Personal Income Taxes and Labor Downskilling: Evidence from 27 Million Job Postings*

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Abstract

Using big data on the near-universe of US firms' job postings, we document measurable, negative effects of local personal income taxes on the level of education, experience, and technological skills required by firms when hiring workers (downskilling). Tax-induced downskilling is identified both at the county level and at individual firms' local establishments. It is driven by changes in high-income earners' taxes. Multi-state firms internally reassign their hiring of low- *vs.* high-quality workers according to local personal income tax changes. This dynamic is more pronounced in industries that rely less on highly skilled labor and on local resources in their production processes, yet mitigated in firms' headquarter states and states that account for a large fraction of sales and employment. Firms also cut IT investment and eventually exit states that increase personal taxes. Our findings point to a "brain-drain" in states with high personal income taxes, showing how taxes bear detrimental effects to the skill composition of local labor markets.

KEYWORDS: State personal income taxes, Skilled labor, Human capital, Firm organizational form
JEL CLASSIFICATION: E24, J23, G31, H24

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1 Introduction

Personal income taxes are a major source of revenue for state and local governments in the United States, accounting for nearly 30% of their total annual tax collection. Personal taxes vary widely across jurisdictions and over time, with state and local tax authorities showing little to no ability to coordinate their policies. This issue came to the forefront of economic debate during the 2008-9 crisis, when local governments increased personal tax rates to cover budgetary deficits that did not qualify for federal assistance.[1] Increases in local personal taxes may carry a number of distortionary consequences. Critically, personal taxes insert a wedge between the level of compensation paid by employers and what is effectively earned by workers. While corporations are able to smooth out the impact of local corporate taxes via operational and accounting measures, workers have limited means to respond to local personal income tax hikes other than curtailing their supply of labor or seeking work elsewhere. The US tax system levies a particularly heavy burden on high-income workers, who generally possess more experience and skills. Personal taxes can shape the local makeup and availability of high-quality workers, affecting firms' ability to tap skilled labor in different labor markets.

This paper examines how personal taxes influence firms' decisions to hire workers across the labor skill spectrum and across different local labor markets. Skilled labor has become a key driver of economic growth in the US (see, e.g., Autor et al. (2003)), yet there is virtually no research on how personal income taxation influence the quality of human capital employed by firms, the composition of the workforce inside corporations, or the profile of skilled workers in a local labor market.[2] Our analysis does so taking advantage of a unique database containing the near-universe of job postings by US corporations over a number of years. For each job ad, the database contains information on the employer, job title, job tasks, location of the position sought, and the date of the posting. It also provides detailed, textured description of the skills required for each particular job. This includes the levels of education required, years of experience, as well as skills necessary to perform the job, such as cognitive ability and software knowledge. The granularity of these data allows us to track how a firm's skill requirements are distributed and evolves over time in a given locality. For firms with operations in

[1] State governments lost $87 billion in tax revenues in 2008-9, the largest loss in history (see www.cbpp.org/research/).

[2] The existing literature on taxation focuses on the quantity of workers employed, overall output, or the movement of physical capital (see, e.g., Ljungqvist and Smolyansky (2016), Giroud and Rauh (2019), Fajgelbaum et al. (2018)).

multiple regions of the country, we can further track their internal decisions regarding the allocation of jobs across different localities, with ultimate consequences for their organizational form.

Our baseline strategy exploits staggered changes in state taxes over time. From 2000 to 2017, there were 250 recorded changes in state personal income tax rates. Following state-level innovations to personal taxation, we trace changes in firms' requirements for labor skill. There are two challenges to drawing inferences on the effect of personal income taxes in this setting. First, local economic conditions may simultaneously drive variation in taxes and firms' need for skilled workers. Second, unobservable firm characteristics may influence their skill hiring choices and their exposure to local taxes. To address the first concern, we sharpen our test strategy by comparing adjacent counties located across state borders. We do so accounting for interstate differences in budgetary deficits, corporate, property and sales taxes, unemployment insurance benefits, and housing prices, among others. Our estimations further impose county-fixed effects and state-border-fixed effects to absorb innate differences across neighboring locations. To address the second concern, we compare job postings of the same firm across different tax jurisdictions during the same time period. Our specifications include interactive firm-year-fixed effects absorbing firm dynamics that could affect inferences.

To start, we put together county-level information on labor force, employment, and earnings from the Quarterly Workforce Indicators (QWI) and the Bureau of Labor Statistics (BLS). Using this information, we design a test that compares counties within a narrow geographical bandwidth near a state border, whereby one state experiences a change in personal income taxes while the other does not. This methodology resembles a regression discontinuity design (RDD) because business conditions are likely to change smoothly across state borders while tax policies change discontinuously. It allows us to minimize confounding effects of local-specific economic conditions by drawing inferences from counties that are spatially close and share identical characteristics (geography, climate, economic activities, population, and workforce makeup). Compared to neighboring counties across shared state lines, counties located in states experiencing increases in personal income tax rates observe a measurable deterioration of labor market conditions over time. To wit, a 1% increase in the average personal income taxes is associated with a 0.8% decline in local, county-level total labor force, a decline of 1.1% in the number of workers employed, and an increase of 0.3% in unemployment rate in the following year. Workers employed in affected counties also make 1% less in pre-tax earnings per payroll in the year following the personal tax increase.

The above empirical patterns are useful in framing the argument that higher state personal income taxes are detrimental to workers as they reduce local employment and depress local wages. Critically, however, that evidence does not shed light on whether personal taxes alter the *quality* and *types of jobs* in the local economy. We investigate this issue by looking into skill requirements contained in firms' job postings across the various locations they operate over time. This analysis is revealing as employers must post ads offering market-specific, competitive packages for different skill levels in order to attract workers available in a local labor market at a given point in time. In doing so, they must take into account the local supply of labor as well as the demand coming from other local employers, publishing job offers that are sensitive to the prevailing local labor market conditions. Those job ads contain information about the feasible demand for workers across different skill levels in a given local market at a particular time.[3]

We examine five aspects of skill requirements, measured by the percentage of job postings containing related specifications. First, we consider the education that a worker is required to have to fill a position. Second, we look into the previous experience that a worker must have. Third, we examine the level of cognitive skills required to perform the job, which include decision-making ability and analytical skills. Fourth, we take into account whether a job posting requires the ability to use computer software, including programming. Finally, we include the ability to operate a computer.

We document a strong, negative relation between personal income taxes and the level of skills required in local job vacancy postings. Compared to adjacent cross-border counties, companies in counties that experience significant personal tax rate increases seek to hire new workers with less education and experience. Our estimates suggest that a 1% increase in personal income taxes leads to a 1.4 (2)-percentage-point drop in the job postings with education (experience) requirements.Firms also reduce their requirements for cognitive skills and workers' ability to use computer software. Our results are new in showing a pronounced "downskilling" effect associated with hikes in state-level personal income taxes. All of our estimations feature the inclusion of state-border-fixed effects, county-fixed effects, and year-fixed effects, suggesting that our inferences are not driven by local characteris-

[3] We showcase the information content of our data in Section 2, where we document a strong county-level relation between the educational requirements contained in job ads data and US Census data on local workers' educational levels.

tics or concurrent economic conditions.

Next, we investigate whether firms actively reallocate their requirements for labor skill across geographical regions as a function of local taxes. To do so, we compare the skill requirements contained in job ads posted by the same firm across different counties at the same point in time. This test setup helps us track the *within-firm* allocation of skilled labor hiring in relation to personal tax changes. Our analysis shows that firms reduce their requirements for skilled labor in states that increase their personal tax rates. When a state increases its personal income taxes by 1%, firms reduce their requirements for education and experience by 1.2-percentage point in the job ads they post in that state relative to ads they post in other states. Firms also post fewer job ads that require cognitive and software skills. Notably, the effects of personal income taxes on firms' skill requirements are driven by tax rates imposed on high-income earners; income brackets that apply to highly educated and highly skilled workers. Tax rate changes concerning low-income brackets, in contrast, do not drive variation in skill requirements.

We study heterogeneity in firms' responses to personal income tax changes to shed light on the economic channels underlying companies' decisions to reallocate their requirements for skilled labor. We first examine whether industries that rely more on skilled labor in their production processes are less responsive to local tax policy changes. We measure an industry's dependence on skilled labor in two ways. First, we consider an industry as "skill-dependent" if it posts a greater percentage of jobs requiring bachelor's degrees and above. Our second measure is based on the percentage of employees in an industry that work in high-skill jobs, as classified by the BLS and the Department of Labor's O*NET program. Across both definitions, we find that firms in skill-dependent industries reduce their requirements for skilled labor when facing high personal income taxes to a lesser extent than do firms in other industries. This documented heterogeneity is important in showing that there are significant replacement costs (or "stickiness") associated with high-skill labor. Firms that face greater costs of replacing skilled workers resist changing their hiring practices despite cross-state differences in personal taxes.

We also explore cross-sectional variation in firms' operational flexibility to reallocate skilled workers. We first compare the interplay between local taxes and hiring across "footloose" and "non-footloose" industries (see Ellison and Glaeser (1997)). Footloose industries are industries with geographically dispersed activities, whose main physical operations can be easily transferred across different locations. We find that firms operating in those industries exhibit a greater response to personal tax hikes by drastically decreasing their requirements for education, experience, cognitive, and technology skills. Job ads that seek workers with higher skills are posted, in contrasts, in low-tax states. We also consider other organizational features that may present frictions in the reallocation of skilled labor inside a firm. In particular, we examine firms' hiring polices in states that generate a large share of their sales and states that house their headquarters ("important states"). We find that firms do not move high-skill jobs out of important states as much as they do in other states. Our investigation reveals a number of operational, geographical, and organizational constraints that firms face in reallocating skilled jobs in response to tax changes.

If firms shift their search for skilled workers away from high-tax states, it is natural to ask whether they also withdraw from technological upgrades in those states (see Autor et al. (2003)). To test this conjecture, we look into firms' local investment in information technology (IT). Tracking firms' IT investment across different personal tax regimes is particularly important in unveiling the degree to which technology interacts with human capital attributes in the production process. We obtain information on establishment-level IT investment from the Ci Technology Database (CiTDB). The CiTDB database reports the quantities and types of IT investment conducted by US business entities in each of their establishments over time, providing the most detailed and up-to-date information on this front (see Bloom et al. (2012) and Zhang (2019)). Our tests show that higher local personal taxes reduce firms' budgets across all of their local IT expenditures; including computer software and hardware, telecommunication services, and other IT-related services. Our results show significant complementarity between investment in technology and high-skill labor. Such complementarity seems to amplify the distortionary effects of local taxes: they not only reduce the employment of high-quality human capital, but also hinder the technological development of local establishments.

Finally, we assess the impact of personal taxes on firms' decisions to exit and enter different local markets. To do so, we first use aggregate information on the number of establishments in a county from the US Census. Our results suggest that higher personal taxes lead to a reduction in the number of local establishments. Similar patterns persist for public, multi-state firms. An increase in local personal taxes is associated with a greater likelihood that firms permanently close their establishments and a lower likelihood that firms open new establishments in a local market. Our findings substantiate the argument that high personal income taxes inhibit firm entry and trigger firm exit, carrying lasting detrimental effects to a state's business environment.

In the last step of our analysis, we conduct a host of robustness tests to ensure that our findings are not sensitive to a specific choice of measurement, sampling, or testing design. To start, we show how local firms' skill requirements respond to personal taxes that apply to earners at various points of the income distribution, ranging from the median to the 99.5^{th} percentile income level. The effects of personal taxes strengthen at higher income levels, consistent with the argument that local taxes affect skilled workers rather than unskilled workers. We further verify that our results persist if we remove cyclical and counter-cyclical tax changes, if we focus on only industries whose operations are less dependent on local demand (tradables), or if we sample on localities that share the same geo-economic features and political leanings. In addition, we vary the geographical bandwidth choice in our adjacent county and also account for locale-specific considerations such as reciprocal tax agreements across states. While our results obtain through the battery of robustness analyses described above, we note that our study faces limitations worth highlighting up front. For example, our dataset does not contain well-populated wage information. We also do not observe individual workers' migration across states or whether they curtail labor supply. These limitations prevent us from making statements about general equilibrium conditions of the labor market or the economy as a whole.

Prior literature has looked at the overall impact of state-level taxes on total employment, investment, and innovation (examples include Gale et al. (2015), Ljungqvist and Smolyansky (2016), Akcigit et al. (2018), Mukherjee et al. (2017)). Existing studies generally consider aggregate counts and quantities, offering limited granular insight on firms' local-level decisions.[4] Differently from other studies, we gauge firms' demand for labor skill by using employers' own descriptions of the type of workers they seek to recruit and the specific skills or credentials they require. Our findings are particularly more textured in showing that firms recruit more skilled workers in low-tax states in lieu of recruiting those workers in high-tax states, leading to a "brain drain" effect in high-tax states. Firms concurrently invest fewer resources in information technology in high-tax states and even exit altogether.

