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Personal Taxes and Firm Skill Hiring: Evidence from 27 Million Job Postings

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Abstract. Using big data on U.S. job postings, we show that firms increase skill requirements when hiring workers in states that cut personal income taxes. We trace a significant driver of this effect to companies' reallocation of skilled job postings across states based on tax differentials. The tax-induced upskilling is observed within occupations and is more pronounced for high-skill positions within firms. It is accompanied and amplified by concurrent increases in information technology expenditures at local-level establishments. In characterizing the mechanism at play, we show that job upskilling is triggered by tax changes affecting middle- and upper middle-class workers. It is pronounced for high-growth firms, for firms in tradable industries, and in urban areas, but it is mitigated among profitable firms. A narrative-based analysis helps us establish causal inferences.

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1. Introduction

Personal income taxes are an important source of revenue for local jurisdictions in the United States. In most states, personal taxes follow a progressive schedule. This disproportionately affects higher-income workers, who generally possess higher skills. Proponents of high personal taxes argue that revenues can be used to address local inequalities and fund social initiatives (Wildasin 2000). On the flip side, tax-cutting states become relatively attractive to high-skill workers and firms seeking to hire them. These dynamics have shaped the U.S. labor market in recent years, creating incentives for firms to adjust their hiring of skilled labor in response to local personal income tax policies.

The creation and allocation of high-skill jobs are critical issues for firms and the economy. Yet, there is very little research on how personal income taxes shape the types of jobs created by firms, the composition of the workforce inside companies, and the skill profile of local labor markets. This paper tackles these issues, showing how local personal income taxes influence firms' decisions to hire workers along the labor skill spectrum and across different locations. Our study builds on a database containing the near universe of online job postings by U.S. firms over several years. For each job ad, the database provides information about the employer, the location of the position sought, and the date of the posting. Using natural language processing, the database further provides a detailed description of the credentials required for each position. This includes the level of education, prior experience, and skills necessary to perform various tasks, such as cognitive ability and computer programming. The granularity of these data allows us to observe how firms' requirements for labor skill evolve over time in a location for a specific occupation. For firms with operations in multiple areas of the country, we can trace their internal decisions regarding the allocation of jobs across places and gauge how these decisions concurrently affect their investment choices and organizational structure.

We utilize a simple conceptual framework to guide our tests. In it, a firm optimizes the hiring of workers along the skill spectrum across two locations ("states"). Personal taxes insert a wedge between the level of compensation paid by the firm and what is effectively earned by workers. Workers choose locations based on job opportunities, local tax rates, and idiosyncratic location preferences. As the tax gap between two states widens, the low-tax state becomes more appealing to workers and the firm. This is so because workers face higher after-tax income and the firm faces lower hiring costs. In equilibrium, the firm assigns more jobs toward the low-tax state, offering lower pretax wages, an effect that is more pronounced for high-skill positions. The model illustrates how the personal tax gap drives differences in worker skill composition across states, leading to "upskilling" in the labor market of tax-cutting states.

We empirically examine how state personal income taxes affect the *types* and *skill profile* of jobs created in a local economy and how *firms reallocate* their skill hiring in response to local taxes. We do so by looking into the skill requirements contained in job ads posted by firms across locations where they operate. This analysis is revealing of prevailing local labor market conditions as firms must post competitive ads in order to attract workers available in a labor market at any given point in time.[1] Along those lines, we study five skill attributes. We first consider whether a job posting requires education and previous job experience. Next, we consider the requirement for cognitive skills, such as decision making, mathematics, and analytical skills. Our last two metrics focus on the listing of information technology (IT)-related skills, either the ability to work with a computer or knowledge regarding programming languages. We compute the proportion of postings listing these skills at the firm-county and firm-occupation-county levels to trace time series variation in skill hiring by a given employer at the same location for a specific occupation.

Our baseline tests exploit variation in personal taxes over time and across states. They track and contrast changes in skill requirements featured in the jobs posted by a firm across locations experiencing personal tax changes versus locations with no tax changes. We find a robust positive relation between the personal income net-of-tax rates and the level of job skill requirements. When a state cuts its personal income taxes by one percentage point, firms increase their requirements for education and experience by about one percentage point in the job ads they post in that state. Those same firms also post more ads that require cognitive and computer skills. Importantly, our estimations impose firm-county fixed effects that absorb innate differences across firms and locations. They further account for interstate differences across a large array of dimensions.[2]

We find that a large portion of the upskilling effect occurs *within occupations*. Tracking the same firm's posting in a location for a given occupation category, we show that skill requirements are modified following local personal income tax changes. We go a step further and study the differential effect of personal taxes on skill requirements for job postings across low-skill, medium-skill, and high-skill occupations. We show that personal taxes do not significantly impact the skill requirements of low-skill occupations. For jobs requiring a medium level of skills, a 1-percentage cut in personal taxes is associated with 0.6- to 0.7-percentage point increases in skill requirements in job ads. This magnitude jumps to two to three percentage points for the high-skill category. These within-occupation results are consistent with our model prediction that tax-induced skill hiring changes should be more pronounced in high-skill occupations.

We set out to verify the validity of our local tax results using the narrative approach of Romer and Romer (2010).[3] This test design seeks to reduce concerns regarding tax changes motivated by local, short-term economic conditions, which could concurrently affect firms' skill hiring decisions. We collect narrative records of state tax changes over our sample period and isolate those designed to cover inherited fiscal deficits, promote long-term growth, or address social inequities. Focusing on these "exogenous" tax events, we show that firms' local job skill requirements do not exhibit changes prior to tax policy innovations but significantly increase (decrease) in the years following tax cuts (increases). The same pre- and posttax change patterns are observed in a within-occupation analysis.

