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

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November 17, 2019

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' establishments. It is driven by taxes on middle-class earners. 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. Together with downskilling, firms cut IT investment in and eventually exit from localities that increase personal taxes. Our findings point to a "brain-drain" in states with high personal income taxes, showing how taxes bear detrimental effects on 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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*We are grateful to Phuong-Anh Nguyen, Carlos Fernando Avenancio-León, John Graham, Sreeni Kamma, Gaurav Kankanhalli, Hyunseob Kim, Tomislav Ladika, Ting Xu, participants at the European Finance Association 2019 Conference, Wabash River Conference 2019, WAPFIN 2019 Conference, Yale Junior Conference 2019, and seminar participants at University of Amsterdam, University of British Columbia, University of Mannheim, and University of North Carolina at Chapel Hill for their helpful comments.

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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 over 26% 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. Notably, 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 thus 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 influences 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 takes 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 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 hiring skill requirements evolve over time in a given locality. For firms with operations in multiple regions of the country,

[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 numbers 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)).

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. 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 causal effect of personal income taxes in this setting. First, fluctuations in local economic conditions may simultaneously drive variation in taxes and firms' need for skilled workers. Second, unobservable firm fundamental changes may influence their skill hiring choices and their exposure to local taxes. To address the first concern, we sharpen our test strategy by contrasting adjacent counties located across state borders. We do so accounting for interstate differences in state-level corporate, property and sales taxes, minimum wages, unemployment insurance benefits, budgetary deficits, GDP growth, and housing prices, among others. Our estimations further impose county- and state-border-fixed effects to absorb innate differences across neighboring locations, and census division-year-fixed effects to absorb regional-level dynamics. 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 cloud our inferences.

To start, we assemble 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 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-percentage-point 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, an increase of 0.3 percentage point in unemployment rate. Workers employed in affected counties also make 1% less in pre-tax earnings.[3]

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. 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 take into account the local labor supply as well as the demand coming from other local employers, publishing job offers that are sensitive to prevailing local labor market conditions. Those job ads thus contain unique information about available workers of different skill levels in a given market at a particular time.[4]

We examine five aspects of skill requirements, each measured by the percentage of job postings listing a specific skill as an employment requisite. First, we consider the level of education that a worker must have to fill a position. Second, we look into whether a worker needs previous experience. Third, we examine the level of cognitive skills required to perform the job, including decision-making ability and analytical skills. Fourth, we consider the ability to operate a computer. Finally, we look at whether a job posting explicitly requires knowledge of certain software, including programming.

We document a strong, negative relation between local personal income taxes and the level of skills featured in local job vacancy postings. Contrasting adjacent cross-border counties, we show that firms in counties that experience personal tax rate increases seek to hire new workers with less education and experience. Our estimates suggest that a 1-percentage-point increase in personal income taxes leads to a 1.5 (2)-percentage-point drop in the job postings with education (experience) requirements. Firms also reduce their requirements for cognitive skills and computer knowledge. Our results are new in showing a pronounced "downskilling" effect associated with local personal income taxes.

Next, we examine whether firms actively reallocate their labor skill requirements across geographical regions as a function of local taxes. To do so, we compare the requirements contained in job ads

[3]Our estimates can be interpreted as labor market elasticity to local taxes and these tax elasticities are comparable to prior studies such as Giroud and Rauh (2019).

[4]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.

posted by the same firm across different states at the same 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 labor skill requirements in states that increase personal tax rates. When a state increases its personal income taxes by 1 percentage point, firms reduce their requirements for education and experience by about 1 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 computer software skills. These estimates translate to elasticities of skill requirements to taxes ranging between 0.3 for education and experience requirements and 1.5 for technology skill requirements. Notably, the effects of personal income taxes on firms' skill requirements display a U-shaped relationship across the income distribution: effects are most pronounced for earners ranked between the 50^{th} to 95^{th} percentiles of the income distribution ("upper-middle class"), but become significantly attenuated for both low-income households and the wealthiest tax filers.

We study heterogeneity in firms' responses to personal income tax changes to shed light on the economic channels underlying their decisions to reallocate skilled labor. We first examine the effects across firms based on their dependence on skilled labor, which is measured by 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. When facing high personal income taxes, firms in skill-dependent industries reduce their requirements for skilled labor to a lesser extent than do firms in other industries. This documented heterogeneity reveals significant replacement costs associated with high-skill labor, costs that discourage firms from changing their hiring despite cross-state differences in personal taxes.

We also explore heterogeneity in firms' operational flexibility to reallocate skilled workers. We first compare the interplay between local taxes and skill requirements across "footloose" and "non-footloose" industries (see Ellison and Glaeser (1997)). Footloose industries have geographically dispersed activities; as such, their main 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. We further consider other organizational features that may present frictions in the reallocation of skilled labor inside firms; in particular, states that generate a large share of their sales and states that house their headquarters ("important states"). We find that firms do not adjust skill jobs in 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 high-skill jobs in response to tax changes.

If firms shift their search for skilled workers away from high-tax localities, it is natural to ask whether they also withdraw from technological upgrades in those areas (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 reveal 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.

We also assess the impact of personal taxes on firms' decisions to exit and enter local labor markets. We find that higher personal taxes in a state increase the likelihood that firms permanently stop posting jobs in the state and reduce the likelihood that firms start to post jobs in the state. Those findings substantiate the argument that high personal income taxes inhibit firm entry into and trigger firm exit from a local labor market, carrying lasting detrimental effects to a state's business environment.

We conclude our main investigation with a test designed along the lines of the narrative approach introduced by Romer and Romer (2010). This exercise helps address the concern that tax policies are put in place to offset concurrent or upcoming government spending, or other factors that affect short-term economic conditions. In this test, we collect narrative records regarding statutory tax changes in our sample period and isolate ones targeted to cover inherited budget deficits or promote long-term economic growth. Results from the event study suggest that education requirements contained in local job postings significantly decline (increase) in the year immediately following a state tax hike (cut), and stabilize afterwards. Such an effect is primarily driven by job postings requiring bachelor's degrees or above. This section is useful in providing a concrete illustration of how personal taxes impact local worker skills (focusing on educational requirements in particular), including the timing and duration of relevant tax effects.

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 verify that our results persist if we focus on only industries whose businesses are less dependent on local demand ("tradables") or if we sample on localities that share the same geo-economic features and even political leanings. In addition, we vary the geographical bandwidth choice in our adjacent-county analyses and account for locale-specific considerations, such as reciprocal tax agreements across states. While our results obtain through the battery of robustness analyses, 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 their labor supply (hours worked or labor force participation). 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. 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. 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 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. 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 middle-class 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 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 base 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 the demand for high-skill jobs 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*).

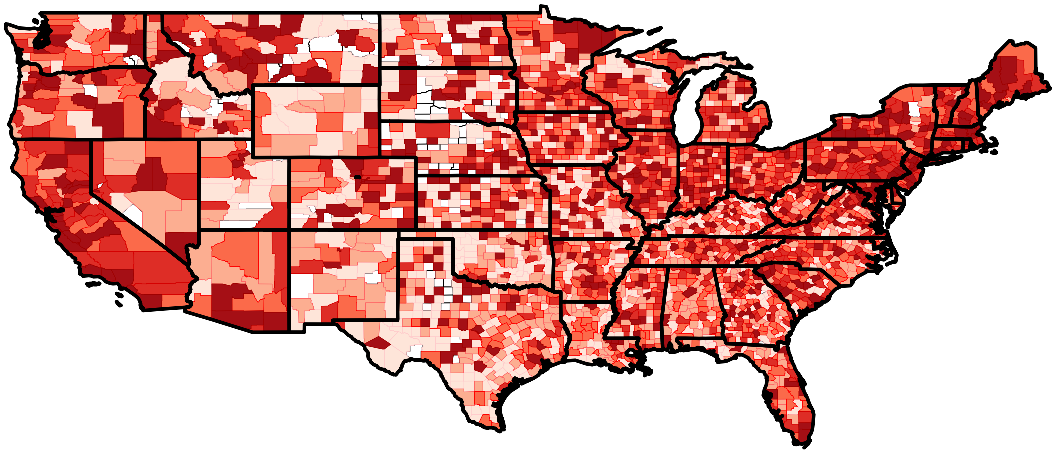
We also consider the percentage of postings requiring computer skills, either the ability to operate a computer (*IT*) or specific software knowledge (*Software*). *Education* is the most common measure of skill and sophistication of a worker. On-the-job experience is also an important aspect of worker 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. IT skills refer to requirements that a worker should know how to operate a computer or should be familiar with certain software package. Finally, 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.

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 level of job skill requirements, proxied by the percentage of job postings requiring bachelor's degrees and above in each county. The color scheme divides the spectrum of education requirements into deciles, with darker (lighter) colors indicating higher (lower) percentages. Firms' requirements for high-skill labor in the beginning of the decade were 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.