[4]Recent work by Giroud and Rauh (2019) shows that higher state-level taxes lead to firms shifting their aggregate employment and investment to low-tax states.

Our study thus shows that higher personal income taxes not only reduce the quantity of local employment, but also disproportionately drive out high-quality jobs and technology, both of which are increasingly important in sustaining economic growth. The brain-drain effect we document uncovers a novel, unintended tax policy outcome that has not been examined in the literature.

A related literature examines whether personal income taxes affect the employment decisions of highly achieved individuals (Young and Varner (2011), Cohen et al. (2015), and Moretti and Wilson (2017)). Moretti and Wilson, in particular, document a net migration of "star scientists" in response to state tax changes. Their work focuses on how these individuals move across places, but provides no information about the firms or institutions they work for. Our analysis, in contrast, considers the tax-induced changes in firms' demand for labor across the entire skill spectrum; not only at the very top. Our study thus provides for a more comprehensive description of the makeup of the US labor force. It is also unique in shedding light on the organization of the internal labor market within a firm. There has been a marked increase in the proportion of skilled labor in the US workforce since the 1980s (see Autor and Dorn (2013) and Goos et al. (2014)). The trend towards upskilling and job polarization became pronounced following the 2008-9 crisis (Jaimovich and Siu (2014)). Hershbein and Kahn (2018) highlight the role of firms in reshaping the labor force in post-recession periods, stating that recessions help firms overcome frictions against upgrading technologies ("creative destruction"). We add to this line of research by showing that firms reallocate their demand for skilled workers differentially across regions of the US according to taxes imposed locally on high-income workers. In doing so, large (muli-state) corporations amplify potentially distortionary effects of personal income taxes on local economic activity and inequality.

2 Data and Variable Definition

2.1 Data Sources

2.1.1 Job Postings

Our primary data source is a "big data" repository containing US employers' job postings provided by BurningGlass Technologies. BurningGlass gathers information from online job postings via data scraping techniques. These data cover the near-universe of online job postings in 2007, and continuously from 2010 through 2017 (see Hershbein and Kahn (2018)). BurningGlass curates job postings by removing duplicate ads and categorizing job descriptions using standardized occupation and skill families (such as O*NET job codes and Standard Occupational Classification (SOC) families). The database includes unique identifiers for each job posting, occupation, industry (organized by NAICS), and geography (county and MSA). It also contains the name of the employer posting the job.

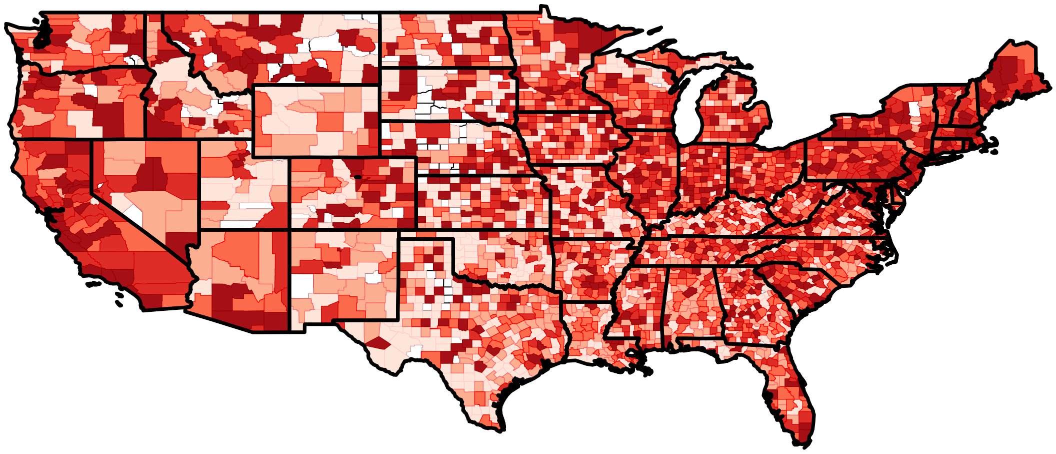
The most distinctive feature of the BurningGlass database is that it provides a detailed description of skill requirements listed in a job vacancy ad. This includes credentials such as the education required to perform the job. It also includes the level of experience required in the same or a similar line of work. Notably, it features textual descriptions of the qualitative skills and abilities for each individual job posting. The rich skill description distinguishes these data from other data sources on job openings, such as the Job Openings and Labor Turnover Survey (JOLTS) provided by the Bureau of Labor Statistics (BLS), which is based on a survey sample of stratified establishments and focuses on the quantity of job openings.

For our baseline analysis, we remove all postings by public sector entities, such as schools and local and federal governments. We also remove postings with missing information on ultimate employer identity and job location, mainly from recruiters' websites which typically do not reveal the employers. We later match BurningGlass employers to Compustat firms based on employer names. This effort is crucial because it allows us to estimate the role of publicly listed firms in shifting skilled workers across different geographical areas of the country. Our matching involves several steps. First, we run a name-matching algorithm to Compustat firms. In some cases, an employer is a subsidiary of a Compustat firm but its name is distinct from its parent, thus the algorithm cannot recognize their connection. To resolve this issue, we match the remaining employer to the subsidiaries of Compustat firms using information extracted from historical Orbis data provided by Bureau van Dijk (BvD). Orbis traces the evolution of firms' organizational structure through time, maintaining the parent–subsidiary correspondence. This historical information is robust to subsidiary opening, closing, and ownership changes, which is crucial for accurate matching. After each round of matching, we manually go through the links identified to ensure the accuracy of our matching. Our final matched sample includes 3,640 nonfinancial firms and 21,350 firm-year observations. Firms in our sample posted about 27 million job vacancy ads.

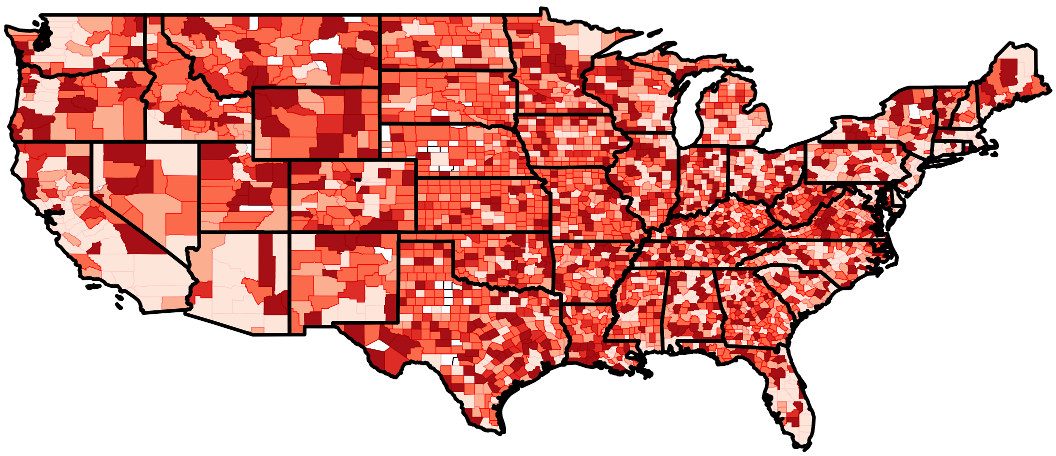
We examine various measures of skill requirements as described in firms' job postings. We follow Hershbein and Kahn (2018) and consider the percentage of job postings with explicit education requirements (*Education*), experience requirements (*Experience*), as well as cognitive skills (*Cognitive*). We also consider the percentage of postings requiring computer skills, either specific software knowledge (*Software*) or the ability to operate a computer (*IT*). *Education* is the most common measure of skill and sophistication of a worker. On-the-job experience is also an important aspect of worker skill, which is accumulated through prior employment. Cognitive ability refers to a worker's ability in terms of decision making, mathematics, research, and analytical skills. Those skills are needed in jobs involving model building, data analytics, management, and so forth. Software requirements range from common software, such as Microsoft Office, to programming languages such as Java and Python. Software knowledge aligns with the increasing adoption of information technology in all lines of careers in recent decades and indicates whether a worker can match up to firms' technology upgrades. Finally, IT skills refer to requirements that a worker should know how to use a computer or should be familiar with certain software package.

Figure 1 depicts the distribution of education required in job postings across all US counties. Panel A uses the first part of our sample (2010–2013) to illustrate the average percentage of job postings that required a degree that is bachelor level or above. The color scheme divides the spectrum of education requirements into deciles, with darker (lighter) colors indicating higher (lower) percentages. The black lines sketch out state borders. Firms' requirements for high-skill labor in the beginning of the decade was concentrated in states located on the East and West Coasts, such as California, New York, and Massachusetts. There were a few states in the Midwest with high skill requirements as well; namely, Minnesota, Illinois, Indiana, and Michigan. Together with Texas, Mountain states such as Wyoming, Colorado, and Utah were among the lowest-ranked in terms of high-education job ads.

Panel B shows the changes in required job skills in the second half of our sample window (2014–2017), proxied by the percentage of job postings requiring bachelor's degrees and above in each county. This later panel suggests a "reversal" in education requirements from pre-2014 levels, with coastal states fading in color at the same time that central states pick up on those requirements. The correlation between a county's pre-2014 average requirement for bachelor and above degrees and its post-



(A) Bachelor and Above Job Requirements, 2010–2013



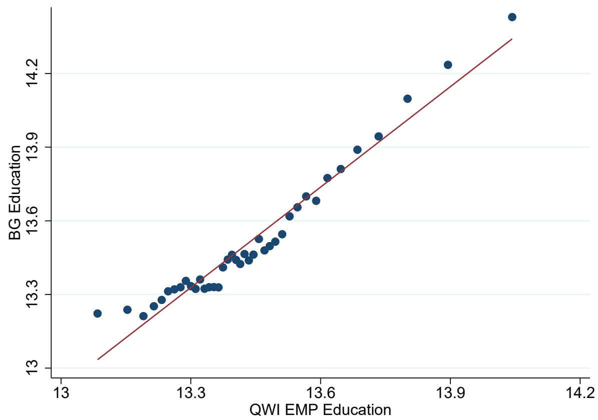
(B) Growth in Bachelor and Above Job Requirements, 2014–2017

Figure 1. Education Requirements for Jobs Posted across US Counties. This figure depicts the distribution of education requirements of job vacancies posted in each US county and its changes over time. Panel A shows the percentage of job postings requiring bachelor's degrees and above in each county during 2010–2013. Panel B shows the cumulative changes in the percentage of jobs requiring bachelor's degrees and above during 2014–2017. Darker colors in Panels A and B indicate greater percentages of postings with high education requirements. The darkest (lightest) shade indicates that a county is in the top (bottom) decile of bachelor- or graduate-degree jobs among all US counties.

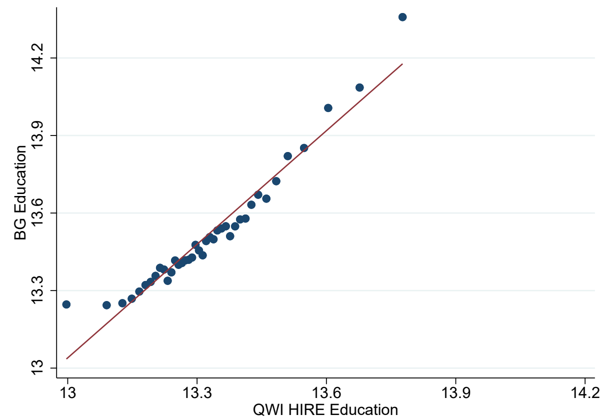
2014 change in that requirement is –0.25. This reversal is consistent with recent narrative suggesting that talented workers and firms are fleeing high-tax states, such as California and New York, towards low-tax states like Texas, Colorado, and Utah (see Rauh and Shyu (2019)).[5]

While the BurningGlass data reflect firms' published requirements for local labor skill, we must verify whether this signal is informative of the skill level of locally targeted workers. Figure 2 shows the correspondence between local firms' requirements for education (based on BurningGlass data) and the education levels of employed workers in the same county (based on QWI data). In Panel A, we

[5] Also see "Bay Area exodus: Here are the companies moving out of California." *San Francisco Business Times*, Oct 2018.



