indicating the percent of consumers with access to one or more, ..., eight or more providers, download speeds greater than 768k, ..., download speeds greater than 1gig, upload speed greater than 10,000k, upload speeds greater than 50,000k, the total number of providers in the jurisdiction, the total number of residential providers in the jurisdiction, and the total number of broadband providers for various speeds. The latter of these are constructed from form 477 tract level data. The "..." imply that I use all data for values in between the given range. As noted in Lubotsky and Wittenberg (2006), the procedure is not a license to include every variable the researcher may think is a proxy variable. Proxy variables can affect other control variables (Bollinger 2003) and "adding proxies that absorb the effects of covariates rather than proxying for the latent variable will be particularly damaging." For this reason, I exclude most of the type of technology variables (dsl, optical fiber, copper, etc.).

A.4 IV Variable Construction

A.4.1 TV and Phone Usage

TV and phone usage at the county and state level are obtained from the 1956 City and County Data Book and 1960 City and County Data Book (Census 1955-1960). These data are at the county rather than municipal level.

A.4.2 Lightning as an IV for IT at the State Level

Andersen et al. (2012) show that lightning strikes are a powerful predictor of IT usage (at the state level) in the United States during the period from 1996 to 2006. Andersen et al. (2012) argue that in places with high lightning density, more power disturbances occur. These power disturbances increase the cost of investing in IT, which then lowers IT investment and internet usage.

As an instrumental variable, I construct a measure of the flash density of lightning using the National Oceanic and Atmospheric Administration's Severe Weather Database. I use data on the annual number of ground strikes from 1986 to 2011 to construct the per year average number of strikes per square mile. Define the flash density of lightning in a jurisdiction as

$$lightning_i = \frac{(\sum_{t=1986}^{2011} strikes_{i,t})/T}{area_i}, \tag{A.3}$$

where $strikes_{i,t}$ is the number of lightning strikes in jurisdiction i in year t, T is the total number of years, and where $area_i$ is the area of the jurisdiction. At the state and county level, this variable can be constructed from publicly released data (NOAA 1986-2012a) at each geographic level; but at the local level, it must be constructed using grid level data on lightning strikes.

To do this at the local level, I obtain grid level data on all lightning strikes from 1986 to 2011 from the National Oceanic and Atmospheric Administration (NOAA 1986-2012b). The data I obtained provide me the precise 4km grid cell that the lightning strikes hit on the map. I then aggregate from the grid level up to the municipal level accounting for the fact that some grids can cross municipal boundaries. I do this aggregation by weighting by the grid area within a municipality and assuming the lighting strikes were distributed uniformly within the grids.

A.4.3 Internet Backbone.

Durairajan et al. (2015) and Durairajan and Barford (2016) construct maps of the internet backbone.[28] However, these maps are not eligible for public use outside of a secure portal due to national security reasons. For this reason, using the data maps constructed by these authors, which are mapped into counties in Durairajan and Barford (2016), I first determine if a county has internet infrastructure running through it. Then, I calculate the crow-flies distance (or linear distance) from the population weighted centroid of each town to the nearest county containing this physical network assuming the long-haul network runs through the midpoint of the county. For towns in a county with such infrastructure, I set this variable to zero. The crow-flies distance avoids any possible correlation with infrastructure.

A.5 Additional Data Sources

CPS. 2003-2011a. "Computer and Internet Usage Tables" https://www.census.gov/topics/population/computer-internet/data/tables.html (Accessed approximately 2013)

CPS. 2003-2011b. "Current Population Survey, Computer and Internet Usage Supplement" Accessed at https://data.nber.org/data/current-population-survey-data.html (accessed approximately 2014)

[28]See also Durairajan et al. (2013).

FCC. 2003-2011. “Form 477 State Data” https://www.fcc.gov/internet-access-services-reports (Accessed approximately 2014)

FCC. 2008-2011. “Form 477 Tract Data” https://www.fcc.gov/internet-access-services-reports (Accessed approximately 2014)

FCC. 2008. “Reference Book” https://www.fcc.gov/oea-archived-data-and-statistical-reports (Accessed approximately 2014)

FCC. 2011. “National Broadband Map” https://broadbandmap.fcc.gov/#/ (Accessed approximately 2013)

MIT Election Data and Science Lab, 2018, “countypres_2000-2016.tab”, County Presidential Election Returns 2000-2016, https://doi.org/10.7910/DVN/VOQCHQ/HEIJCQ, Harvard Dataverse, V6, UNF:6:ZZe1xuZ5H2l4NUiSRcRf8Q== [fileUNF] (accessed 2019)