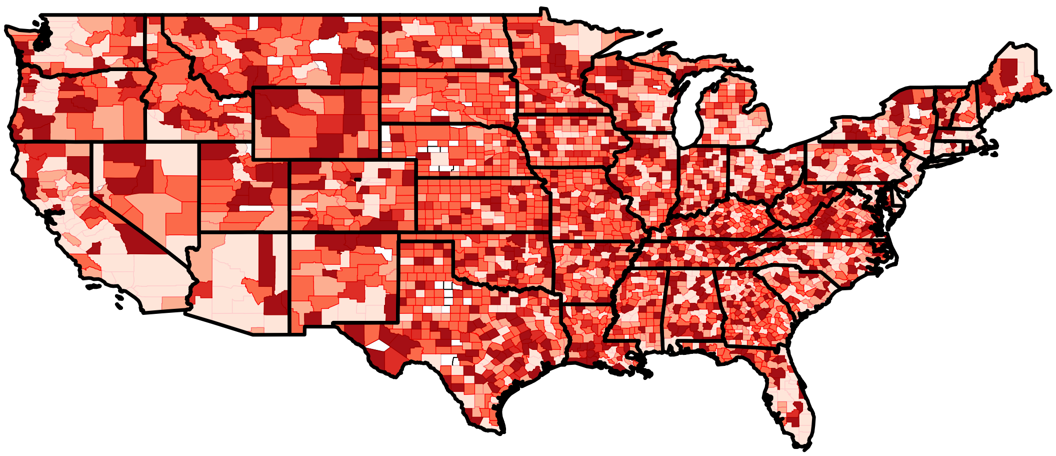
Panel B shows the changes in required job skills in the second half of our sample window (2014–2017). This later panel suggests a "reversal" in education requirements from pre-2014 levels, with coastal states fading in color at the same time that central states pick up on those requirements. The correlation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

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



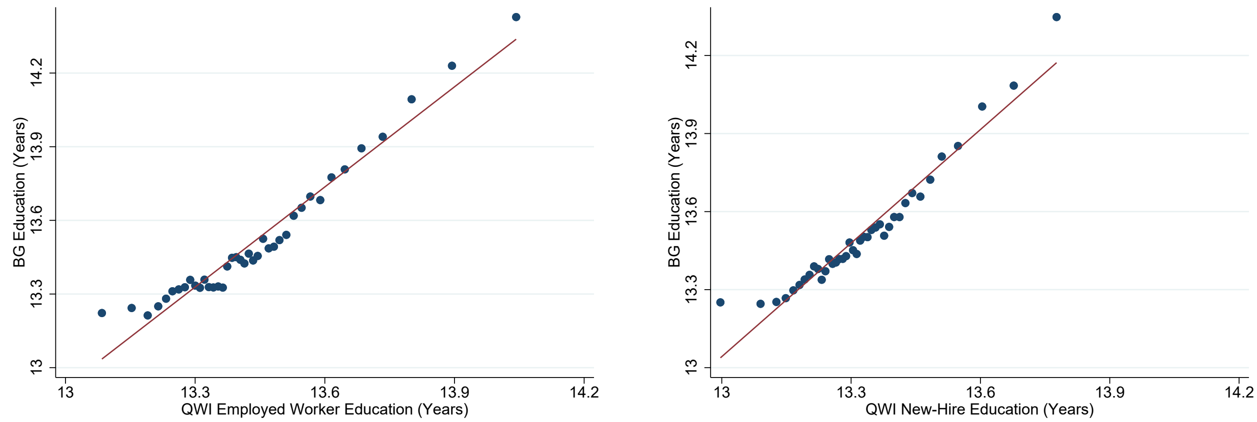
(A) Bachelor and Above Job Requirements, 2010–2013



(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.

verify whether this signal is informative of the skill level of targeted local workers. Figure 2 shows the correspondence between the required years of education indicated in local job postings (based on BurningGlass data) and the years of education received by workers in the same county (based on QWI data). In Panel A, we examine the average education level of all employed workers, while in Panel B we look at newly hired workers' education level. 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 highly-educated workers. These patterns suggest that the skill requirements portrayed by BurningGlass data provides a reasonable representation of the equi-



(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 (in years) and the average education levels of workers employed in the same county (in years). 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.

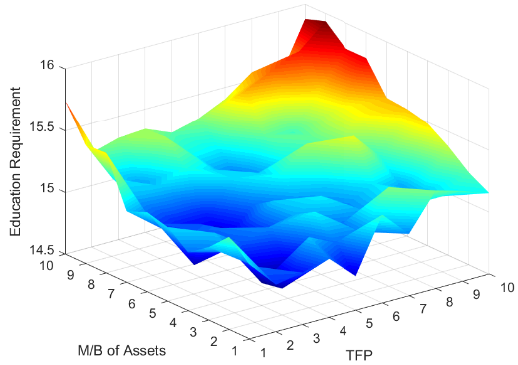
librium skill content in the targeted local labor markets.

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.

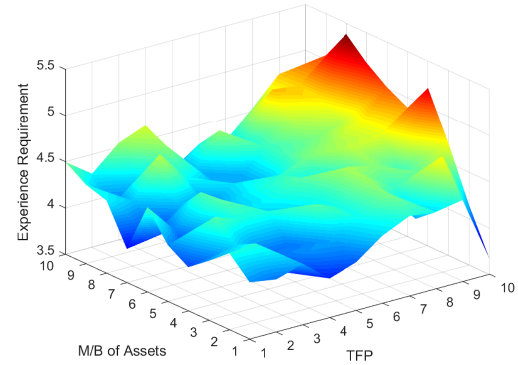
Panel A (alternatively, C) reports the association between firms' requirements of years of education, total factor productivity (patents filed), and firm value.[6] Panel B (D) looks at the same association while examining firms' requirements for workers' years of job experience. In each panel, the axis 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

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

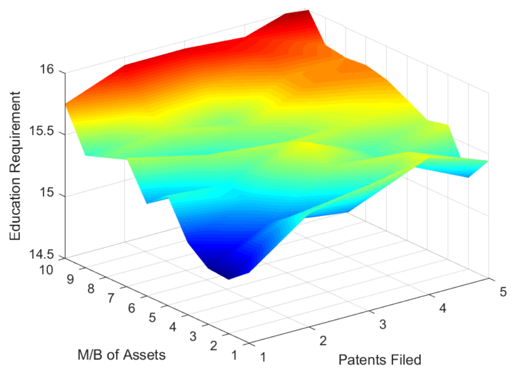
[7]We divide firm-year observations into TFP deciles in Panels A and C. In Panels B and D, we divide firms into five groups based on patent filings. Specifically, we assign firms that file only one patent to group 1, firms that file 2–5 patents to group 2, firms that file 6–10 patents to group 3, 11–50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



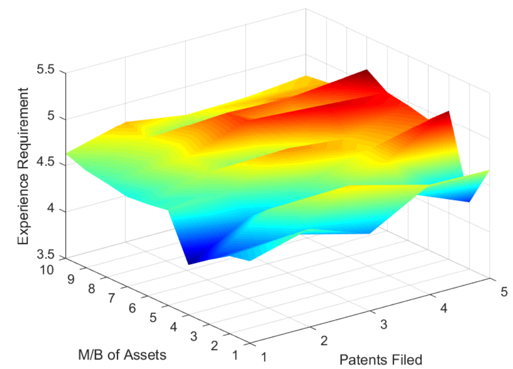
(A) Worker Education, Firm Productivity, and Value



(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.

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 recruit 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. 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 marginal tax rates 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, including 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 taxes. In this way, for every additional dollar increase in state and local taxes, a SALT deduction could partially offset the higher tax burden by the marginal tax rate that a taxpayer faces at the federal level. Top earners tend to benefit more from SALT than standard deductions.[8] However, these same individuals are often hit with the 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 obtain the effective average tax rates faced by taxpayers, defined 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 others. 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.[9] In other words, using Taxsim one can design a personal income tax metric that 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

[8] In 2011, only 12% of tax filers with adjusted gross income (AGI) below \$50,000 claimed SALT deductions, whereas the ratio was above 95% for those with AGI greater than \$250,000 (Source: IRS SOI Tax Stats).

[9] For instance, Taxsim automatically sets the total deduction amount to the greater between the standard deduction and all itemized deductions, triggering the AMT when eligible conditions are met.

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.[10] We assume away other forms of income and associated tax deductions, so that the effective tax rates are directly affected by personal income.[11] 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 the effective average tax rates at other comparable 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 on average collect over 26% of their aggregate revenues from personal income taxes, while only 4% come from corporate income taxes.[12] 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 of the country, 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 same 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.