(A) BG Education Requirements and Worker Education



(B) BG Education Requirements and New-Hire Education

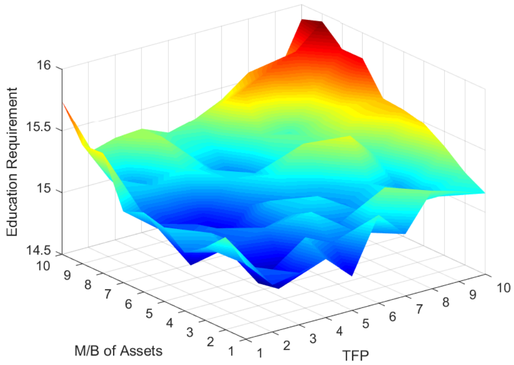
Figure 2. BG Education Requirements and Education Levels of Employed Workers. This figure shows the relation between local firms' posted education requirements and the average education levels of workers employed in the same county. Panel A plots the average education level of all employed workers and Panel B depicts the average education of newly hired workers. The average worker education are computed from QWI data, and information regarding local firms' education requirements comes from BurningGlass data. The dots in each panel represent 40 equal-sized bins based on worker education and the education requirements indicated by local job postings.

examine the average education level of all employed workers, while in Panel B we look at newly hired workers at various education levels. There is a clear, close correspondence between the local requirements for skill and the local employment of skill. Counties in which firms require higher education in their job postings also hire more educated workers. These patterns suggest that the skill requirements portrayed by BurningGlass data provides a reasonable representation of the equilibrium skill content in the targeted local labor markets.

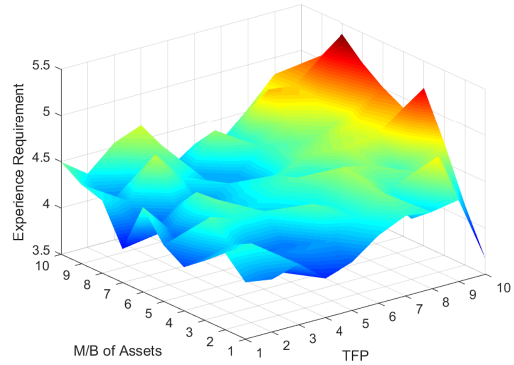
Work on the importance of skilled labor often revolves around the idea that labor skill contributes to firm value and productivity (see, e.g., Moretti (2004) and Acemoglu and Autor (2011)). We look at this connection in our data by depicting the association between firms' skill requirements in job ads, firm productivity, and market valuation. Figure 3 describes the relevant correlation patterns. We use the market-to-book ratio of firm assets (*M/B of Assets*) as a measure of firm value, and use total factor productivity (*TFP*) and the number of patents filed (*Patents Filed*) as proxies for firm productivity. If high-quality human capital is an important input, we should expect high-skill hires to be concentrated in firms that are more productive and highly valued by the market.

Panel A (alternatively, C) reports the association between firms' requirements of years of education, total factor productivity (patents filed), and firm value.[6] Panel B (D) looks at the same asso-

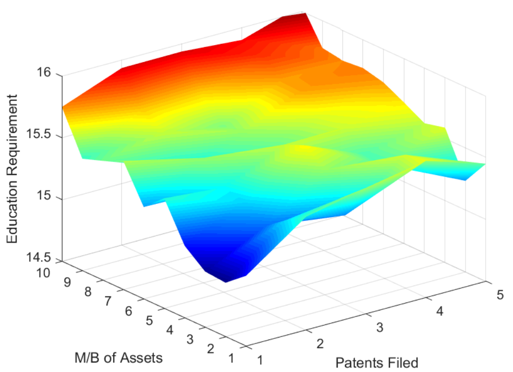
[6] We thank Xuan Tian and Yifei Mao for sharing data on firms' patent filings.



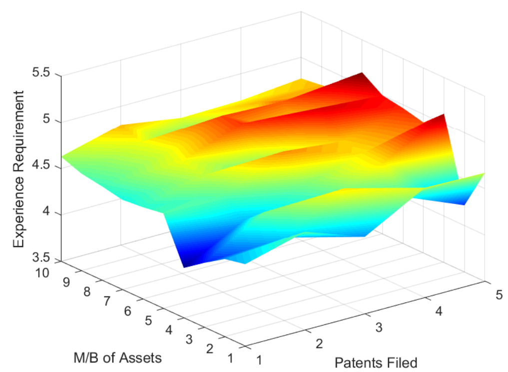
(A) Worker Education, Firm Productivity, and Value



(B) Worker Experience, Firm Productivity, and Value



(C) Worker Education, Firm Innovation, and Value



(D) Worker Experience, Firm Innovation, and Value

Figure 3. Skilled Hiring, Firm Productivity, and Value. This figure shows the correlation between skill requirements, firm productivity, and firm value. Both education and experience requirements are reported in years. Panels A and B use total factor productivity (*TFP*) as a proxy for productivity and Panels C and D use the number of patents filed (*Patents Filed*) each year as a measure of productivity. Firm value is proxied by the market-to-book ratio of total assets (*M/B*). In each panel, the axis extending to the left indicates deciles of firm value, the axis extending to the right represents deciles of *TFP* or five groups of *Patents Filed*, and the axis pointing up shows firms' skill requirements. The surface indicates the level of education or experience required by firms with associated levels of productivity and value, with colors towards the red spectrum representing higher skill requirements.

ciation while examining firms' requirements for worker year of experience. In each panel, the axis extending to the left indicates deciles of firm value, the axis pointing to the right represents productivity grids, and the vertical axis shows firms' skill requirements.[7] The surface represents the level of education or experience required by firms with associated levels of productivity and valuation ratios. Across all panels, high labor skills are positively associated with both high firm productivity and high firm value. Notably, firms that rank highest according to (both) innovation and valuation metrics re-

[7]We divide firm-year observations into TFP deciles in Panels A and C. In Panels B and D, we divide firms into five groups based on patent filings. Specifically, we assign firms that file only one patent to group 1, firms that file 2–5 patents to group 2, firms that file 6–10 patents to group 3, 11–50 patents to group 4, and above 50 patents to group 5.

cruit the highest-skilled workers. These patterns are consistent with the view that skilled labor is a key element for value creation, particularly in cases where innovation is a major driver of value.

2.1.2 Personal Taxes

The US federal and state governments levy taxes on individuals based on many factors. For the vast majority of workers, labor income is the most important factor determining the personal tax rates they face. Federal taxes follow a progressive system, with current marginal tax rates varying from 10% to 37% of taxable income. State income taxes, on the other hand, vary widely across jurisdictions. The majority of the US states impose progressive tax rates, with California charging the highest tax on top earners, followed closely by Minnesota, Oregon, and New Jersey. Nine states, including Washington, Florida, and Texas, do not tax individual incomes. Eight states, such as Colorado, Illinois, and Indiana, maintain a flat tax rate across all income levels. Individuals filing itemized deductions in their tax forms can claim a deduction of state and local taxes (SALT) towards their federal income tax obligations. Top earners tend to benefit more from SALT than standard deductions. However, these same individuals are often hit with alternative minimum tax (AMT), which limits their ability to offset the impact of local personal income taxes.

We rely on the TaxSim program provided by the NBER to calculate the effective total average tax rates faced by tax payers, calculated as the sum of state and federal taxes divided by gross income. TaxSim calculates federal and state taxes for given income levels in a state-year using the specifics of state and federal tax codes, accounting for factors such as mortgage interest deductions, dividend income, the cross-deduction between federal- and state-level taxes, among other factors. While state statutory tax rates mainly drive the variation in the total average tax rate, our measure takes into consideration the many complex interactions between state and federal taxes. In other words, the total average tax rate captures the entire tax burden that workers face in choosing between jobs at different locations and jobs paying different wages.

To pin down the relevant income level for our study, we gather income data from the World Inequality Database (WID). This database tracks the wage income and capital gains of individuals ranking at a certain percentage of the US population over time. According to this database, individuals at the 90^{th} percentile earned an annual wage of around $101,315 in 2017, while individuals at the 10^{th}

percentile level made about \$5,548. The income distribution becomes highly skewed as we approach the right tail, with individuals ranking at the 99.9^{th} percentile making above \$1.1 million in wage income. As a baseline, we take that a representative high-skilled individual in our sample ranks at 90^{th} percentile in the income distribution for primary wage earnings and long term capital gains.[8] We assume away other forms of income and associated tax deductions, so that the effective tax rates are directly affected by personal income.[9] In later analyses, we show that our results do not hinge on this particular assumption of the income distribution ranking. Instead, our results are robust to looking at effective tax rates at other percentiles of income levels.

Aside from personal taxes, we also obtain information on state corporate income taxes, state sales taxes, and local property taxes over time. State and local governments collect over 26% of their aggregate revenues from personal income taxes, while only 4% come from corporate income taxes.[10]

There is a large degree of heterogeneity across states regarding the relative importance of personal taxes and corporate taxes. Figure 4 uses ten states as examples illustrating such heterogeneity. The top row considers five states in coastal areas, while the bottom row refers to five interior states (South, Midwest, and Mountain states). Coastal states generally source a greater fraction of their revenues from personal income taxes. Notably, personal income tax revenues account for 63% of total revenue for New York state, 47% for California, and 70% for Oregon. Corporate income taxes, on the other hand, only account for 11%, 8%, and 5%, respectively in those states. In interior states, in contrast, personal taxes are less dominant in local governments' income streams. They constitute 38% of Montana's total tax revenue, 38% for Iowa, and 33% for Alabama. In Florida and Tennessee, personal taxes account for less than 1% of total tax revenue.

Figure 5 tracks changes in personal income taxes over time and contrasts them against changes in corporate taxes. Panel A shows the number of states that change personal or corporate income

[8]Based on aggregate data from BG, workers in positions such as software engineer, project manager, and pharmacist have annual salaries around \$100,000, while positions such as supervisors, technicians, and IT support staff offer annual salaries of around \$50,000.

[9]We follow Moretti and Wilson (2018) and make the following assumptions: the taxpayer is a married joint filer, had zero dependent exemptions, zero childcare expenses, no other sources of income, and zero itemized deductions other than the deduction for state income tax payments calculated by TaxSim.

[10]Corporate income taxes and sales taxes are obtained from the University of Michigan tax database, the tax foundation, and the Book of the States. Property tax data come from the US Census American Community Survey. We exclude the following state-year observations due to regime changes related to nonstandard forms of corporate taxation under which taxes are measured by gross receipts on business activities: Ohio after 2005, Texas after 2007, Michigan prior to 2012, and Nevada after 2015.

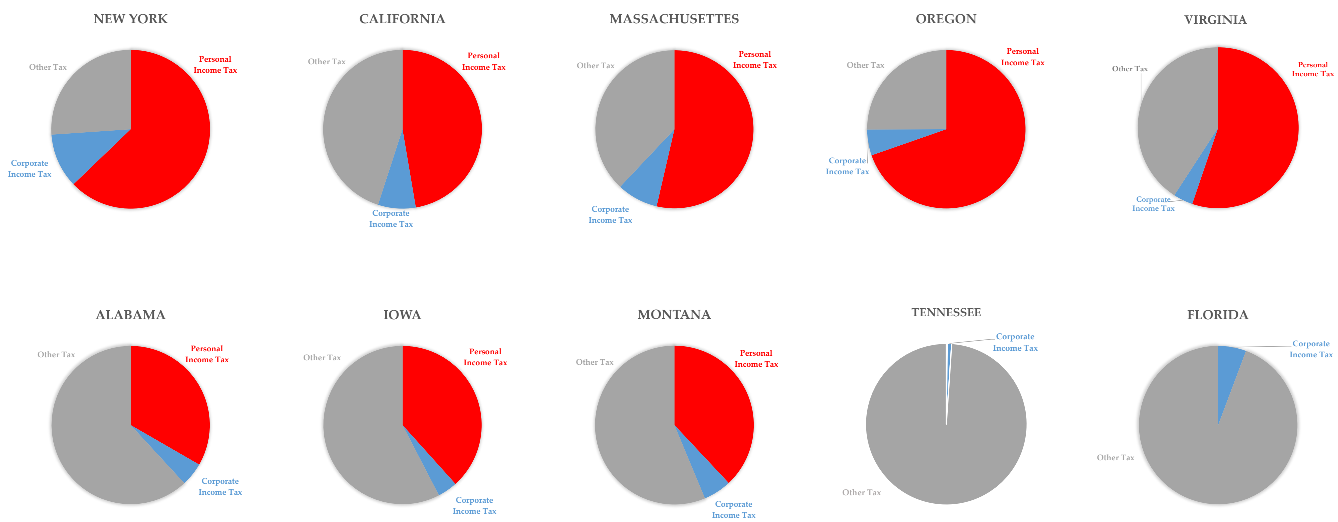


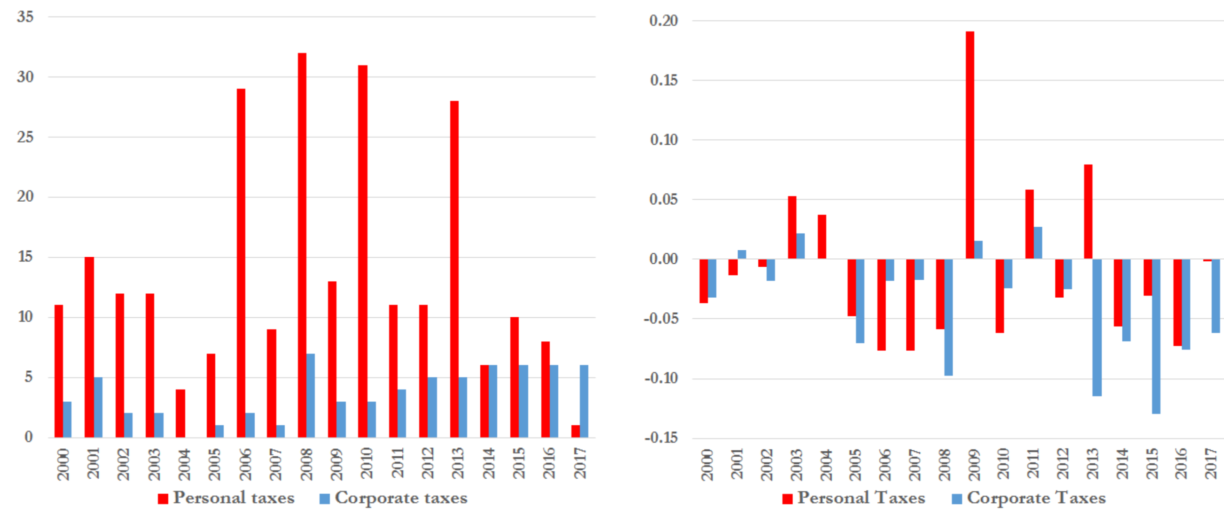
Figure 4. Breakdown of State Governments Tax Revenues. This figure shows the relative importance of personal and corporate income taxes for state governments' revenues. The shares of tax revenues are averages over 2000–2017. Data source: US Census Bureau.