NOAA. 1986-2012a. “County and State Summaries” https://www.ncdc.noaa.gov/data-access/severe-weather/lightning-products-and-services (accessed approximately 2015)

NOAA. 1986-2012b. “Gridded Summaries” https://www.ncdc.noaa.gov/data-access/severe-weather/lightning-products-and-services (accessed approximately 2015)

Pro Sales Tax. 2003-2011. “Pro Sales Tax Monthly Database.” https://www.prosalestax.com/

United States Census. 1955-1960. “Census County and City Databook” https://www.icpsr.umich.edu/web/ICPSR/studies/12 (Accessed approximately 2016)

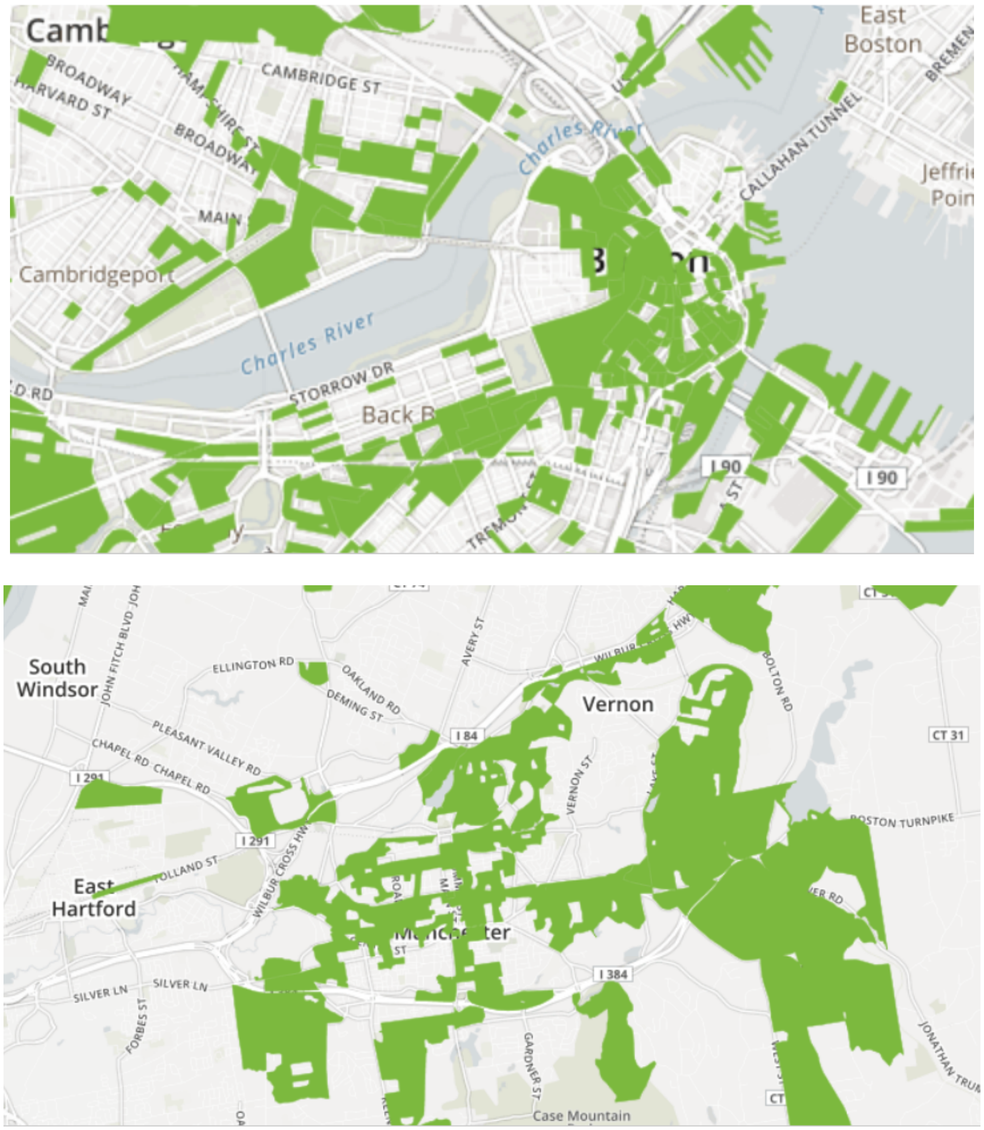
United States Census. 1998-2012. “Quarterly e-Commerce Reports” https://www.census.gov/retail/ecommerce/historic_releases.html (Accessed approximately 2014)