[10] Based on aggregate 2017 data from BurningGlass, 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.

[11] 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.

[12] 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.

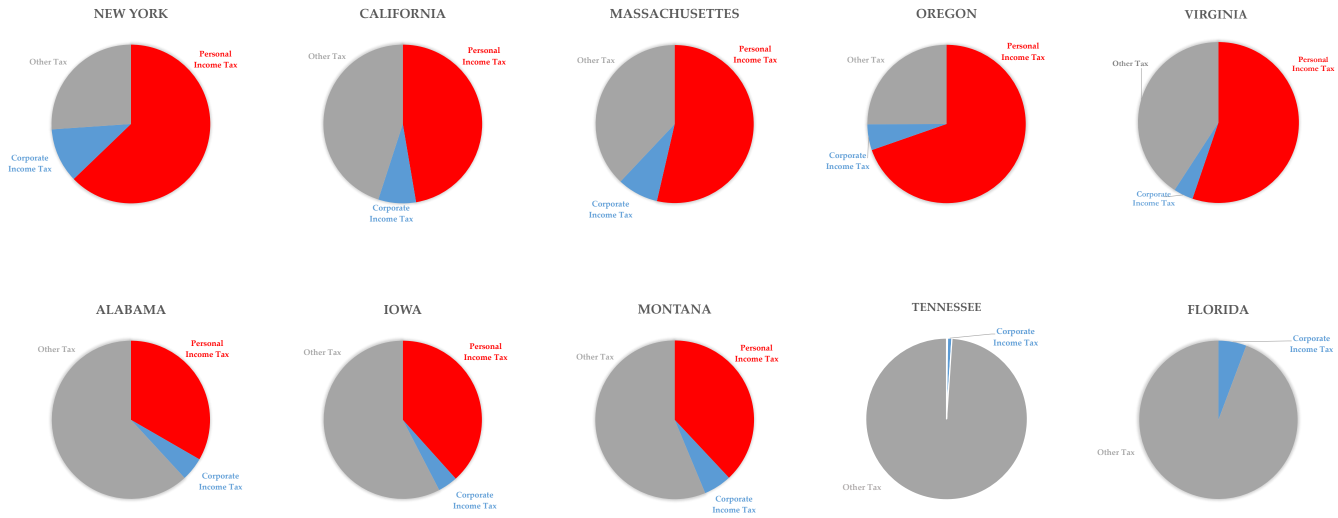
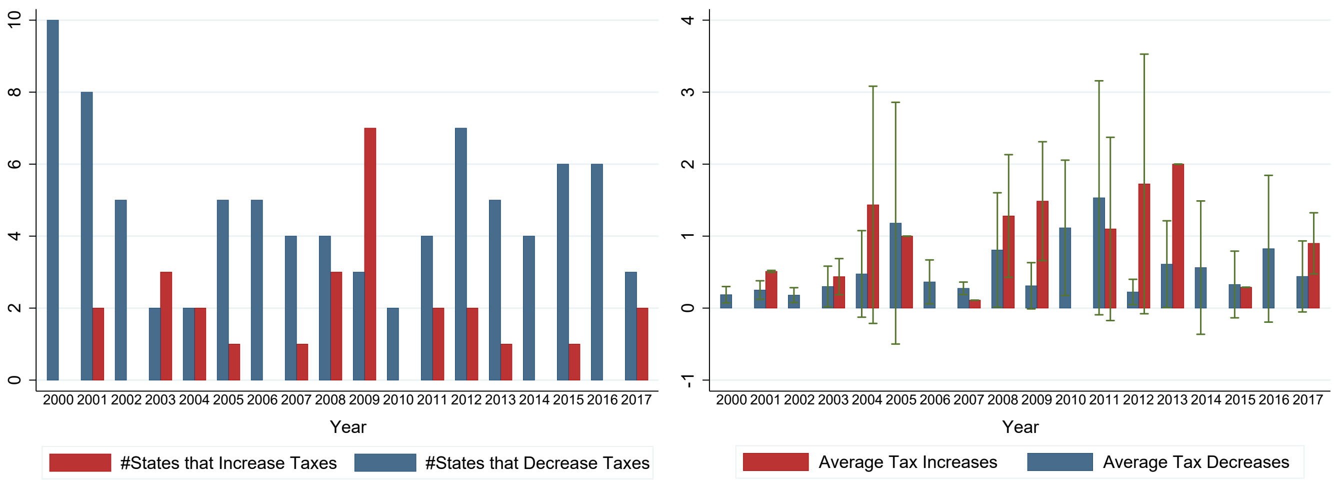


Figure 4. Breakdown of State Governments Tax Revenues. This figure shows the relative importance of personal and corporate income taxes for state governments' revenues. The shares of tax revenues are averages over 2000–2017.

Figure 5 tracks statutory changes in state personal income taxes over time. Panel A shows the number of states that changed their personal income tax rates in a given year. Red columns represent the number of states that increased their personal taxes and blue columns represent the number of states that cut taxes. Panel B shows the average change in personal taxes across all states in a given year, with red (blue) columns indicating the average increase (decrease) in rates. The vertical lines represent one-standard-deviation intervals around the mean. The figure makes it clear that state governments change personal taxes frequently. In 2000, 2001, and 2009 alone, 10 states altered their personal tax rates. Following the 2008-9 financial crisis, state personal taxes experienced drastic changes, with 2010 and 2011 having the most aggressive tax cuts, and 2009 and 2013 seeing the largest tax hikes. The average rate changes in these years exceeded 1%, which is a substantial magnitude compared to the sample average of top bracket tax rates, 5.6%. The rich variation of personal income taxes across states and over time provides a good setting for us to study their effect on firms' 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



(A) Number of States with Personal Tax Changes

(B) Average Personal Tax Changes (%)

Figure 5. State Changes in Personal Income Taxes over Time. This figure shows the variation in personal income tax rates during the period of 2000–2017. Panel A presents the number of states that changed their tax rates per year and Panel B presents the average tax changes across states. In each panel, red columns indicate tax increases and blue columns indicate tax cuts. In Panel A, the vertical axis indicates the number of states that changed their top personal tax rates in a given year. In Panel B, the vertical axis represents the average rate change across all states that increased or decreased their top personal taxes. The solid lines indicate the one-standard-deviation range around the mean.

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.[13] 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

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

percentage points.

We control for both state- and county-level covariates in our empirical tests. First, we control for state corporate taxes and sales taxes, and property taxes imposed by the local government. We also control for other state-level policies including unemployment insurance, number of tax incentives, and minimum wage. Taking into account the fact that income tax revenues are often used to fund fiscal spending, we control for state government direct spending in health, education, public welfare, and infrastructure. All spending items are scaled by local GDP. We next include proxies for local economic conditions such as state GDP, state government budget surplus as a percentage of GDP, county housing price index, total label force, and county median household income. In addition, we control for local demographic information such as African American population and Asian population, both measured as a percentage of total county population. Finally, we include a measure of projected education level of new hires in a given county. This measure is defined as the weighted average education level of workers newly hired by all industries that are present in a given county in a given year, with the weights being the percentage of new hires in the county employed by each industry-year. This measure resembles a Bartik instrument that projects the education demand at the national level to the local county. It thus helps control for changes in skill demand that are driven by industry-level or macroeconomic conditions.

Control variables are constructed using data from various sources. State-level GDP data come from the Bureau of Economic Analysis (BEA), while unemployment insurance information comes from the Department of Labor. Information on state budgetary surplus and minimum wages is compiled by the Institute for Public Policy and Social Research (IPPSR). Home Price Index (HPI) is obtained from the Federal Housing Finance Agency (FHFA). Local demographic information as well as property taxes come from American Community Survey (ACS) prepared by the US Census.

Lastly, we gather information on firms' establishment-level 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 and employment of an industry at the county level. This information is used to compute the geographical concentration of a firm or an industry. 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 48,000 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.[14]

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 fluctuations in local economic circumstances. Second, corporate responses to tax changes across states may be confounded by changes in firm fundamentals, such as profitability, growth, and investment decisions. 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)). In particular,

[14] The average cognitive and IT requirements in our sample are lower than those reported by Hershbein and Kahn (2018) because we do not condition our sample based on the existence of education requirements.