taxes in a given year, while Panel B shows the average percentage change in each type of tax across all states. In each panel, red columns represent changes in personal taxes while blue columns represent changes in corporate taxes. The figure makes it clear that state governments change personal taxes far more frequently than they do corporate taxes. In 2006, 2008, and 2010 alone, around 30 states altered their personal tax rates. Corporate income taxes, on the other hand, have remained quite steady: only two states changed their corporate taxes in 2006, seven in 2008, and three in 2010. Personal taxes suffered the largest hikes following the 2008-9 financial crisis, with the average state increasing its personal income tax rate by nearly 0.2% (corporate taxes only registered minimal increases).[11] The rich variation of personal income taxes across states and over time provides an ideal setting for us to study the effect of such taxes on firm hiring policies.

2.1.3 IT Investment

We gather information on firms' investment in technology from the Ci Technology Database (CiTDB), a proprietary database that collects the quantities and types of technology investment conducted by US firms at the establishment level. This database contains information on several dimensions of

[11] Changes in personal taxes are generally *not* accompanied by concurrent changes in corporate taxes. During the 2000–2017 period, only 10% of personal income tax changes were accompanied by corporate income tax changes.



(A) Number of States with Tax Changes (B) Average Tax Changes (%)

Figure 5. State Changes in Personal and Corporate Income Taxes over Time. This figure shows the variation in personal and corporate income tax rates during the period of 2010–2017. Panel A presents the number of states with tax changes and Panel B presents the average tax changes across states.

firms' IT investment, including their acquisition of computers and detailed budgetary items such as those allocated for hardware, telecommunication, and other devices. It also contains firm identity together with the location and time of IT investment.

CiTDB provides the most comprehensive coverage on IT investments to date, and has been used in academic studies on US firms' policies to upgrade or adopt technology.[12] We examine a host of detailed budgetary items that firms allocate in each of their establishments, including the budget for personal computers (*PC Budget*), hardware devices (*Hardware Budget*), telecommunication services (*Comm. Budget*), and servers (*Server Budget*). All variables are calculated on a per-employee basis.

2.1.4 Other Data Sources

We draw data on county- and state-level macroeconomic variables such as labor force, unemployment rate, and average earnings from the BLS and the QWI published by the Census Bureau. In our base tests, we use as dependent variables the log of total labor force in a given county (*Labor Force*), the log number of workers that are locally employed (*Employed Workers*), and the log of monthly average earnings (*Average Earnings*). We present the local unemployment rate (*Unemployment Rate*) in percentage points.

[12]We thank Miao Ben Zhang for sharing the link between CiTDB and Compustat.

We collect control variables from multiple sources. State-level GDP data come from the Bureau of Economic Analysis (BEA), while unemployment insurance information comes from the Department of Labor. We also obtain county-level Home Price Index (HPI) from the Federal Housing Finance Agency (FHFA). State budgetary surplus is compiled by the Institute for Public Policy and Social Research (IPPSR). Lastly, we gather information on facility-specific location, employment, and sales from the National Establishment Time-Series (NETS) database produced by Walls & Associates. We supplement this database with the Census County Business Patterns (CBP), which provides information on the number of establishments at the county level. This information is used to compute the geographical concentration of an industry as well as firms' exit and entry decisions. A comprehensive description of our variable definitions and data sources is provided in Appendix A.

2.2 Summary Statistics

Table 1 presents summary statistics for the main variables in our analyses. Panel A shows statistics for all the tax variables, among which our key variable of interest is *Personal Taxes*. All tax variables are presented in percentage terms. Personal income taxes have an average level of 18.6% and a standard deviation of 3.8%.

TABLE 1 ABOUT HERE

Panel B presents statistics for our county-level data. The counties in our sample have an average labor force of 47,000 individuals, with 45,000 of them currently employed (the average unemployment rate is 6%). The average payroll in the sample is about $1,750 per month. At the county level, 42% of BurningGlass job postings contain education requirements; 36% contain experience requirements. Employers in an average county also post 19% (18%) jobs that require cognitive (IT) skills.

Panel C reports summary statistics for variables used in tests performed over public firm data. The unit of observation is at the firm-county-year level. The public firm sample has similar statistics as the county sample in terms of education and cognitive skill requirements. The two samples differ slightly in other dimensions. For example, job ads posted by publicly listed firms are more likely to require software knowledge and ask for more on-the-job experience.

3 Empirical Methodology

There are two major challenges in identifying the effects of state-level tax rates on firm behavior. First, tax codes do not change randomly; state-level adjustments to tax rates are often associated with local economic circumstances. Second, corporate responses to tax changes across states may be confounded by firm characteristics, such as profitability, size, and asset mix. We use two empirical strategies to address these challenges.

Our first empirical design exploits variation in tax rates and labor market conditions in contiguous counties located alongside, but across a state border (see Heider and Ljungqvist (2015) and Ljungqvist and Molyansky (2016)). In particular, we sample on counties located within a certain bandwidth of a shared state border, whereby one side of the border experiences a change in personal taxes while the other side does not. By limiting the sample to counties that are in such close geographical proximity, we increase the likelihood that we are comparing areas with similar underlying demographics and economic conditions. In this setting, our testing sample is a state-border-county-year panel.

While there is no consensus on what is a "close" geographical proximity around state borders, we experiment with various choices, each balancing the standard trade-off between bias and precision. In our main analysis, we keep counties within an 80-mile bandwidth on each side of a given border, as 80 miles is the cutoff for the bottom tercile of US counties' distance to a state border. Figure 6 illustrates our methodology using state-level statutory changes in personal tax rates in 2013. Red and blue indicate our "treatment" counties, with red (blue) indicating counties located inside states that experience increases (decreases) in personal taxes. Counties in gray are the associated "control" counties.

In later analyses, we vary the sample selection criteria in several ways. For example, we limit the population or business establishments on each side of the border to rule out scenarios that the counties in our treatment and control groups differ substantially even if they are geographically close. We also narrow the geographical bandwidth to 50 miles to a state border. Finally, we adopt a county-pair design, selecting only counties located next to a state border and pairing each of these counties with an adjacent county on the opposite side of the border. By comparing within two neighboring counties across two states, our analysis reveals the incremental impact of state personal taxes beyond other economic conditions that are arguably similar in those two counties. We later show that our results

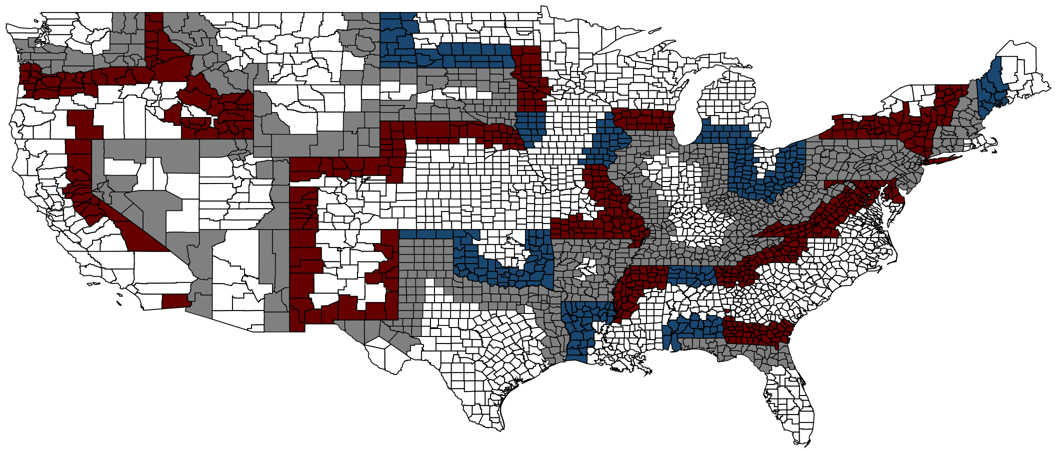


Figure 6. Illustration of Contiguous County Test. This figure illustrates the empirical strategy that focuses on counties near state borders using state-level statutory changes in personal income tax rates for tax year 2013. Red (blue) shades indicate states with increases (decreases) in personal tax rates (treatment states) and gray shades indicate states that are adjacent to treatment states without any changes in personal taxes (control states). Only counties whose centroids are within 80 miles to a treatment state border are shaded.

are robust to all of such alternative choices.

In our county-level analysis, we estimate the following regression specification:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}. \tag{1}$$

In Eq. (1), $Y \in \{$*Education, Experience, Cognitive, Software, IT*$\}$, c represents a county, b represents a state border, and t represents the year of observation. $Personal\ Taxes_{c,t-1}$ is the personal income tax rate in the state of county c in year $t-1$. The specification features controls for county- (γ_c), border- (λ_b), and census division-year-fixed effects ($\tau_{d,t}$). County-fixed effects demean the dependent and independent variables by county, allowing us to make inferences regarding *in-county* time series variation in personal taxes, employment outcomes, and the requirements for labor skill. Controlling for border-fixed effects further helps focus the comparison between treatment and control counties that lie around a certain state-pair border, instead of comparing those that are not located in adjacent states. Finally, controlling for census division-year-fixed effects helps remove regional-economy dynamics that could affect local business conditions and tax policy decisions. *Controls* includes corporate taxes and sales taxes in the same state, property taxes in the same county, the log of state GDP, state government budget surplus as a proportion of state GDP, state unemployment insurance, and the total number of tax incentives in the state.[13] It also includes the log of housing price index in the

[13]The unemployment insurance system provides temporary income maintenance for unemployed workers. It affects

county. Standard errors are clustered by county.

Our second empirical design examines *within-firm* allocation of skilled labor across geographical locations (counties and states). This design fixes a public firm-year observation and examines whether the firm posts fewer skilled positions in states that have increased their personal income taxes relative to states that have not. To implement this design, we assemble a firm-county-year panel where each observation is the average of a given skill measure across all job postings listed by firm i in county c in year t. Using this firm-level sample, we estimate the following regression model:

$$Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}. \tag{2}$$

In Eq. (2), $Y \in \{$*Education*, *Experience*, *Cognitive*, *Software*, *IT*$\}$. We control for county- (γ_c) and firm-year-fixed effects ($\eta_{i,t}$). Controlling for firm-year-fixed effects achieves two purposes. First, it allows us to estimate the allocation of skill requirements by the same firms across different geographical locations. Second, it exhausts firms' time-evolving idiosyncratic characteristics, preventing them from contaminating our inferences. As such, β_1 represents the extent to which firms reallocate their requirements for skilled labor from counties with increases in personal income taxes to counties without such changes at a given point in time. Standard errors are clustered at the firm-county level.

4 Main Results

4.1 Taxes and Employment: County-Level Evidence

We first study how personal income taxes influence local labor market conditions using the model specified in Eq. (1). The estimation accounts for state-border-, county-, and year-fixed effects, with counties located within 80 miles of state borders. This test design allows us to interpret the coefficient of personal taxes as the response of local employment to changes in personal income taxes in a given state, compared to contiguous counties in an adjacent state.