United States Census. 2000. “2000 Census” Accessed at https://www.socialexplorer.com/explore-maps (accessed approximately 2014)

United States Census. 2005-2011. “American Community Survey, 5 Year Estimates” Accessed at https://www.socialexplorer.com/explore-maps (accessed approximately 2013)

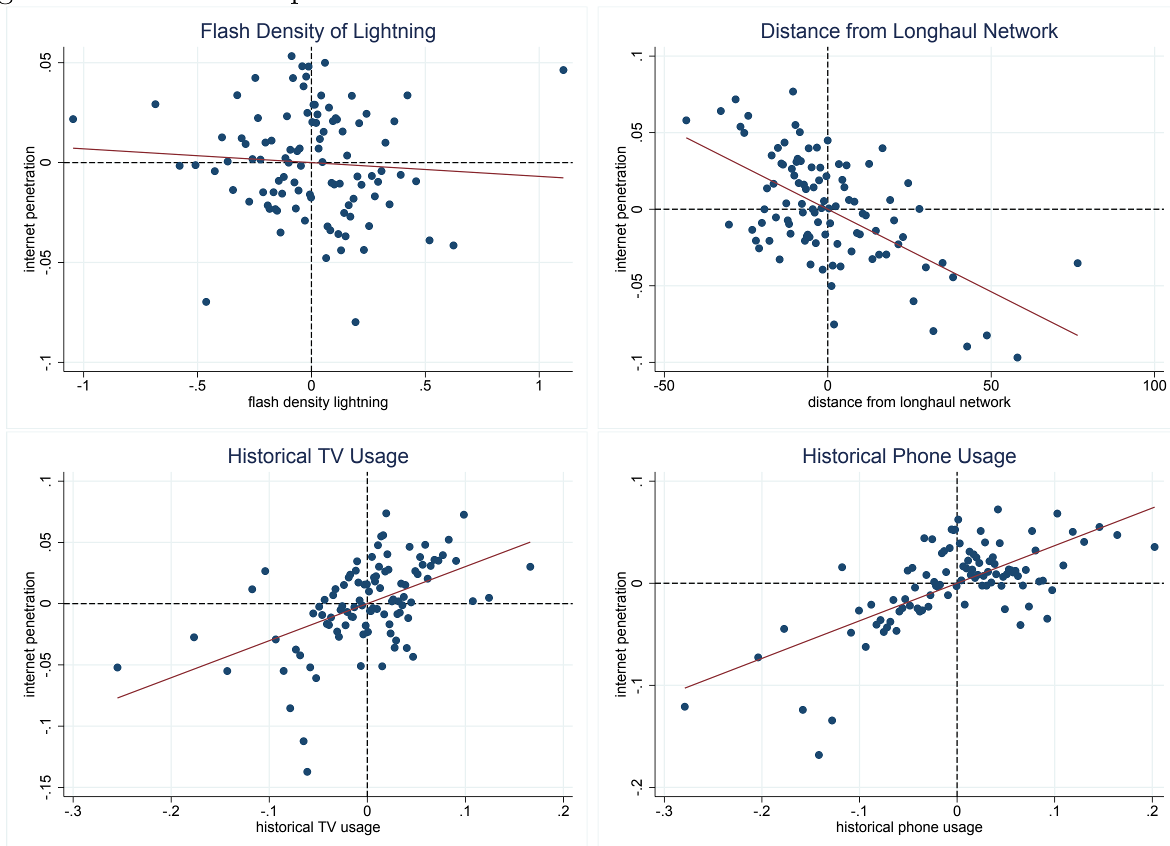
United States Census. 1967-2012. “Census of Governments, Revenue Data” Accessed at a website no longer working (accessed approximately 2016)

Figure A.1: Examples of Service Provider Maps



The upper figure shows areas of Boston and Cambridge, MA that are serviced by more than four broadband providers. The second figure shows a similar map for the smaller towns of South Windsor, East Hartford, Manchester, and Vernon, CT. The provider areas serviced by four or more providers clearly do not correspond to town boundaries.

Figure A.2: Relationship Between Instruments and Internet Penetration at the Local Level



The graph shows the relationship between the fraction of households with access to four or more providers and each instrumental variable in the local cross-sectional data. To make this figure, I regress internet penetration on state fixed effects and control variables from the regression; I repeat this procedure each instrument. I predict the residuals and then I then bin the data into 100 equally sized bins and plot the line of best fit. Note, the slope here is not the precise first stage coefficient because the first stage includes all four instruments.