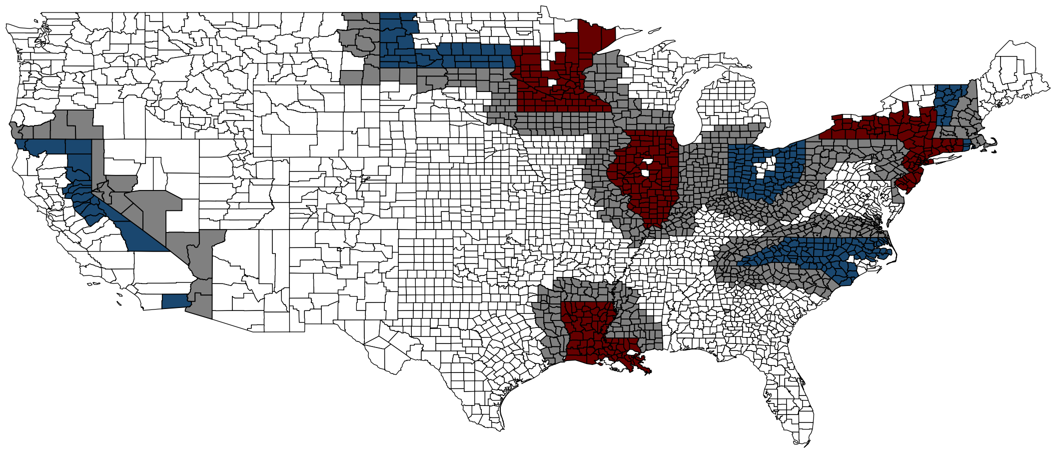


Figure 6. Illustration of Contiguous County Test. This figure illustrates the empirical strategy that focuses on counties near state borders using changes in state-level average personal income tax rates for tax year 2011 (excluding changes with magnitude smaller than 0.05%). Red (blue) shades indicate 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 state border are shaded.

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 movements in underlying demographics and economic conditions. In this setting, our testing sample is a state-border-county-year panel.

Since 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 whose centroids are within an 80-mile bandwidth on each side of a given border, as 80 miles is the cutoff for the bottom tercile distance of US counties' centroids to a state border. Figure 6 illustrates our methodology using changes in state-level average personal tax rates in 2011. 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. We later show that our results 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*, *IT*, *Software*$\}$, 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 the set of control variables listed in Section 2.1.4. 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 adjust skilled positions in states that have changed their personal income taxes relative to states that have not. To implement this test, 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*, *IT*, *Software*$\}$. 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 between counties with personal income taxes changes 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. It also attracts a positive and significant coefficient in the unemployment model. The estimates suggest that a 1-percentage-point 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. Our estimates suggest personal tax elasticities of −0.2 for labor force, employment, and average earnings, and an elasticity of 1 for unemployment rates. These magnitudes are on par with those of Giroud and Rauh (2019), who also document an elasticity of employment to personal income tax rates of −0.2. Overall, our 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 personal income taxes on local firms' skill requirements. 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-percentage-point increase in personal taxes is associated with a 1.5 (2)-percentage-point decline in the jobs postings listing education (experience) requirements in a given county. These estimates imply elasticities to personal taxes of 0.6 for education and 1.1 for experience requirements. Other skill dimensions exhibit higher elasticities, ranging from 2.9 for cognitive skill requirements and 4 for technology requirements. The higher sensitivity of cognitive and technology skills to personal taxes may be a result of both supply-side and demand-side effects. First, workers possessing those skills are often more mobile and thus can curtail their supply of labor to a greater extent in response to higher personal taxes. In addition, technology skills can be obtained through training instead of formal education. As such, seeing an increase in personal taxes, firms may find it less costly to retrain their existing workers than to hire new workers from the external labor market.

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 as well. Notably, coefficients for *Personal Taxes* are all negative, being both economically and statistically significant. For example, a 1-percentage-point increase in personal taxes leads to an around 1-percentage-point reduction in the job postings with explicit education and experience requirements. The same income tax increase triggers a comparable reduction in requirements of cognitive skills and software knowledge. It also elicits lower IT requirements (by 2.1 percentage points). These magnitudes translate to tax elasticities of 0.3 for education and experience, 1 for cognitive skills, and of 1.6 for IT requirements.

Taken altogether, our results highlight the active role of firms in allocating skilled jobs across states in response to differences in personal taxes.[15] They point to a pronounced "brain drain" effect in high-

[15] Our findings are related to Giroud and Mueller (2018), who show that firms can transmit local shocks across US regions. While they focus on the number of workers employed by firms, we discuss the skill content of jobs created by firms.

tax states. Given the importance of skilled labor in fostering economic growth, losing high-skill job posts is likely to generate a persistent, negative impact on the local economy. Results from the firm-level estimation generally suggest smaller tax elasticities than do county-level results. This may occur for several reasons. First, the county sample focuses on comparison across state borders, whereby it is easy for workers to relocate to a low-tax state. Second, the county sample contains pass-through entities, for which personal taxes reduce corporate income and thus amplify the reduction of skilled hires.[16] Finally, the firm sample features large, public corporations, who face certain organizational frictions that may prevent them from changing their hiring policies promptly after a change in personal taxes. We discuss these frictions next.

4.3 Heterogeneity in Firm Responses

We examine a number of firm- and industry-level characteristics that could mitigate or exacerbate the effect of personal tax changes 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 using 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 in reallocating skilled workers using the geographical dis-

[16] 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.

persion 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).[17] 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*

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

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 25 alternative versions of Eq. (3). To cut clutter, we only report the 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 markets 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 jurisdictions, 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 disentangle these competing dynamics.

We evaluate the effect of personal taxes on local IT investment at the establishment level. Specifically, we regress measures of IT investment on local personal taxes while controlling for establishment-fixed effects. Results are presented in Table 5. Our estimates suggest that a 1-percentage-point increase in personal income taxes is associated with firms decreasing their per-employee computer budget by $102 and hardware budget by $423 (these figures represent about 10% of the average per worker IT budget at the establishment level). Firms also substantially cut budgets for telecommunication services and the acquisition of servers following personal tax hikes.

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 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' exit and entry from the local labor market. Among other things, this examination allows us to gauge in further detail the extent to which firms completely stop hiring from a locality when it levies a heavier tax burden on skilled workers.

Our analysis examines whether personal taxes affect a public firm's exit from and entry to the labor market of a state. We define a firm's participation in the local labor market in two ways. First, *Exit* equals 1 if a firm has posted jobs in a given state in the previous year, but stops posting from the current year forward, and 0 otherwise. *Entry* equals 1 when a firm starts posting jobs in a given state for the first time in our sample period.[18] When testing firms' decision to exit (enter) a state, we sample only on firms that have not exited (entered) the state by the previous year.[19] In these firm-level tests, we adopt a similar methodology as Eq. (2), controlling for state- and firm-year-fixed effects.

Panel A of Table 6 reports the results. Our estimates suggest that a 1-percentage-point increase in personal taxes is associated with a firm being 0.6% more likely to exit a state and 0.4% less likely to enter a state. These economic magnitudes are meaningful, accounting for a 4–8% change relative to the sample average of firm exit and entry rates. These results support the notion that higher personal taxes drive incumbent firms out of the local labor market and discourage other firms from entering.

TABLE 6 ABOUT HERE

4.6 Personal Taxes at Other Income Levels

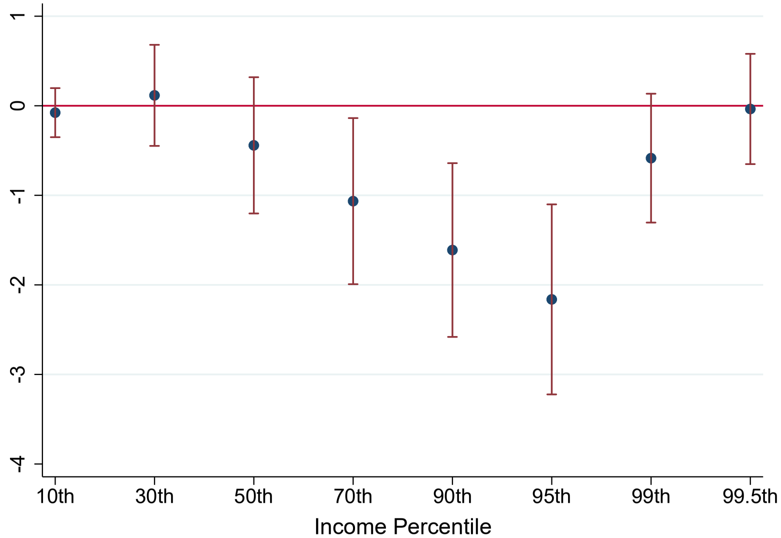
Our baseline tests revolve around personal tax rates levied on individuals whose income levels rank at the 90^{th} percentile of the population. Given that wage levels of skilled workers vary widely across the US, we consider personal income taxes faced by workers making other levels of income, starting with the 10^{th} percentile all the way through the 99.5^{th} percentile of the income distribution.