Table 2 presents the results. *Personal Taxes* attracts negative and statistically significant coefficients in labor force, employment, and earnings regressions. They also attract a positive and signif-

their future job search and thus local labor supply.

icant coefficient in the unemployment model. The estimates suggest that a 1% increase in personal tax rates is associated with a 0.8% drop in the total labor force of a given county, a decline of 1% in the number of workers employed, an increase of 0.3 percentage points in unemployment rates, and a 1% decline in workers' average earnings. These findings are consistent with personal income taxes having a detrimental impact on local labor markets.

TABLE 2 ABOUT HERE

4.2 Taxes and Firms' Requirements for Skilled Labor

Table 3 presents results pertaining to the impact of local personal income taxes on the requirements for skilled labor at the firm level. In Panel A, we sample contiguous counties located within 80 miles near state borders, aggregating job postings issued by all employers in a given county, including public and private firms. All regressions account for state-border-, county-, and year-fixed effects. We find a strong negative effect of personal income taxes on local skill requirements. Specifically, *Personal Taxes* yields negative coefficients across all of our measures of labor skill. The estimates suggest that a 1% increase in personal taxes is associated with a 1.4 (2)-percentage-point decline in the jobs postings listing education (experience) requirements in a given county. These magnitudes are economically meaningful. The estimated effect on education (experience), for example, accounts for a 3 (5.5)% drop relative to the sample mean. Personal taxes also drive reductions in the requirements for cognitive, software, and IT skills.

TABLE 3 ABOUT HERE

Panel B examines the allocation of skilled labor *within* firms. Specifically, we estimate Eq. (2), which compares the skill requirements of a firm in a high-tax county to the skill requirements of *the same firm in the same year*, but in a low-tax county *anywhere in the US*. Our results point to a significant downskilling effect in this setting. Notably, coefficients for *Personal Taxes* are virtually all negative, being both economically and statistically significant. For example, a 1% increase in personal income taxes leads to a 1.2-percentage-point reduction in the job postings with education and experience requirements. The same income tax increase triggers a comparable reduction in the requirements for cognitive skills and software knowledge. It also elicits higher IT requirements (by 1.8 percentage points). Taken altogether, our results highlight the active role of firms in allocating skilled jobs across states following local personal tax changes. They point to a pronounced "brain drain" effect in high-tax states. Given the importance of skilled labor in propelling economic growth, losing high-skill job posts is likely to generate a persistent, negative impact on the local economy.

4.3 Heterogeneity in Firm Responses

We examine a number of firm- and industry-level characteristics that could presumably mitigate or exacerbate the effect of personal tax hikes on firms' requirements for local labor skill. This examination helps us understand the economic channels underlying firms' decisions to reallocate skilled labor across states in response to local tax policies.

First, we gauge the costs associated with skill reallocation using an industry's dependence on skilled labor that is innate to its production process. If a firm belongs to an industry that depends heavily on local qualified workers, shifting skilled jobs across states can be very costly. Skill dependence is measured in two ways. First, we classify an industry as "skill dependent" if the percentage of jobs requiring bachelor's degrees and above posted by firms in that industry is above the median level across all industries (*Skill Dependent*). Our second measure of skill dependence is the Labor Skill Index (*LSI*) introduced by Ghaly et al. (2017). The BLS and the US Department of Labor's O*NET program classifies occupations into five skill categories. *LSI* is the weighted average of skill content across all occupations that serve the industry. This index ranges between 0 and 5, with higher values indicating that an industry is more dependent on skilled labor. To the extent that searching for skilled workers in a new location can be costly, we expect firms in skill-dependent industries to exhibit more resilience to personal tax hikes.

Next, we examine an industry's flexibility to in reallocating skilled workers using the geographical dispersion of that industry's operations. Specifically, we compare the responses of "footloose" and "non-footloose" industries (cf. Giroud and Rauh (2019)). Footloose industries refer to industries that are geographically dispersed. Such industries are likely to rely less on any particular local resources and face lower costs to reallocate their operations. For each industry i, we construct a footloose index, *Footloose*, as $1-\sum_s |P_{i,s}-P_s|$, where $P_{i,s}$ is the share of industry i's operations in state s relative to the entirety of its operations. P_s denotes the share of business operations that take place in state s relative to the national sum. Industry operations are defined based on both employee counts (*Employment*) and the number of establishments (*Establishment*). An industry whose operations are geographically concentrated has a high deviation from the national distribution, P_s, thus a low footloose index (non-footloose industry).[14] Low footloose industries are more dependent on local resources and may exhibit a more muted response to personal taxes by reallocating skilled labor to a lesser extent.

Finally, we look into dimensions of corporate organizational structure that might create frictions for the reallocation of skilled workers. Specifically, we consider a firm's differential sensitivity to personal income taxes in economically relevant states as well as its headquarter state (*HQ State*). The economic relevance of a state for a firm's operation is defined by the percentage of sales that the firm generates in that state relative to its total sales generated in all US states in a given year (*State Sales Relevance*). Firms' headquarter state information comes from Compustat. We expect that a firm's skill requirements should be less sensitive to personal taxes in economically relevant states and in its headquarter state ("home bias").

To test these cross-sectional predictions, we estimate regressions of skill requirements on interactions between personal taxes and the above-mentioned characteristics. Formally, we estimate the following regression model:

$$
\begin{aligned}
Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + \beta_2 Personal\ Taxes_{c,t-1} \times Characteristics_{i,t-1} \\
+ Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}, \quad (3)
\end{aligned}
$$

where *Characteristics* include firms' dependence on skilled labor (*Skill Dependent* and *LSI*), geographical dispersion of an industry (*Footloose*), and firms' organizational structure (*State Sales Relevance* and *HQ State*). Similarly to Eq. (2), the specification controls for county- (γ_c) and firm-year-fixed effects ($\eta_{i,t}$), with the latter absorbing the main effects of firm characteristics.

Table 4 presents results from 30 alternative versions of Eq. (3). To cut clutter, we only report the

[14] For example, the retail industry is more geographically dispersed, therefore more footloose, compared to car manufacturing, which is concentrated in certain locations.

coefficients on interaction terms, β_2, together with their standard errors. The head of each row shows the characteristic we focus on.

TABLE 4 ABOUT HERE

Panel A documents the modulating effects of firms' innate need for high-skill workers. The interaction terms related to skill dependence are predominantly positive and statistically significant, indicating that firms that rely critically on high-quality human capital in their operations are less likely to cut local skilled labor in lieu of hiring in a new labor market. This finding suggests that some firms may disproportionately bear the burden from personal taxes imposed on their workers' income. Panel B presents the results for footloose industries. Across both definitions of the footloose index, firms in geographically dispersed industries are significantly more responsive to variation in personal taxes. This finding highlights operational flexibility as an important determinant of how firms respond to frictions in local labor markets. Finally, Panel C shows that the economic and organizational relevance of local markets mitigates firms' reallocation of skilled jobs. Following an increase in personal taxes, firms do not seem to shift their high-skill jobs out of their main product market locations or their headquarter states as much as they do to other states.

Taken altogether, our analyses on firms' heterogeneous responses to personal income taxes generate valuable insights about the determinants of firms' skill allocation across different geographical regions. Specifically, firms weigh the tax-induced costs of hiring locally against the frictions related to searching for skilled workers in a different labor market. Firms that rely heavily on local skilled labor and local product markets forego job reallocation to a certain extent. In contrast, firms in operationally flexible industries adapt to personal tax increases by relocating skilled labor to low-tax states.

4.4 Taxes and IT Investment

As firms move skilled jobs out of high-tax regions, they may also redistribute highly productive physical assets, such as technology investment. While research on skill-biased technology change posits that technological upgrades are coupled with greater reliance on high-skill workers (see, e.g., Autor et al. (2003) and Autor and Dorn (2013)), the existing literature has not examined how changes in the skill composition of workers may affect firms' investment in technology at the establishment level. Our setting allows us to examine this question. As personal taxes increase the costs of human capital, firms may reduce their capital investment alongside reductions in their requirements for skilled labor. At the same time, it is also conceivable that firms may try to compensate for the loss of human capital by upgrading their technology and facilitating automation. Our data allow us to empirically distentangle these competing dynamics.

We evaluate the effect of personal taxes on local IT investment at the establishment level, with the results presented in Table 5. Our estimates suggest that a 1% increase in personal income taxes is associated with firms decreasing their per-employee computer budget by 16% and hardware budget by 20%. Firms also substantially cut budgets for telecommunication services and the acquisition of servers following increases in personal taxes.

TABLE 5 ABOUT HERE

Our findings point to an unambiguous, negative effect of personal taxes on technology adoption. Firms not only shift their requirements for labor skill away from high-tax states, but they also decelerate their technological upgrades in those states. As the lack of skilled labor compounds with a slowdown in technological development, high personal income taxes may predictably become a hindrance to local economic growth.

4.5 Firm Exit and Entry

Our main analysis of firms' skill requirements focuses on the intensive margin of employment (hiring of workers into existing operations) and generates implications for how personal taxes change firms' requirements for labor along the skill spectrum. In this section, we expand our lens to the extensive margin and examine existing firms' local exit and entry decisions. Among other things, this examination allows us to gauge in further detail the extent to which firms move their operations out of a locality when it levies a heavier tax burden on skilled workers.

Our first analysis at the extensive margin relates the number of establishments of existing firms in a given county to personal income taxes. Tracking changes in local establishments reveals whether firms close down local operations when taxes make human capital more expensive. Information regarding firms' establishments come from County Business Patterns (CBP) prepared by the US Census. In implementing this test, we maintain our contiguous county design, sampling on counties near state borders (cf. Eq. (1)).

Panel A of Table 6 reports the results. We start with a linear OLS model. We then supplement this method with a Poisson regression, which accounts for nonlinearity in the likelihood that a firm may have a second or a third establishment in a given county. Based on OLS estimates (in Column (1)), a 1% increase in personal taxes is associated with a 1.2% decline in the number of establishments in a county. The marginal effect from the Poisson estimate suggests a similar magnitude. These results show new evidence that tax-induced costs of human capital lead firms to close down business facilities.[15] They also agree with our prior results on IT investment, suggesting that physical investment becomes less valuable as firms lose high-skill workers.

TABLE 6 ABOUT HERE

In the second part of our extensive margin analysis, we consider whether personal taxes affect a public firm's exit from and entry to a state. Information on a firm's establishment in a given state comes from NETS. We define a firm's participation in the local market in three ways. First, *Exit* equals 1 if a firm has establishments in a given state in the previous year, but closes its establishments starting the current year of observation, and 0 otherwise. *Entry* equals one when a firm opens an establishment in a given state for the first time in our sample period. Finally, we define *Presence* as an indicator for whether a firm has any establishment in a given state during the year of observation.[16] In these firm-level tests, we adopt the same methodology of Eq. (2), controlling for state- and firm-year-fixed effects. The coefficients thus compare the same firm's exit and entry decisions in a given state relative to all other states. This removes the possibility that a firm's overall expansion or contraction coincides

[15] Pass-through entities (S corporations, partnerships, and sole proprietorships) are included in our local establishment sample and are taxed at state personal income rates. As discussed in Giroud and Rauh (2019), state personal income tax hikes can reduce pass-through entities' business activities due to the higher tax rates imposed on firm incomes. Our firm-level analysis focuses on Compustat firms (C corporations) and cleanly identifies skilled labor as the channel through which personal taxes affect firms' exit and entry decisions.

[16] We multiply *Exit*, *Entry*, and *Presence* by 100, so that the coefficients will suggest the percentage of likelihood that a firm leaves, enters, or recruits in the local market.

with trends of tax regimes.[17]

Panel B of Table 6 presents the results. Columns (1) and (2) show that a 1% increase in personal taxes is associated with a firm being 0.12% more likely to exit a state and 0.03% less likely to enter a state. These economic magnitudes are meaningful, accounting for a 5–8% change relative to sample average levels of firm exit and entry decisions. Column (3) continues to show that the same tax increase is associated with a firm being 0.3% less likely to maintain any establishments locally. These results support the notion that higher personal taxes drive incumbent firms out of the local market and discourage other firms from entering.

In all, our results on the extensive margin confirm the argument that high personal taxes are detrimental to the local business environment. Critically, increases in personal taxes lead firms to move their production out of the area and discourage new firms from entering, resulting in fewer business entities in the local economy.

4.6 Personal Taxes at Other Income Levels

Our baseline tests rely on personal tax rates levied on individuals whose income levels rank at the 90^{th} percentile of the population. Given that wage levels of skilled workers vary broadly in the US, we consider personal income taxes faced by workers making other levels of income, starting with income at the 10^{th} percentile to the 99.5^{th} percentile in the income distribution. Table 7 shows the results. Panel A reports the results from our county-level tests and Panel B reports the results from firm-level tests. Based on results from Panel A, low-income (10^{th} percentile income) tax rates do not generate a meaningful effect on local job postings. As one moves up the income ladder, there is a hump-shaped relationship between personal taxes and firms' skill requirements. The negative effect of personal taxes first intensify, reaching their highest levels at the 95^{th} income percentile. Yet, these effects diminish at the top income level both in terms of economic magnitudes and statistical significance. At the 99.5^{th} percentile, the impacts of personal taxes become significantly weaker than those at the 90^{th} or 95^{th} percentile.