Table A.1: Regression of Usage on Penetration

Standard Errors in ( ) and R^2 in [ ].

	(1) Usage	(3) eBay	(3) Local Usage
A. Candidate Proxy Variable			
% Households with Access to Any Service	0.051	0.376***	0.132***
	(0.152)	(0.079)	(0.015)
	[0.003]	[0.144]	[0.015]
% Households with Access to Speed $\geqslant$ 6000k	0.296**	0.513***	0.309***
	(0.118)	(0.179)	(0.031)
	[0.087]	[0.262]	[0.094]
% Households with Access to Speed $\geqslant$ 3000k	0.017	0.405***	0.169***
	(0.145)	(0.061)	(0.021)
	[0.000]	[0.166]	[0.027]
% Households with Access to Providers$\geqslant$ 1	-0.078	0.331***	0.107***
	(0.091)	(0.042)	(0.013)
	[0.006]	[0.112]	[0.010]
% Households with Access to Providers $\geqslant$ 2	0.108	0.400***	0.180***
	(0.146)	(0.132)	(0.022)
	[0.012]	[0.162]	[0.031]
% Households with Access to Providers $\geqslant$ 3	0.348**	0.498***	0.253***
	(0.144)	(0.181)	(0.027)
	[0.121]	[0.249]	[0.063]
% Households with Access to Providers $\geqslant$ 4	0.446***	0.560***	0.317***
	(0.129)	(0.135)	(0.032)
	[0.199]	[0.312]	[0.100]
% Households with Access to Providers $\geqslant$ 5	0.409***	0.578***	0.347***
	(0.141)	(0.117)	(0.032)
	[0.168]	[0.327]	[0.121]
% Households with Access to Providers $\geqslant$ 6	0.380***	0.442***	0.309***
	(0.122)	(0.124)	(0.031)
	[0.145]	[0.187]	[0.096]
B. Details and Statistics			
N	51	50	29,130
Unit of Analysis	State	State	Town

Each cell represents a different regression. Each row of columns (1) - (3) reports the coefficient on the variable listed, the standard error in (), and the R^2 in [] from the univariate regression of the form $I_s^* = \theta + \delta I_i + \nu_i$ with standard errors robust to heteroskedasticity in columns (1)-(2) and clustered at the state level in column (3). Both I_i^* and I_i are standardized such that δ represents the effect of a one standard deviation increase in penetration. The dependent variable in column (1) is the fraction of homes in a state with internet access at home as measured by the CPS. The dependent variable in column (2) is the per capita number of eBay purchases in the state measured by Einav et al. (2014). In column (3) the dependent variable is local internet usage, which is constructed in section A.1.4. ***99%, **95%, *90%

Table A.2: Correlation of Providers and Prices

A. Specification				Placebo
Internet Penetration Variable:	(1) Residential Providers	(2) Total Providers	(3) $\geq$ 4 Providers	(4) Mobile Providers
No Controls	-0.577***	-0.161**	-2.730***	-0.168
	(0.200)	(0.076)	(0.257)	(0.312)
	[0.050]	[0.048]	[0.026]	[0.004]
Control for ln(population)	-0.485**	-0.143	-2.128***	0.198
	(0.198)	(0.155)	(0.472)	(0.410)
	[0.070]	[0.048]	[0.052]	[0.040]
Control for ln(population), demographics	-0.383*	-0.200	-2.106***	0.216
	(0.207)	(0.155)	(0.606)	(0.376)
	[0.093]	[0.095]	[0.089]	[0.078]
B. Details and Statistics				
N	94	94	94	94
Unit of Analysis	Locality	Locality	Locality	Locality
Average Price in 2007	$15.27	$15.27	$15.27	$15.27

Each cell represents a different regression. Standard errors are in ( ) and the R^2 in [ ]. Each row adds various controls. Each cell reports the coefficient on the variable listed in the column heading, the standard error and the R^2 from a town level regression of the form $\varphi_i = a + bI_i + \nu_i$ with robust standard errors. The price of internet services excluding government taxes is φ_i per month and I_i is internet penetration. Column (1) uses the number of residential providers and column (2) uses the number of residential and commercial providers. Column (3) uses the percent of households with access to four or more providers. As a placebo test, column (4) uses the number of cell phone providers. The average monthly price in 2007 is given in the last row of the table. ***99%, **95%, *90%