Figure 7 depicts the results for education and experience requirements.[20] Panels A and B report the results from the county sample, and Panels B and D report the results from the public firm sample. In each panel, coefficients on personal income taxes for various income levels are presented together with corresponding 90% confidence intervals. Our estimation suggests that changes to taxes affecting

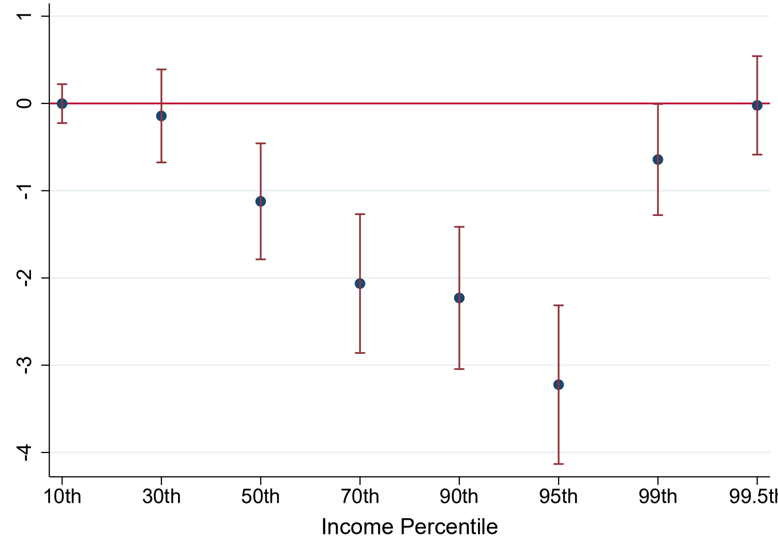
[18]We multiply *Exit* and *Entry* by 100, so that the coefficients will suggest the percentage likelihood that a firm leaves and enters the local labor market.

[19]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.

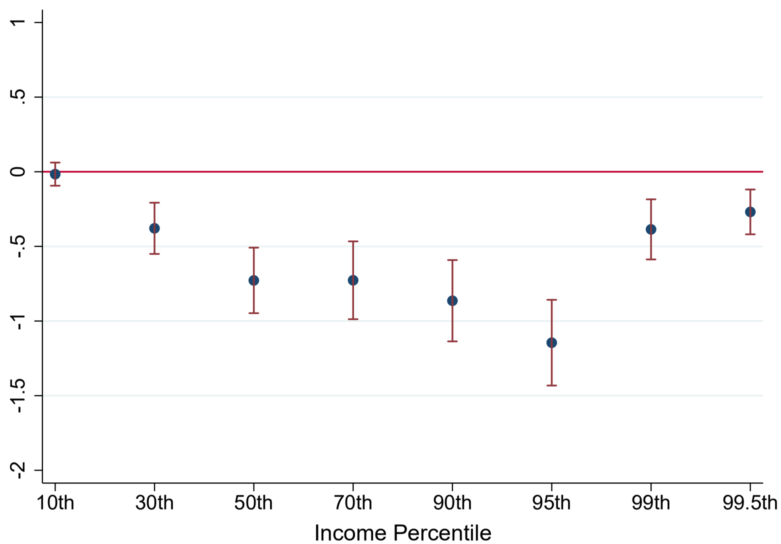
[20]Detailed regression results for all skill requirements are presented in Appendix B.



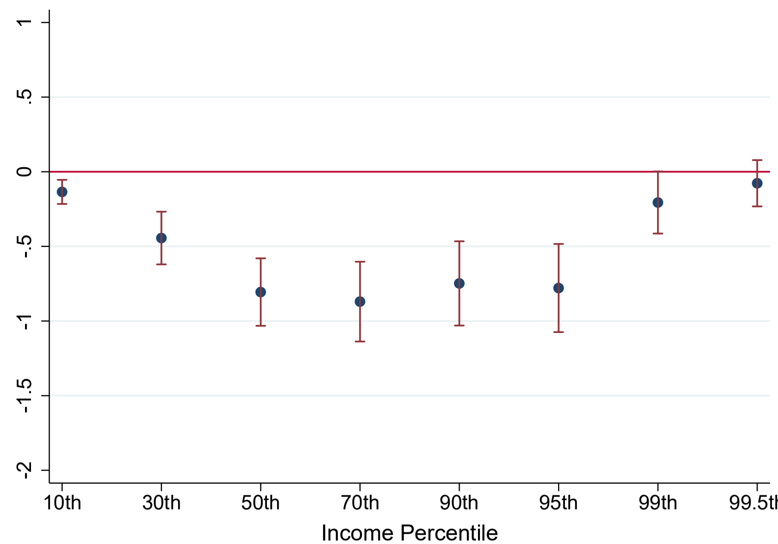
(A) County-Level: Effects on Education Requirements



(B) County-Level: Effects on Experience Requirements



(C) Firm-Level: Effects on Education Requirements



(B) Firm-Level: Effects on Experience Requirements

Figure 7. Personal Tax Brackets. This figure shows the effects of personal tax rates at different income brackets on the education and experience requirements of local job postings. In each panel, the dots represent the coefficient estimates corresponding to personal taxes at a certain income percentile, and the solid intervals represent the 90% confidence intervals for the estimates.

low-income earners (10^{th} percentile income) do not generate a meaningful effect on local job postings. As one moves up the income ladder, there is a U-shaped relationship between personal taxes and firms' skill requirements. The negative effects of personal taxes first intensify, reaching the highest levels at the 95^{th} income percentile, but the effects diminish at the very top of the income distribution both in terms of economic magnitudes and statistical significance. At the 99^{th} percentile, the impact of personal taxes on labor skill requirements 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 local earners with relatively high income levels (upper "middle class"), 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.

4.7 Narrative Approach

An examination of the impact of taxes on employment has to deal with the concern that tax policy may endogenously respond to dynamics that also shape the local economy. 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). To help tackle this concern in a way that abstracts from the use of involved econometric techniques, we adopt the "narrative approach" proposed by Romer and Romer (2010), which identifies the political economy narratives behind tax policy changes across different jurisdictions over time. The goal of this analysis is to isolate tax policy changes that are "exogenous" to short-term local economic conditions. Following Romer and Romer, we collect local narratives from politicians, journalists, and policy analysts regarding a change in state personal income tax policy and infer the underlying motives of the change. Under this approach, one classifies tax shocks that are not systematically correlated with other factors affecting output as exogenous, such as tax policy changes designed to improve fairness, promote long-run economic growth, or changes resulting from inherited budget deficits, which primarily reflect economic conditions in the past. This stands in contrast to "endogenous" tax changes, which are policy responses to concurrent or upcoming changes in government spending, or ones designed to offset other factors that are likely to change output growth in the near future.

We focus on large statutory tax rate changes that occurred during our sample period, keeping only events during the years of 2011 through 2015 to allow for both pre- and post-event windows. Accordingly, we define "tax events" as cases where a state changes its top personal tax rate by at least 25 basis points (we do so excluding txes meant to affect "millionaires"). We exclude tax changes that are soon followed by a reversal within three years. In the scenario where a state changes its tax rates gradually over a few years, we only keep the first event. Finally, we search extensively on Google News and Factiva for news articles discussing a tax shock, removing tax events classified as "endogenous."

The above filters leave us with 16 exogenous tax events, among which 4 events are tax increases and 12 are tax cuts. We adopt an event-study approach to estimate the effects of these tax shocks, using $[-2,2]$ years around each event. The event study utilizes the adjacent-county sample that includes all counties whose centroids are within 80 miles to the border of a state introducing a tax change. Using this sample, we estimate the following regression:

$$Y_{c,b,T,t} = \sum_{t=-2}^{2} \beta_t \times Treatment_{c,b,T} \times 1_t + Controls_{c,T+t-1} + \gamma_c + \lambda_b + \tau_{T+t} + \epsilon_{c,b,T,t}, \tag{4}$$

where *Treatment* is assigned a value of 1 for counties in states that increase personal taxes in year T and a value of –1 for states that decrease tax in year T. For counties in the control group, *Treatment* is set to 0. T is the year of the tax change, and 1_t is an indicator for years in the event window.