These results suggest that firms' job postings are influenced by personal income taxes imposed on

[17] We conduct this analysis at the state level as the dataset becomes exceedingly large if we consider all firm-county-year combinations, including observations when firms do not post any jobs.

local earners with relatively high income levels, but not by tax rates on low-income workers. They are also less affected by tax rates imposed on the wealthiest individuals (i.e., "millionaire tax"). Given that individuals with income levels between the 50^{th} and the 95^{th} percentiles are more likely to use online postings for their job search than the very wealthy, this analysis helps validate our argument that personal income taxes affect firms' local job postings through the most relevant demographic group.

TABLE 7 ABOUT HERE

5 Robustness Checks

We conduct several additional analyses to ensure the robustness of our findings. They are designed to address alternative explanations and enhance the comparability among the localities that we sample on. First, we address the possibility that the baseline results may be driven by local business cycles. Second, as we look across state borders, we seek to identify politically and economically matched comparison groups. Third, we apply additional filters to the range of geographical locations used in our tests to verify that the results are not driven by a specific sampling choice (e.g., distance to the border). Finally, we assess the potential influence of issues such as cross-state migration and commuting workers on our estimations. We discuss each of these tests in turn.

One competing explanation for our findings is that declines in firms' skill requirements might be influenced by other economic circumstances affecting the locations we study and that personal tax rates simply respond to such circumstances. For example, state governments may increase personal taxes to cover budgetary deficits that are a result of deteriorating local economic conditions. While we have added controls for such circumstances (e.g., state budgetary deficits), state tax policies may still exhibit differential responses to deficit accounts (e.g., some states may be more reluctant to increase taxes). We address this concern by removing large tax movements that are preceded by local booms or busts, in particular, cyclical and counter-cyclical tax movements (see Mukherjee et al. (2017)). Cyclical tax movements are defined as cases where a state imposes a tax rate that is in the top (bottom) quartile of its own tax rates over the sample period immediately following a year of local boom (bust). Similarly, counter-cyclical tax movements are defined as cases where a state imposes a top-quartile (bottom-quartile) tax rate following a year of local bust (boom). Local booms (busts) are defined as cases where state GDP growth is above 4% (below 2%). We identify 114 (out of 414) state-years for which tax changes were associated with significant changes in economic conditions. Removing such events led to a reduction in sample size by 20% (47%) in the firm-level (county-level) data. Panels A and B of Table 8 show that our baseline results continue to obtain with the remaining samples.

TABLE 8 ABOUT HERE

Variation in local product demand could also affect the interpretation of our results. Specifically, personal taxes may affect local households' demand for goods and services. The reduced hiring that we document may thus reflect firms' response to the decline in local demand, instead of changes in local labor market characteristics. We address this issue by examining whether our results hold in a sample of firms operating in tradable industries; activities that do not rely heavily on the demand of local customers. Following Mian and Sufi (2014), we define non-tradable sectors as retail trade (NAICS 44 and 45) and accommodation and food services industries (NAICS 72). Tradable industries comprise the remaining industries. In Panel C of Table 8, we repeat the baseline tests at the firm level while restricting the sample to only tradable industries. Our results remain unchanged.[18]

We further consider the possibility that some neighboring states may have distinctly different political climate and geographical features, which are likely to be associated with state policy preferences (see Pence (2006), Neumark et al. (2014), and Mukherjee et al. (2017)). This argument suggests that counties located in those states, even if adjacent to one another, may not share similar political or economic conditions. We address this possibility in two ways. First, we restrict our sample to counties around state borders whereby the two neighboring states have the same political party in power. Information regarding governing parties comes from the Book of the States. Second, we remove from our sample state borders that draw the boundaries between US Census regions (such as the Northeast, Midwest, South, and West regions). The remaining sample thus consists of counties located in neighboring states that belong to the same Census region. Results from Panel D and E of Table 8 show that our baseline results continue to hold for both of these sample restrictions.[19]

[18] Our results are robust if we further exclude real estate rental and leasing (NAICS 53), educational services (NAICS 61), and health care and social assistance (NAICS 62) from the sample.

[19] Our results are also robust if we drop all state borders formed by major rivers (e.g., the Mississippi River, the Colorado

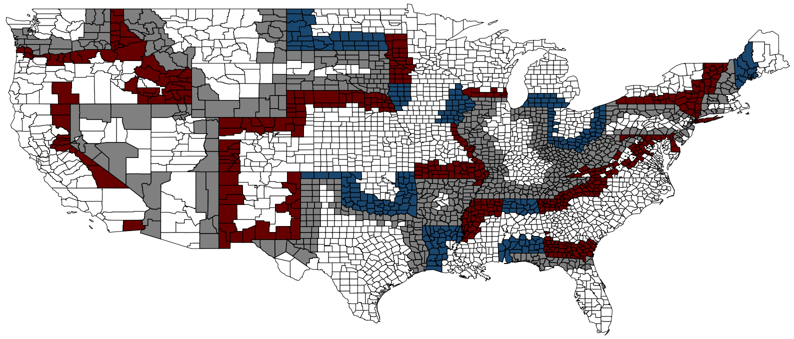
In the next step, we sharpen the adjacent-county design illustrated by Figure 6 in several ways. To start, we impose additional restrictions on the amount of business activities hosted by counties on each side of a shared state border. The goal is to ensure that our treatment and control counties do not differ substantially in terms of economic development and demographic composition. Accordingly, we construct our sample as follows. On each side of a state border, we start by including counties located right on the border and keep layering on adjacent counties towards inner state. We stop once the total number of establishments hosted by all of these counties reaches 50,000 or the maximum distance to border reaches 80 miles. In a separate test, we follow the same procedure and stop sampling once the total working-age population (age ranging from 20 to 64) residing in the counties on one side of the border reaches 500,000 or the maximum distance reaches 80 miles. Panels A and B of Figure 7 illustrate these alternative spatial specifications using 2013 statutory tax changes. Compared to the sample shown in Figure 6, these new filters remove more counties located in the northeast side of the US, a region that is densely populated and replete with businesses.

As a next sample design, we narrow the geographical bandwidth to 50 miles from the state border. Panel C of Figure 7 shows the remaining counties. This design removes inner state counties across the US, but more so in the West, where the geography is expansive and population is sparse. Lastly, we follow a strict county-pair design, including only adjacent county pairs separated by a state border. The empirical estimation further controls for county-pair-fixed effects to hone in the comparison within such adjacent county pairs. As shown in Panel D of Figure 7, the county-pair design imposes the most restrictive criteria and results in the smallest number of counties included in the testing sample.

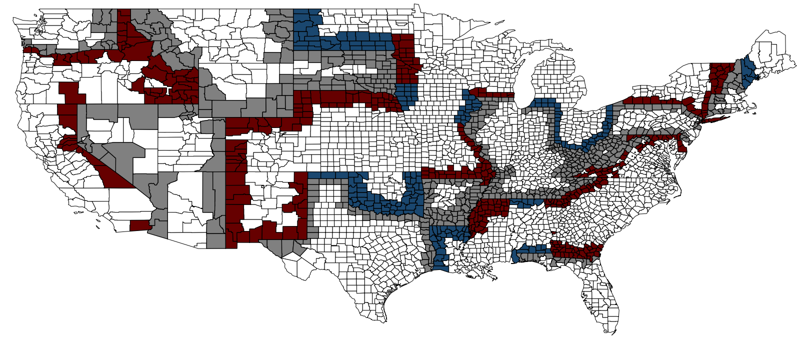
Table 9 reports results from all of the above sampling procedures. Panel A presents results when we require counties on each side of the border to collectively contain no more than 50,000 establishments. Panel B shows results from the criterion that each of these sets of counties should not have a total population over 500,000. Panel C presents results for a sample consisting of counties within 50 miles of a state border, while Panel D reports results from the county-pair design. Our baseline results are robust to all of these design choices.

TABLE 9 ABOUT HERE

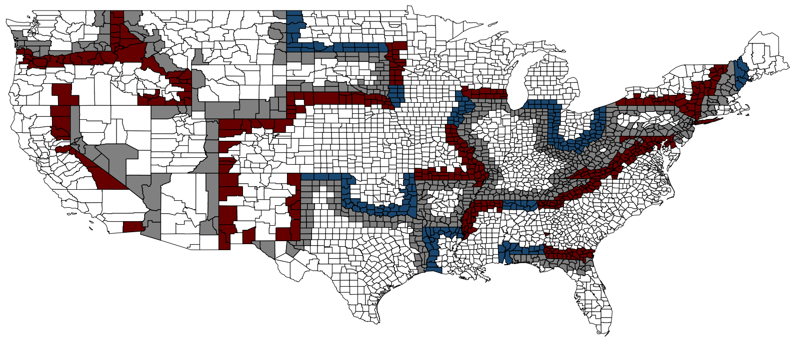
River, and the Ohio River), as areas on opposite sides of a river may not be comparable.



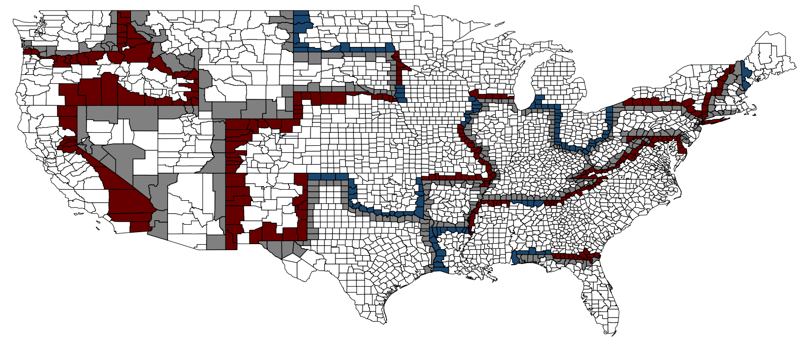
(A) Distance to Border ≤ 80 miles and # Establishments ≤ 50,000



(B) Distance to Border ≤ 80 miles and Population ≤ 500,000



(C) Distance to Border ≤ 50 miles



(D) County Pairs across State Borders

Figure 7. Illustration of Alternative Sampling Choices. This figure illustrates the sample selection criteria for the robustness tests reported in Table 9. In Panel A, we include counties within 80 miles to a state border and require the total number of establishments on each side of the border not to exceed 50,000. In Panel B, we include counties within 80 miles to a border and require the total working-age population on each side of the border not to exceed 500,000. In Panel C, we include counties within 50 miles to a state border. In Panel D, we sample on adjacent county pairs located across a state border. Counties are colored based on 2013 statutory tax changes. Red (blue) shades indicate states with increases (decreases) in personal tax rates and gray shades indicate neighboring states that did not change their personal taxes.

Finally, we evaluate the effect of focusing on near state-borders on some of our base estimations. To reduce tax burdens, residents of a high-tax state may move residence across the border or choose to commute, seeking employment in a neighboring low-tax state. Complicating matters, some states tax nonresidents' employment incomes originated within their jurisdictions. While the geographic proximity of adjacent counties near a state border offers for clean identification, it also allows for situations in which cross-border migration (residence or place of work) could bias our results; both attenuate or accentuate them. To address this concern, we first restrict our sampling to counties whose distances to state borders are above 20 miles yet below 80 miles, under the assumption that migration or commuting costs get higher as distance from the borders lengthens. Second, we sample on counties located along the border of two states that share a reciprocal tax agreement. A reciprocal tax agreement specifies that workers who commute across these state borders effectively pay wage income taxes to the residency state (and not the work state). Such an agreement greatly simplifies tax returns and reduces workers' incentive to commute across state borders to take advantage of gaps between personal taxes across states. Table 10 reports results from these two tests. Our baseline results obtain across these specifications, suggesting that a higher likelihood of cross-border migration or worker commuting across state borders does not unduly influence our results.

TABLE 10 ABOUT HERE

6 Concluding Remarks

This paper provides novel evidence on the effect of personal income taxes on firms' requirements for high-skill labor. Using unique data on firm job postings, we show that firms respond to higher state-level personal income taxes by reducing their requirements for skilled labor locally and shifting the requirements to other states. Tax-induced downskilling is accompanied by reductions in technology investment, and is primarily driven by changes in tax rates imposed on high-income earners. The effect persists both at the aggregate county level and in a sample of public firms. It is not driven by unobservable, innate characteristics of the local area or time-varying characteristics of the firm. It is also robust to unobservable factors that influence the pairing between a firm and a county.

Our analysis shows that firms' relocation of labor skill requirements across states is mitigated when firms rely more heavily on local skilled labor. The sensitivity to personal taxes is also attenuated for states that are central to firms' operations. Finally, firms that have greater flexibility to relocate are more responsive to personal tax changes. These cross-sectional variations outline the tradeoffs faced by firms when state-level personal income taxes increase the cost of skilled labor.

In all, our study points to the detrimental effects of rising personal income taxes on local labor markets. We find that firms play an active role in transferring their skilled hires from high- to low-tax states. This reallocation effect not only leads to a "brain drain" across high-tax regions of the country, but also alters the technology investment among establishments across states. As state governments fail to coordinate their tax policies, the disparity of personal taxes across states shapes the vibrancy of local labor markets and the organizational structure of corporations in the United States.

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Appendix A Variable Definitions

Job Skill

- *Education* (% Postings): Percentage of job postings that require high school or above education. Source: BurningGlass
- *Experience*(% Postings)):Percentage of job postings that require previous work experience. Source: BurningGlass
- *Cognitive* (% Postings): Percentage of job postings that require decision making ability and analytical skills. Source: BurningGlass
- *Software* (% Postings): Percentage of job postings that require knowledge of software programs. Source: BurningGlass
- *IT* (% Postings): Percentage of job postings that recruit for computer related jobs. Source: BurningGlass

Local Business Patterns

- *Labor Force*: The log number of all persons with age of 16 and older who are classified as employed or unemployed. Source: Bureau of Labor Statistics
- *Employed Workers*: The log number of all employed persons. Source: Bureau of Labor Statistics
- *Unemployment Rate* (in %): The number of unemployed people as a percent of the labor force. Source: Bureau of Labor Statistics
- *Average Monthly Earnings*: Average monthly earnings for workers who started a job that turned into a job lasting a full quarter. Source: Quarterly Workforce Indicators
- *Log(Establishment) (CBP)*: The log number of establishments. Source: US Census

Firm Performance

- *M/B of Assets*: (Total Asset + Common Shares Outstanding × Closing Price (Fiscal Year) − Common Equity)/Total Asset Source: Compustat
- *TFP*: The residuals from a panel regression that regresses the log of firm sales on the log of employees, the log of capital, and the log of inventory in raw materials. Source: Compustat
- *Patent Filed*: The log number of patents filed by a firm in a given year.

Controls

- *Corporate Taxes*: The corporate tax rate charged by a state
- *Sales Taxes*: The sales tax rate charged by a state
- *Property Taxes*: The median real estate tax paid divided by median housing price in a county. Source: US Census
- *Log(GDP)*: The log of gross domestic product in a state. Source: Bureau of Economic Analyses
- *Budget Surplus*: State government budget surplus, scaled by gross state product. Source: Institute for Public Policy and Social Research, Michigan State University
- *Unemployment Insurance*: The log of unemployment insurance, which is calculated as the top tax rate (*UT_RATE*) multipled by the maximum base wage (*UI_BASE*). Source: US Department of Labor
- *Tax Incentives*: The total number of financial assistance and tax incentives. Source: *Site Selection*
- *Log(HPI)*: The log of housing price index. Source: Federal Housing Finance Agency (FHFA)

Conditioning Characteristics

- *Skill Dependent*: A dummy variable that equals one if an industry (4-digit NAICS level) generates above-median fraction of job postings that require bachelor's degrees and above. Source: BurningGlass Technologies
- *LSI*: The weighted average of skill levels across all occupations in a 3-digit NAICS industry. The skill level of an occupation is based on the 5-tier skill index defined by US Department of Labor
- *Footloose (Employment)*: $1 - \sum_s |EmploymentShare_{is} - EmploymentShare_s|$, where s is a state and i is a 4-digit NAICS industry. $EmploymentShare_{is}$ is the total number of workers employed in state s by industry i scaled by the total workers employed by industry i in a given year. $EmploymentShare_s$ is the total number of workers employed in state s scaled by the total workers employed in the US in a given year. Source: CBP
- *Footloose (Establishment)*: $1 - \sum_s |EstablishmentShare_{is} - EstablishmentShare_s|$, where s is a state and i is a 4-digit NAICS industry. $EstablishmentShare_{is}$ is the total number of establishments located in state s owned by industry i scaled by the total establishments that belong to industry i in a given year. $EstablishmentShare_s$ is the total number of establishments in state s scaled by the total establishments in the US in a given year. Source: CBP
- *State Sales Relevance*: The percentage of sales that a firm produces in a state relative to the total sales across all US territories in a given year. Source: NETS
- *HQ State*: A dummy variable indicating whether a state is a firm's head quarter state. Source: Compustat

Technology Investment

- *PC Budget*: The budget for personal computers per employee. Source: CiTDB
- *Hardware Budget*: The budget for hardware purchases per employee. Source: CiTDB
- *Comm. Budget*: The budget for telecommunication services per employee. Source: CiTDB
- *Server Budget*: The log dollar value of the budget for software purchases per employee. Source: CiTDB

Table 1
Summary Statistics

Panel A reports summary statistics for state tax variables. Panels B and C report summary statistics for our variables of interest for the county-level and firm-level sample, respectively. These variables include labor market outcomes from QWI, job skill measures from BurningGlass, technology investment from CiTDB, number of establishments from CBP and NETS, and control variables.

Panel A: Tax Variables

Variable	Mean	Median	Std. Dev.	25^{th} Pct	75^{th} Pct
Personal Taxes (%)	18.567	17.811	3.762	16.249	21.004
Corporate Tax (%)	6.925	7.100	2.421	6.000	8.500
Sales Taxes (%)	5.057	5.600	1.803	4.230	6.000
Property Taxes (%)	0.972	0.828	0.495	0.598	1.284

Panel B: County Sample

Variable	Mean	Median	Std. Dev.	25^{th} Pct	75^{th} Pct
Local Business Patterns					
Labor Force (in thousands)	47.992	11.541	161.337	5.020	31.165
Log(Labor Force)	9.505	9.354	1.437	8.521	10.347
Employed Workers (in thousands)	45.107	10.809	150.631	4.691	29.298
Log(Employed Workers)	9.442	9.288	1.437	8.454	10.285
Unemployment Rate (in %)	6.038	5.500	2.630	4.100	7.400
Average Earnings	1,749.2	1,686.0	540.6	1,395.7	2,006.5
Log(Average Earnings)	7.424	7.431	0.279	7.242	7.605
Job Skill					
Education	41.735	42.857	15.897	31.579	52.367
Experience	36.408	36.607	13.302	28.276	44.598
Cognitive	18.968	17.891	10.984	11.561	25.257
Software	12.258	10.366	9.568	5.440	16.838
IT	17.583	16.080	11.395	9.375	24.109
Exit and Entry					
# Establishment	2,336	535	8,073	227	1,464
Local Indicators					
Log(GDP)	12.235	12.239	0.980	11.635	12.923
Budget Surplus	0.777	0.876	5.674	–2.576	3.851
Unemployment Insurance	11.284	11.223	0.525	10.889	11.597
Tax Incentives	25.171	26.000	4.172	24.000	28.000
Log(HPI)	5.319	5.227	0.489	4.953	5.607

Panel C: Public Firm Sample

Variable	Mean	Median	Std. Dev.	25^{th} Pct	75^{th} Pct
Job Skill					
Education	49.793	50	42.557	0	100
Experience	44.062	40	40.715	0	87.500
Cognitive	25.968	0	35.302	0	50
Software	20.359	0	33.110	0	33.333
IT	26.529	0	36.453	0	50
Conditioning Characteristics					
Skill Dependent	0.279	0	0.449	0	1
LSI	2.614	2.564	0.669	2.150	3.168
Footloose (Employment)	0.666	0.675	0.171	0.556	0.808
Footloose (Establishment)	0.653	0.671	0.179	0.514	0.785
State Sales Relevance	7.149	2.976	12.963	1.334	6.673
HQ State	0.061	0	0.239	0	0
Technology Investment					
PCs	0.955	0.493	0.880	0.607	1.200
PC Budget	711	985.028	285.714	133.333	1000
Hardware Budget	1727.800	2949.596	948.900	302.307	1833.333
Comm. Budget	987.891	3047.220	458.200	200	997.750
Server Budget	675.392	1546.032	166.667	43.250	600
Exit and Entry					
Exit (%Likelihood)	0.499	0	7.053	0	0
Entry (%Likelihood)	1.527	0	12.263	0	0
Presence (%Likelihood)	16.805	0	37.391	0	0
Local Indicators					
Log(GDP)	12.855	12.913	0.945	12.227	13.465
Budget Surplus	–0.444	–0.319	5.511	–3.758	2.687
Unemployment Insurance	11.375	11.340	0.526	10.919	11.729
Tax Incentives	26.085	27	3.701	24	28
Log(HPI)	5.872	5.887	0.476	5.524	6.222

Table 2

County-Level Employment and Personal Taxes

This table examines the effects of personal income taxes on local workforce conditions. Tests include counties within 80 miles from state borders. The unit of observation is at the state-border-county-year level. Control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. In the regression model below, c represents a county, b represents a state border, d represents a census division, and t represents a year: Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}$$

Dep. Var.:	(1) *Labor Force*	(2) *Employed Workers*	(3) *Unemployment Rate*	(4) *Average Earnings*
Personal Taxes	–0.008**	–0.011***	0.311***	–0.010***
	(0.003)	(0.003)	(0.047)	(0.004)
Controls	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes
Observations	75,808	75,808	75,808	74,978
Adjusted R^2	0.997	0.997	0.837	0.876

Table 3
Requirements for Skills and Personal Taxes
This table examines the effect of personal tax changes on firms' requirements for labor skill. Panel A shows results for employers' requirements for skilled labor in counties within 80 miles from state borders. The unit of observation is at the state-border-county-year level. Panel B shows the within-firm allocation of skilled labor across states for multi-state firms. The unit of observation is at the firm-county-year level. In both panels, the dependent variables include the the percentage of job postings requiring education (*Education*) , experience (*Experience*), cognitive skills (*Cognitive*), knowledge of specific software (*Software*), and general IT knowledge (*IT*). Control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. Standard errors are clustered by county in Panel A and by firm-county in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A shows the estimates from the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panel B shows the estimates from the following specification, where i represents a firm, c represents a county, and t represents a year:

$$Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}.$$

Panel A: County-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.439**	–2.060***	–2.762***	–2.648***	–3.607***
	(0.583)	(0.489)	(0.461)	(0.378)	(0.436)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	32,936	32,936	32,936	32,936	32,936
Adjusted R^2	0.540	0.523	0.603	0.680	0.659

Panel B: Firm-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.165***	–1.193***	–1.011***	–1.206***	–1.788***
	(0.147)	(0.152)	(0.129)	(0.119)	(0.129)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	1,566,797	1,566,797	1,566,797	1,566,797	1,566,797
Adjusted R^2	0.521	0.436	0.426	0.427	0.456

Table 4

Heterogeneity in Firms' Response to Personal Taxes

This table reports estimates of cross-sectional variations in multi-state firms' responses to personal tax changes according to firm and industry characteristics. The unit of observation is at the firm-county-year level. Panel A examines the interactive effect of personal taxes and an industry's reliance on human capital on firms' hiring policies. *Skill Dependent* is an indicator that equals 1 if a firm's industry has a requirement for bachelor and above degrees that is above the median level across all industries. *LSI* represents labor skill index, which is an industry-level average requirements for high-skill jobs (based on the definition from Census). Panel B examines the differential responses from "footloose" and non-footloose industries. *Footloose (Employment)* is the dispersion of an industry's employment across states and *Footloose (Establishments)* is the dispersion of an industry's establishments across states. Panel C examines the interactive effect of personal taxes and the economic importance of a state to a firm. We gauge the importance of a state for a firm using its ability to generate sales for the firm (*State Sales Relevance*) and also according to whether it houses the firm's headquarter (i.e., *HQ State*). Control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. In the regression below, i represents a firm, c represents a county, and t represents a year. Standard errors are clustered by firm-county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

$$Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + \beta_2 Personal\ Taxes_{c,t-1} \times Characteristics_{i,t-1} + Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}.$$

Panel A: Skill Level

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes × *Skill Dependent*	0.083**	0.081**	0.259***	0.139***	0.139***
	(0.033)	(0.034)	(0.032)	(0.031)	(0.032)
Personal Taxes × *LSI*	0.031	0.019	0.108***	0.046**	0.067***
	(0.023)	(0.024)	(0.021)	(0.019)	(0.020)

Panel B: Footloose Industries

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes × *Footloose (Employment)*	–0.396***	–0.004	–0.329***	–0.161*	–0.169*
	(0.107)	(0.110)	(0.100)	(0.094)	(0.099)
Personal Taxes × *Footloose (Establishments)*	–0.386***	–0.021	–0.360***	–0.165*	–0.174*
	(0.102)	(0.106)	(0.096)	(0.091)	(0.096)