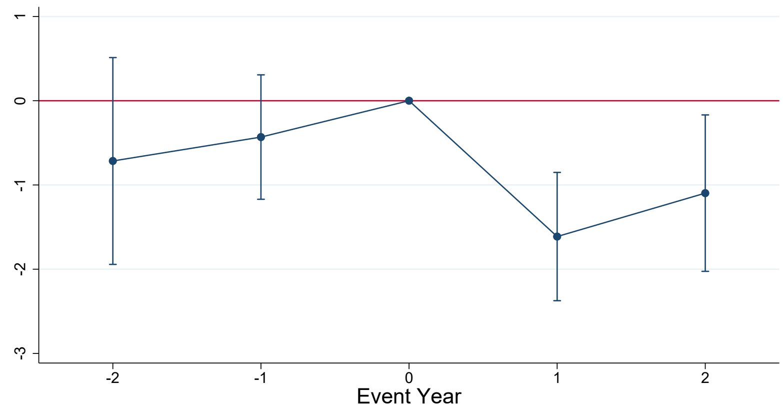
In applying the narrative approach to our setting, we focus on local firms' education requirements and further investigate changes in the level of education required by firms following a tax event. Figure 8 presents the results from the narrative analyses. In Panel A, we examine whether firms increase the percentage of job postings that explicitly mention education requirements. In Panel B, we look into the average years of education required by firms within the job ads that contain education requirements. Panel C shows the percentage of postings specifying that a worker should have a bachelor's degree or above. In all panels, the dots represent coefficient estimates for β_t from Eq. (4) and the vertical lines represent confidence intervals. Year 0 is absorbed as the benchmark, so the coefficients shown in each plot capture the education requirements relative to year 0.

Panels A and B of Figure 8 show that after a tax hike (cut), an average firm posts 1.5% fewer (more) jobs containing education requirements and specifies an education reduction (increase) of 0.1 years conditional on having an education requirement. The patterns in Panel C suggest that the effects are mainly driven by job postings requiring a bachelor's degree or above. These hiring responses emerge immediately after the policy shocks and remain stable in the two-year post-event period we consider.

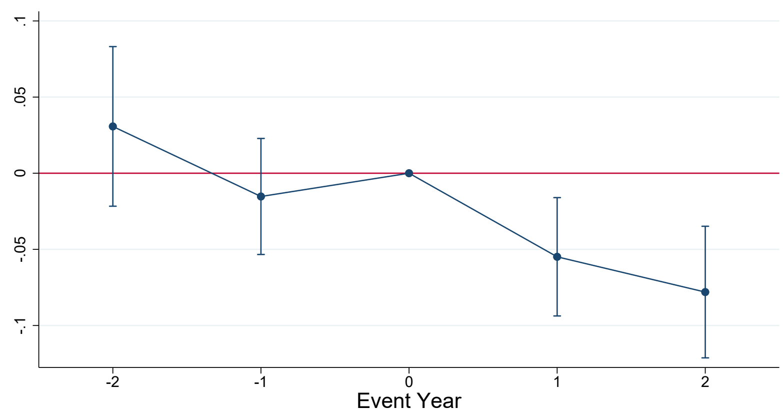
5 Robustness Checks

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, as we look across state borders, we seek to identify politically and economically matched comparison groups. Second, 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.

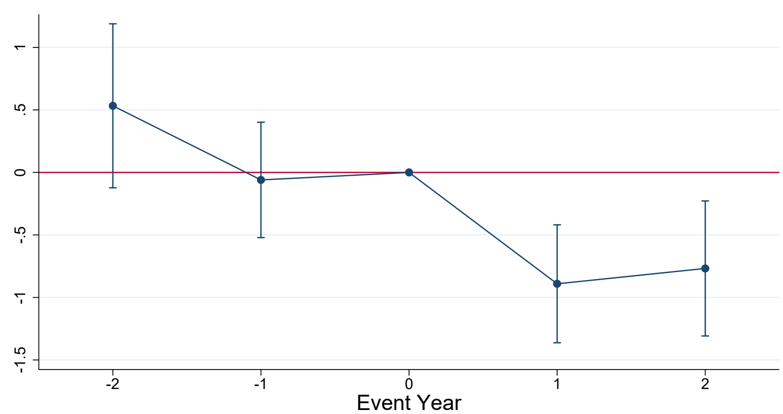
First, we consider the argument that variation in local product demand could affect the interpretation of our results. Specifically, personal taxes may affect local households' demand for goods and services. The changes in skilled hiring that we document may thus reflect firms' response to changes in 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 whose business activities 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 A of Table 7, we repeat the baseline tests at the firm level while restricting the sample to only tradable industries.



(A) Education Requirements (%)



(B) Average Education Level (Years)



(C) Bachelor Degrees and Above (%)

Figure 8. Narrative Approach. This figure shows the education requirements contained in local job postings surrounding statutory changes in top personal income tax rates. Panel A shows the percentage of job postings containing education requirements. Panel B shows the average level of education (in years) required. Panel C shows the percentage of job postings containing education requirements that specify a bachelor's degree or above. In each panel, the dots represent coefficient estimates of β_t ($t \in [-2, 2]$) in Eq. (4) and the vertical lines represent the corresponding 90% confidence intervals. Year 0 is used as the benchmark. All tests follow the adjacent-county design, including counties whose centroids are within 80 miles to a state border.

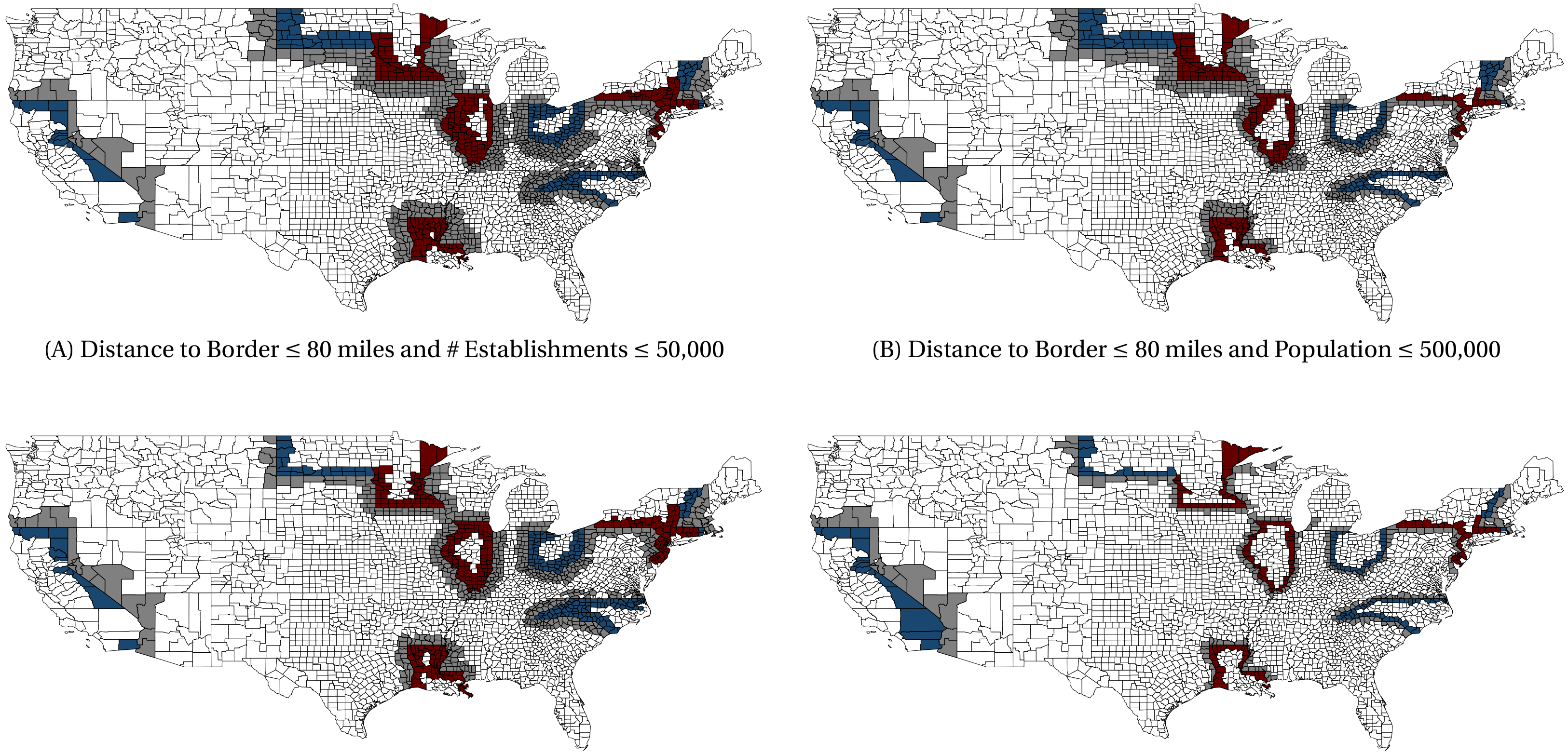
Our results remain unchanged.[21]

TABLE 7 ABOUT HERE

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 three 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. Finally, we drop state borders formed by major rivers (e.g., the Mississippi River, the Colorado River, and the Ohio River), as areas on opposite sides of a river may not be comparable. Results from Table 7 show that our baseline results continue to hold for all of these sample restrictions.

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. Panels A and B of Figure 9 illustrate these alternative spatial specifications using 2011 tax changes. Compared to the sample shown in Figure 6, these new filters

[21] 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.