Panel C: Firm Organization Structure

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes × *State Sales Relevance*	0.722***	0.638***	0.922***	0.694***	0.669***
	(0.043)	(0.043)	(0.041)	(0.042)	(0.042)
Personal Taxes × *HQ State*	0.174***	0.153***	0.255***	0.246***	0.229***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)

Table 5
Technology Investment and Personal Taxes
This table examines the effect of personal tax changes on the within-firm allocation of IT investment across states for multi-state firms. The unit of observation is at the establishment-year level. The dependent variables include firms' budget to purchase personal computers, all hardware devices, telecommunication services, and servers. All dependent variables are scaled by the number of employees in the establishment. Control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. All regressions control for establishment-fixed effects and time trend. Standard errors are clustered by firm-county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Dep. Var.:	(1) *PC Budget*	(2) *Hardware Budget*	(3) *Comm. Budget*	(4) *Server Budget*
Personal Taxes	–109.851***	–361.428***	–293.769***	–59.631***
	(3.350)	(10.900)	(13.193)	(7.388)
Controls	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Observations	679,158	909,129	909,129	594,221
Adjusted R^2	0.614	0.335	0.196	0.355

Table 6
Firm Exit and Entry: Local Establishments
This table examines firms' exit and entry in response to personal tax changes. Panel A presents results for the log number of establishments in counties within 80 miles of state borders. Panel B presents results for a firm's exit and entry decisions. The unit of observation is at the firm-state-level. *Exit* is an indicator that equals one if a firm has establishments in a state in the previous year, but closes its establishments from the current year forward. *Entry* is an indicator that equals 1 if a firm opens an establishment for the first time in a given state. *Presence* is an indicator for whether a firm has any establishment in a given state. In both panels, control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. Standard errors are clustered by county in Panel A and are clustered by firm-state in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A shows the estimates from the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panel B shows the estimates from the following specification, where i represents a firm, s represents a state, and t represents a year:

$$Y_{i,s,t} = \beta_1 Personal\ Taxes_{s,t-1} + Controls_{s,t-1} + \gamma_s + \eta_{i,t} + \epsilon_{i,s,t}.$$

Panel A: Number of Establishments (County-Level Evidence)

Dep. Var.: *Log(Establishments)*	(1)	(2)
Methodology:	OLS	Poisson
Personal Taxes	–0.012***	–0.013***
	(0.003)	(0.003)
Controls	Yes	Yes
County-FE	Yes	Yes
State-Border-FE	Yes	Yes
Census Division-Year-FE	Yes	Yes
Observations	36,719	36,721

Panel B: Exit and Entry (Firm-Level Evidence)

	(1)	(2)	(3)
Dep. Var.:	*Exit* (%Likelihood)	*Entry* (%Likelihood)	*Presence* (%Likelihood)
Personal Taxes	–0.025*	–0.121***	–0.270***
	(0.013)	(0.018)	(0.072)
Controls	Yes	Yes	Yes
State-FE	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes
Observations	2,428,685	2,428,685	2,428,685
Adjusted R^2	0.083	0.157	0.437

Table 7

Personal Tax Rates of Other Income Levels

This table presents the effect of personal income taxes at various income levels on firms' requirements for labor skill. Panel A presents results from the county-level sample and Panel B presents results from the firm-level sample. In both panels, control variables include corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. Standard errors are clustered by county in Panel A and are clustered by firm-county in Panel B. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A shows the estimates from the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panel B shows the estimates from the following specification, where i represents a firm, c represents a county, and t represents a year:

$$Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}.$$

Panel A: County-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes (10^{th} Pctl)	–0.166	–0.067	–0.210	–0.131	–0.154
	(0.163)	(0.132)	(0.136)	(0.118)	(0.133)
Personal Taxes (50^{th} Pctl)	–0.272	–1.114***	–1.364***	–1.380***	–1.961***
	(0.446)	(0.394)	(0.317)	(0.271)	(0.322)
Personal Taxes (70^{th} Pctl)	–0.925*	–1.995***	–2.291***	–1.970***	–2.851***
	(0.546)	(0.474)	(0.407)	(0.331)	(0.391)
Personal Taxes (90^{th} Pctl)	–1.439**	–2.060***	–2.762***	–2.648***	–3.607***
	(0.583)	(0.489)	(0.461)	(0.378)	(0.436)
Personal Taxes (95^{th} Pctl)	–2.005***	–3.089***	–2.396***	–2.643***	–3.450***
	(0.639)	(0.547)	(0.469)	(0.382)	(0.444)
Personal Taxes (99^{th} Pctl)	–0.339	–0.616	–0.200	–0.797***	–0.978***
	(0.446)	(0.391)	(0.325)	(0.261)	(0.307)
Personal Taxes (99.5^{th} Pctl)	0.166	–0.004	0.009	–0.224	–0.459*
	(0.379)	(0.346)	(0.267)	(0.235)	(0.263)

Panel B: Firm-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes (10th Pctl)	–0.165***	–0.199***	–0.123***	–0.158***	–0.129***
	(0.040)	(0.042)	(0.035)	(0.032)	(0.035)
Personal Taxes (50th Pctl)	–1.074***	–1.257***	–1.527***	–1.254***	–1.877***
	(0.124)	(0.127)	(0.106)	(0.097)	(0.105)
Personal Taxes (70th Pctl)	–1.170***	–1.505***	–1.272***	–1.169***	–1.817***
	(0.142)	(0.146)	(0.123)	(0.113)	(0.123)
Personal Taxes (90th Pctl)	–1.165***	–1.193***	–1.011***	–1.206***	–1.788***
	(0.147)	(0.152)	(0.129)	(0.119)	(0.129)
Personal Taxes (95th Pctl)	–1.392***	–1.329***	–1.131***	–1.224***	–1.816***
	(0.155)	(0.159)	(0.135)	(0.124)	(0.135)
Personal Taxes (99th Pctl)	–0.498***	–0.408***	–0.198**	–0.475***	–0.726***
	(0.111)	(0.114)	(0.101)	(0.093)	(0.100)
Personal Taxes (99.5th Pctl)	–0.298***	–0.121	–0.137*	–0.284***	–0.415***
	(0.086)	(0.088)	(0.079)	(0.074)	(0.079)

Table 8
Robustness: Local Economic Conditions and Comparability Across Localities
This table examines whether our results are driven by variation in local economic conditions or the political and geographical distinctions across the counties we sample on. In Panels A and B, we exclude observations where large personal tax changes are preceded by large changes in local state GDP growth. In Panel C, we examine the effect of personal taxes on the hiring of tradable industries. In Panel D, we compare neighboring states with similar political environment by focusing on state borders whereby the two states are governed by the same party. In Panel E, we focus on state borders whereby the two neighboring states are located within the same Census region. Standard errors are clustered by county in Panels A, D, and E, and are clustered by firm-county in Panels B and C. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panels A, D, and E show the estimates from the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panels B and C show the estimates from the following specification, where i represents a firm, c represents a county, and t represents a year:

$$Y_{i,c,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \eta_{i,t} + \epsilon_{i,c,t}.$$

Panel A: Removing Cyclical and Counter-Cyclical Tax Changes (County-Level)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Education*	*Experience*	*Cognitive*	*Software*	*IT*
Personal Taxes	–1.090	–2.437***	–4.152***	–3.025***	–4.597***
	(0.823)	(0.651)	(0.583)	(0.506)	(0.580)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	21,002	21,002	21,002	21,002	21,002
Adjusted R^2	0.560	0.546	0.634	0.691	0.683

Panel B: Removing Cyclical and Counter-Cyclical Tax Changes (Firm-Level)

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Education*	*Experience*	*Cognitive*	*Software*	*IT*
Personal Taxes	–1.077***	–1.156***	–0.938***	–1.174***	–1.788***
	(0.170)	(0.175)	(0.149)	(0.137)	(0.149)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	1,358,879	1,358,879	1,358,879	1,358,879	1,358,879
Adjusted R^2	0.514	0.430	0.422	0.423	0.451

Panel C: Only Tradable Industries (Firm-Level)

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.127***	–1.408***	–0.980***	–1.526***	–2.084***
	(0.182)	(0.187)	(0.162)	(0.156)	(0.166)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	1,126,456	1,126,456	1,126,456	1,126,456	1,126,456
Adjusted R^2	0.467	0.388	0.384	0.392	0.418

Panel D: Same Political Party in Power (County-Level)

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–0.459	–1.609***	–2.041***	–2.253***	–3.068***
	(0.711)	(0.609)	(0.564)	(0.487)	(0.550)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	17,965	17,965	17,965	17,965	17,965
Adjusted R^2	0.578	0.541	0.620	0.684	0.664

Panel E: Same US Census Region (County-Level)

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.941***	–2.254***	–3.038***	–2.777***	–3.735***
	(0.555)	(0.461)	(0.470)	(0.378)	(0.437)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	27,937	27,937	27,937	27,937	27,937
Adjusted R^2	0.539	0.529	0.604	0.682	0.661

Table 9

Robustness: Adjacent County Design

This table shows the robustness of county-level results to various alternative sampling choices. In Panel A, tests include counties within 80 miles from a state border and require the number of establishments at each side of the border not to exceed 50,000. In Panel B, tests include counties within 80 miles from a state border and require the total working-age population at each side of the border not to exceed 500,000. In Panel C, tests include counties within 50 miles from a state border. In Panel D, we implement a county-pair design, sampling on pairs of adjacent counties that are separated by a state border and controlling for county-pair-fixed effects. All regressions control for corporate taxes, sales taxes, property taxes, the log of state GDP, state budget surplus, state unemployment insurance, the number of tax incentives, and the log of county housing price index. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panels A through D show the estimates from the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year:

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panel E shows the estimates from the following specification, where c represents a county, p represents a pair of counties across a state border, d represents a census division, and t represents a year:

$$Y_{c,p,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \zeta_p + \tau_{d,t} + \epsilon_{c,p,t}.$$

Panel A: Distance to Border ≤ 80 miles and # Establishments ≤ 50,000

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.301*	–2.266***	–2.146***	–2.099***	–3.016***
	(0.665)	(0.548)	(0.477)	(0.387)	(0.454)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	26,749	26,749	26,749	26,749	26,749
Adjusted R^2	0.514	0.482	0.570	0.638	0.620

Panel B: Distance to Border ≤ 80 miles and Population ≤ 500,000

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.920***	–2.392***	–2.393***	–1.973***	–2.820***
	(0.740)	(0.601)	(0.494)	(0.433)	(0.508)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	18,381	18,381	18,381	18,381	18,381
Adjusted R^2	0.501	0.476	0.556	0.622	0.600

Panel C: Distance to Border ≤ 50 miles

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.478**	–2.378***	–2.691***	–2.730***	–3.575***
	(0.651)	(0.532)	(0.489)	(0.411)	(0.481)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	20,449	20,449	20,449	20,449	20,449
Adjusted R^2	0.537	0.525	0.616	0.690	0.661

Panel D: County-Pair Design

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.913**	–2.457***	–2.319***	–2.150***	–2.841***
	(0.865)	(0.709)	(0.553)	(0.478)	(0.575)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
County-pair-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	19,198	19,198	19,198	19,198	19,198
Adjusted R^2	0.516	0.508	0.604	0.661	0.639

Table 10
Robustness: Commuters

This table shows the robustness of county-level results when we limit the possibility of worker migration across state borders. In Panel A, tests include counties within 80 miles but not within 20 miles from a state border. In Panel B, tests include only state borders with reciprocal agreements where personal income taxes are collected by the state of residence. All regressions use the following specification, where c represents a county, b represents a state border, d represents a census division, and t represents a year. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

$$Y_{c,b,t} = \beta_1 Personal\ Taxes_{c,t-1} + Controls_{c,t-1} + \gamma_c + \lambda_b + \tau_{d,t} + \epsilon_{c,b,t}.$$

Panel A: Distance to Border ≤ 80 miles and ≥ 20 miles

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.494**	–1.952***	–3.018***	–2.828***	–3.923***
	(0.621)	(0.557)	(0.528)	(0.428)	(0.491)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
State-Border-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	24,649	24,649	24,649	24,649	24,649
Adjusted R^2	0.532	0.507	0.587	0.667	0.650

Panel B: Reciprocal State Borders Only

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *Software*	(5) *IT*
Personal Taxes	–1.239	–3.001***	–3.645***	–2.635***	–3.625***
	(1.095)	(0.910)	(0.760)	(0.630)	(0.667)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
County-pair-FE	Yes	Yes	Yes	Yes	Yes
Census Division-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	6,869	6,869	6,869	6,869	6,869
Adjusted R^2	0.599	0.611	0.661	0.727	0.720