(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 9. Illustration of Alternative Sampling Choices. This figure illustrates the sample selection criteria for the robustness tests reported in Table 8. 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 state-level average personal income tax changes for tax year 2011 (excluding changes with magnitude smaller than 0.05%). 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.

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 9 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 9, the county-pair design imposes the most restrictive criteria and results in the smallest number of counties included in the testing sample.

Table 8 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 8 ABOUT HERE

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 9 reports results from these two tests. Our baseline results obtain across both specifications, suggesting that a higher likelihood of cross-border migration or worker commuting across state borders does not unduly influence our results.

TABLE 9 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 middle class 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.

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

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

Exit and Entry

- *Exit*: An indicator for a firm stopping posting jobs in a state from the current year going forward, and zero otherwise. The variable is multiplied by 100.
- *Entry*: An indicator for a firm posting jobs in a state for the first time, and zero otherwise. Year 2010 is not counted as a year of entrance. The variable is multiplied by 100.

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
- *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*
- *Minimum Wage* : State-level minimum wage per hour. Source: Institute for Public Policy and Social Research, Michigan State University
- *Education Spending*: State government total education direct expenditure, scaled by gross state product. Source: State Policy Database

- *Public Welfare Spending*: State government public welfare and veterans' services direct expenditure, scaled by gross state product. Source: State Policy Database
- *Infrastructure Spending*: State government expenditure in infrastructure (including air transportation, general public buildings, highways, parking, parks and recreation, sanitation, and water transportation), scaled by gross state product. Source: State Policy Database
- *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
- *Log(HPI)*: The log of housing price index. Source: Federal Housing Finance Agency (FHFA)
- *Log(Median Income)* : The log of median household income in the area. Source: US Census
- *%African American Population*: The percentage of local population that are black. Source: US Census
- *%Asian Population*: The percenrage of local population that are Asian. Source: US Census
- *Health Spending*: State government total health and hospitals direct expenditure, scaled by gross state product. Source: State Policy Database
- *Education of New Hires*: The average education of local new hires, calculated as the average of national NAICS-3 new hire education weighted by local NAICS-3 new hire counts, i.e., $\sum_j \omega_{j,c,t-1} \times Edu_{j,t}$, where j indicates an industry, c indicates a county, and t indicates a year. $\omega_{j,c,t}$ is the share of new hires in county c that are employed by industry j in year t. $Edu_{j,t}$ is the average education level of new hires by industry j in year t. Source: QWI

Conditioning Characteristics

- *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

Appendix B Effects from Different Income Brackets

We examine the effects of personal income taxes across the entire income distribution on the skill requirements of local job postings. We repeat our baseline specification, shown in Eq. (1) and Eq. (2), while substituting personal taxes for 90^{th} percentile income level with taxes for other income brackets, ranging from 10^{th} to 99.5^{th} percentile. Table B.1 shows the results. Panel A shows the results for county-level sample, and Panel B shows the results from the firm-level sample. From both testing samples, we find little to no effect for personal taxes targeting earners at the bottom of the income distribution (i.e., 10^{th} percentile), but strong effects for relatively high-income earners. The effects of personal taxes are concentrated for income levels between 70^{th} to 95^{th} percentiles, but significantly weaken for tax rates targeting very top income households.

Table B.1
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. Control variables are the same as used in Table 3. 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: County-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes (10^{th} Pctl)	–0.077	–0.002	–0.041	–0.034	–0.123
	(0.166)	(0.135)	(0.129)	(0.128)	(0.112)
Personal Taxes (30^{th} Pctl)	0.116	–0.143	0.207	0.438	–0.056
	(0.342)	(0.323)	(0.264)	(0.300)	(0.259)
Personal Taxes (50^{th} Pctl)	–0.442	–1.122***	–1.465***	–2.055***	–1.485***
	(0.461)	(0.403)	(0.321)	(0.329)	(0.280)
Personal Taxes (70^{th} Pctl)	–1.065*	–2.064***	–2.475***	–3.001***	–2.064***
	(0.562)	(0.482)	(0.407)	(0.397)	(0.341)
Personal Taxes (90^{th} Pctl)	–1.611***	–2.229***	–3.076***	–3.904***	–2.783***
	(0.588)	(0.494)	(0.451)	(0.437)	(0.389)
Personal Taxes (95^{th} Pctl)	–2.162***	–3.223***	–2.757***	–3.758***	–2.779***
	(0.643)	(0.551)	(0.455)	(0.439)	(0.387)
Personal Taxes (99^{th} Pctl)	–0.585	–0.643*	–0.523	–1.265***	–0.945***
	(0.436)	(0.386)	(0.319)	(0.305)	(0.262)
Personal Taxes (99.5^{th} Pctl)	–0.036	–0.022	–0.182	–0.652**	–0.335
	(0.373)	(0.342)	(0.264)	(0.262)	(0.233)

Panel B: Firm-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes (10th Pctl)	–0.016	–0.135***	–0.089**	–0.066*	–0.125***
	(0.047)	(0.049)	(0.039)	(0.040)	(0.036)
Personal Taxes (30th Pctl)	–0.379***	–0.444***	–0.931***	–1.081***	–0.857***
	(0.104)	(0.107)	(0.086)	(0.087)	(0.080)
Personal Taxes (50th Pctl)	–0.728***	–0.806***	–1.543***	–1.959***	–1.318***
	(0.133)	(0.137)	(0.113)	(0.113)	(0.104)
Personal Taxes (70th Pctl)	–0.727***	–0.870***	–1.376***	–2.053***	–1.326***
	(0.158)	(0.162)	(0.136)	(0.136)	(0.126)
Personal Taxes (90th Pctl)	–0.864***	–0.748***	–1.304***	–2.278***	–1.558***
	(0.165)	(0.171)	(0.144)	(0.144)	(0.133)
Personal Taxes (95th Pctl)	–1.145***	–0.779***	–1.454***	–2.327***	–1.592***
	(0.174)	(0.179)	(0.150)	(0.151)	(0.138)
Personal Taxes (99th Pctl)	–0.386***	–0.206	–0.381***	–0.961***	–0.657***
	(0.122)	(0.126)	(0.110)	(0.110)	(0.102)
Personal Taxes (99.5th Pctl)	–0.269***	–0.077	–0.220***	–0.504***	–0.380***
	(0.091)	(0.094)	(0.084)	(0.084)	(0.078)

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	42.124	43.301	15.925	31.957	52.711
Experience	36.828	37.084	13.303	28.696	45.016
Cognitive	19.002	17.910	10.930	11.688	25.246
IT	17.747	16.296	11.425	9.582	24.251
Software	12.406	10.526	9.610	5.567	16.996
Local Controls					
Unemployment Insurance	11.284	11.223	0.525	10.889	11.597
Tax Incentives	25.171	26.000	4.172	24.000	28.000
Minimum Wage	6.498	6.750	1.199	5.150	7.250
Health Spending	0.015	0.013	0.006	0.011	0.017
Education Spending	0.057	0.055	0.008	0.051	0.062
Public Welfare Spending	0.028	0.026	0.008	0.022	0.033
Infrastructure Spending	0.022	0.021	0.005	0.018	0.024
Log(GDP)	12.235	12.239	0.980	11.635	12.923
Budget Surplus	0.777	0.876	5.674	–2.576	3.851
Log(HPI)	5.319	5.227	0.489	4.953	5.607
Log(Median Income)	10.581	10.570	0.264	10.400	10.747
%African American Population	9.376	2.248	14.732	0.748	10.854
%Asian Population	1.233	0.615	2.184	0.330	1.198
Education of New Hires	13.404	13.450	0.815	13.392	13.513

Panel C: Public Firm Sample

Variable	Mean	Median	Std. Dev.	25^{th} Pct	75^{th} Pct
Job Skill					
Education	49.594	50	42.587	0	100
Experience	43.894	40	40.738	0	87.500
Cognitive	25.955	0	35.343	0	50
IT	26.469	0	36.465	0	50
Software	20.338	0	33.133	0	33.333
Conditioning Characteristics					
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					
PC Budget	713.987	285.714	1302.350	133.333	1000
Hardware Budget	1731.982	948.900	3273.851	302.307	1833.333
Comm. Budget	991.207	458.200	3407.522	200	997.750
Server Budget	676.545	166.667	1608.282	43.250	600
Exit and Entry					
Exit (%Likelihood)	15.716	0	36.396	0	0
Entry (%Likelihood)	4.397	0	20.502	0	0
Local Controls					
Unemployment Insurance	11.395	11.408	0.552	10.889	11.755
Tax Incentives	26.061	27.000	3.844	24.000	29.000
Minimum Wage	7.717	7.250	0.881	7.250	8.100
Health Spending	0.016	0.015	0.006	0.012	0.018
Education Spending	0.056	0.054	0.008	0.051	0.061
Public Welfare Spending	0.032	0.031	0.008	0.026	0.037
Infrastructure Spending	0.021	0.020	0.004	0.018	0.023
Log(GDP)	12.743	12.717	0.925	12.159	13.289
Budget Surplus	-0.519	-0.319	5.772	-4.378	2.692
Log(HPI)	5.889	5.915	0.490	5.515	6.264
Log(Median Income)	10.863	10.840	0.260	10.685	11.016
%African American Population	14.273	8.981	14.672	3.268	20.297
%Asian Population	4.695	2.957	5.861	1.348	5.369
Education of New Hires	13.528	13.533	0.375	13.468	13.602

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, state unemployment insurance, the number of tax incentives, state minimum wage levels, the log of state GDP, and state budget surplus. 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 jobs 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*), general IT knowledge (*IT*), and knowledge of specific software (*Software*). Control variables include corporate taxes, sales taxes, property taxes, state unemployment insurance, the number of tax incentives, state minimum wage levels, the log of state GDP, state budget surplus, the log of county labor force, the log of county housing price index, the projected average education of new hires at the county level, the percentage of county population that are African American, the percentage of county population that are Asian, and state government expenditures on health and hospitals, education, public welfare, and infrastructure. 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) *IT*	(5) *Software*
Personal Taxes	–1.519**	–2.178***	–2.987***	–3.784***	–2.715***
	(0.591)	(0.498)	(0.450)	(0.436)	(0.389)
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	32,882	32,882	32,882	32,882	32,882
Adjusted R^2	0.542	0.521	0.606	0.660	0.681

Panel B: Firm-Level Evidence

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–0.864***	–0.748***	–1.304***	–2.278***	–1.558***
	(0.165)	(0.171)	(0.144)	(0.144)	(0.133)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	1,385,248	1,385,248	1,385,248	1,385,248	1,385,248
Adjusted R^2	0.513	0.432	0.417	0.448	0.419

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. *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 are the same as those used in Table 3. 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: Worker Skill Importance

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes × LSI	0.045*	0.050**	0.122***	0.087***	0.059***
	(0.024)	(0.025)	(0.022)	(0.021)	(0.020)

Panel B: Operational Flexibility

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes × Footloose (Employment)	–0.388***	–0.005	–0.366***	–0.213**	–0.201**
	(0.104)	(0.107)	(0.097)	(0.097)	(0.092)
Personal Taxes × Footloose (Establishments)	–0.385***	–0.026	–0.394***	–0.216**	–0.202**
	(0.102)	(0.105)	(0.095)	(0.095)	(0.091)

Panel C: Firm Organization Structure

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes × State Sales Relevance	0.716***	0.631***	0.920***	0.670***	0.696***
	(0.043)	(0.044)	(0.041)	(0.042)	(0.042)
Personal Taxes × HQ State	0.175***	0.159***	0.263***	0.240***	0.255***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)

Table 5
Technology Investment and Personal Taxes
This table examines the effect of personal tax changes on IT investment at the establishment level. The unit of observation is an establishment-year. 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 are the same as those used in Table 3. 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	–108.701***	–469.522***	–388.680***	–55.136***
	(3.706)	(13.600)	(16.490)	(7.797)
Controls	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Observations	592,385	783,908	783,908	592,385
Adjusted R^2	0.618	0.341	0.197	0.355

Table 6
Firm Exit and Entry
This table examines firms' exit and entry in response to personal tax changes. *Exit* is an indicator that equals 1 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. Both measures are multiplied by 100 so that the coefficients represent likelihood of entry and exit associated with personal taxes. In Column (1), the sample includes all firms that have not entered a state, and in Column (2), the sample includes all firms that have not exited a state. The testing sample spans from 2010 through 2017. Year 2010 is not counted as a year of entry. Control variables include state-level taxes, other state policies such as unemployment insurance, the number of tax incentives, and state minimum wage levels, and four measures of state fiscal spending. They also include state economic conditions, demographics, and the projected average education of new hires at the state level. The table shows estimates from the following specification, where i represents a firm, s represents a state, and t represents a year. Standard errors are clustered by firm-state. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

Dep. Var.:	(1) *Exit* (%Likelihood)	(2) *Entry* (%Likelihood)
Personal Taxes	0.588**	–0.373***
	(0.274)	(0.104)
Controls	Yes	Yes
State-FE	Yes	Yes
Firm-Year-FE	Yes	Yes
Observations	294,360	954,601
Adjusted R^2	0.584	0.248

Table 7
Robustness: Local Economic Conditions and Comparability Across Localities
This table examines whether our results are driven by variation in the political and geographical distinctions across the counties we sample on. In Panel A, we examine the effect of personal taxes on the hiring of tradable industries. In Panel B, 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 C, we focus on state borders whereby the two neighboring states are located within the same Census region. In Panel D, we remove state borders that are defined by major rivers. Control variables are the same as in Table 3. Standard errors are clustered by firm-county in Panel A, and are clustered by county in Panels B and C. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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

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

Panels B and C 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 A: Only Tradable Industries (Firm-Level)

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–0.778***	–0.998***	–1.388***	–2.611***	–1.928***
	(0.204)	(0.210)	(0.180)	(0.185)	(0.173)
Controls	Yes	Yes	Yes	Yes	Yes
County-FE	Yes	Yes	Yes	Yes	Yes
Firm-Year-FE	Yes	Yes	Yes	Yes	Yes
Observations	1,125,906	1,125,906	1,008,445	1,008,445	1,008,445
Adjusted R^2	0.459	0.385	0.356	0.392	0.375

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

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–0.377	–1.578**	–2.511***	–3.565***	–2.494***
	(0.723)	(0.632)	(0.532)	(0.531)	(0.488)
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	17,927	17,927	17,927	17,927	17,927
Adjusted R^2	0.585	0.543	0.625	0.668	0.685

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

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–1.940***	–2.269***	–3.241***	–3.880***	–2.794***
	(0.563)	(0.472)	(0.455)	(0.438)	(0.390)
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	27,883	27,883	27,883	27,883	27,883
Adjusted R^2	0.545	0.529	0.608	0.663	0.683

Panel D: Removing Major River Borders (County-Level)

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–2.759***	–2.411***	–3.276***	–4.040***	–3.253***
	(0.672)	(0.535)	(0.497)	(0.528)	(0.477)
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	23,608	23,608	23,608	23,608	23,608
Adjusted R^2	0.556	0.551	0.635	0.682	0.704

Table 8
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. Control variables are the same as in Table 3. Standard errors are clustered by county. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panels A through C 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 D 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) *IT*	(5) *Software*
Personal Taxes	–1.386**	–2.380***	–2.336***	–3.139***	–2.096***
	(0.666)	(0.553)	(0.461)	(0.444)	(0.386)
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	26,727	26,727	26,727	26,727	26,727
Adjusted R^2	0.518	0.482	0.574	0.622	0.640

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

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–1.911***	–2.539***	–2.482***	–2.908***	–1.940***
	(0.740)	(0.602)	(0.486)	(0.500)	(0.432)
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	18,361	18,361	18,361	18,361	18,361
Adjusted R^2	0.506	0.477	0.560	0.603	0.624

Panel C: Distance to Border ≤ 50 miles

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–1.632**	–2.519***	–2.877***	–3.737***	–2.784***
	(0.658)	(0.537)	(0.483)	(0.476)	(0.421)
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	20,434	20,434	20,434	20,434	20,434
Adjusted R^2	0.541	0.526	0.620	0.663	0.691

Panel D: County-Pair Design

Dep. Var.:	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Software*
Personal Taxes	–2.643***	–2.686***	–2.550***	–2.789***	–1.744***
	(0.802)	(0.631)	(0.497)	(0.527)	(0.453)
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	19,162	19,162	19,162	19,162	19,162
Adjusted R^2	0.502	0.491	0.593	0.626	0.646

Table 9

Robustness: Migration Across Borders

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. Control variables are the same as in Table 3. 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

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Education*	*Experience*	*Cognitive*	*IT*	*Software*
Personal Taxes	–1.512**	–2.075***	–3.224***	–4.114***	–2.921***
	(0.629)	(0.569)	(0.514)	(0.495)	(0.447)
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	24,652	24,652	24,652	24,652	24,652
Adjusted R^2	0.536	0.508	0.591	0.651	0.667

Panel B: Reciprocal State Borders Only

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	*Education*	*Experience*	*Cognitive*	*IT*	*Software*
Personal Taxes	–3.039***	–4.096***	–5.027***	–4.814***	–3.553***
	(1.148)	(0.994)	(0.786)	(0.722)	(0.694)
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	6,867	6,867	6,867	6,867	6,867
Adjusted R^2	0.610	0.616	0.676	0.728	0.733