We also examine the role of other local tax policies, including corporate income taxes, sales tax, property tax, and general tax incentives, on firms' skill requirements. This investigation helps address the concern that other taxes may comove with personal income taxes in a state and affect our inferences. On that front, we show that changes in personal taxes are not strongly related to other tax policy changes in the same state. Personal taxes are also uniquely important in eliciting the upskilling effects from local firms. Reductions in other tax obligations do not generate a comparable effect.

We design several tests to flesh out the mechanisms underlying the reallocation of high-skill jobs across states. First, similar to the approach used by Giroud and Rauh (2019), we compare how the skill hiring of a firm's establishment responds to its own-state personal tax rates and to tax rates in other states where the firm has operations. The coefficients of other-state taxes carry the opposite sign to own-state taxes. Our evidence suggests that part of the shift in job skills is explained by multistate firms reallocating skill requirements from tax-increasing to tax-cutting states.

We subsequently explore heterogeneity in firms' responses to tax changes as a way to pin down key economic frictions driving our findings. In this set of tests, we first consider the role of geographical diversification. We find that firms with geographically dispersed operations are less affected by personal tax shocks in a single state. In contrast, firms with more concentrated operations, such as those in tradable industries, exhibit a stronger response to local personal tax changes. Moreover, among all localities of operation, firms are particularly responsive to personal tax cuts in states that account for the greatest portion of their employees. They also adjust their hiring more in urban areas, where the supply of skilled workers is higher. Finally, we show that financial performance helps firms mitigate the fluctuations in tax-induced labor costs. Specifically, profitable firms are significantly less responsive to changes in personal tax rates than nonprofitable ones, whereas high-growth firms respond more strongly to tax changes.

We then look into how wages offered for jobs requiring different skill levels respond to local personal tax changes. If local personal income taxes disproportionately affect high-skill workers, one would expect wages in high-skill job postings to be more responsive to personal tax changes than wages in low-skill postings. Indeed, we find that firms offer lower wages when personal taxes are cut, with the effect being more pronounced for high-skill jobs. These results support the argument that tax cuts reduce the costs of skilled labor faced by employers, promoting high-skill job growth. Moreover, we note that the wage adjustment in response to personal tax changes likely has mitigated firms' incentives to cut skill hiring. Without wages as the moderating factor, the effects of taxes on skill requirements would have been larger than the level we document.

We also examine how firms' skill hiring varies with taxes levied on workers at different points of the income distribution in a given location. This analysis allows us to evaluate the effectiveness of tax cuts at various income levels in stimulating high-skill job creation. We find that changes to taxes affecting low-income individuals (those at the 10th percentile of the income distribution) do not affect skilled job postings. As we move up the income ladder, the positive effect of lower personal taxes on required labor skills progressively intensifies, peaking at the 95th income percentile. The connection between taxes and job skills eventually disappears when we consider taxes affecting the very top earners (99th percentile or higher of the income distribution). Our tests show that links between personal tax rates and job skill credentials are rooted in the middle and upper middle class. They are not observed for low-income individuals, who are unlikely to qualify for high-skill jobs, nor for extremely wealthy individuals, who are unlikely to seek jobs from online ads or to depend on wage income from those jobs.

Aside from examining tax effects on firms' hiring policies, we look into whether personal income taxes affect firms' local investments and operations. This analysis focuses on IT investment, which complements high-skill human capital (Autor et al. 2003, Autor and Dorn 2013). We show that lower local personal taxes prompt firms to increase budgets dedicated to local IT expenditures, including software, hardware, and telecommunication services. In the narrative-based framework, we document sharp increases in IT expenditures following large tax cuts. More importantly, firms that increase IT investments to a greater extent also advertise for more IT-relevant skills in their job postings. Our results imply that personal tax cuts encourage the employment of high-skill human capital as well as technology spending, highlighting the importance of technology-labor complementarity.

To conclude and corroborate our analysis, we gauge the aggregate effect of personal taxes on all vacancy postings in a locality using census-based data. As we move from a firm-based to locale-based analysis, we continue to find a strong effect of personal tax rates on job skill requirements. We also verify these findings using the Quarterly Workforce Indicator (QWI) data provided by the U.S. Census Bureau, where we obtain statistics on the education attainment of locally employed workers. Using this alternative data source, we find that lower personal taxes are associated with a greater proportion of educated workers in a county. These analyses are consistent with our baseline results, showing that the upskilling effect we document is not limited to publicly traded employers and is meaningful for local economies as a whole.

Our study provides novel evidence that multistate firms reallocate their hiring of skilled workers away from high-tax states. Those firms concurrently invest far fewer resources in IT in high-tax states. Our findings highlight the role played by large companies in transmitting tax policy shocks across different areas of the country. The analysis complements important recent work showing that firms respond to regional and industry shocks via their internal capital and labor markets (see, e.g., Maksimovic and Phillips 2002; Becker et al. 2013; Giroud and Mueller 2015, 2019; Tate and Yang 2015). In this regard, our study is also connected to the recent work that documents an increasing spatial separation between high- and low-skill workers, accompanied by a growing gap in earnings and skill premium across areas (Moretti 2013, Diamond 2016, Diamond and Gaubert 2022). Complementing this literature, we show that government fiscal policies can influence the place-skill sorting in the United States. In particular, holding fixed the innate characteristics of a locality (such as demographics, amenities, housing prices, etc.), changes in personal taxes affect the worker skill composition and the type of jobs offered in the area.

An extensive literature explores the role of state-level tax policies on aggregate employment and economic activities. Many studies focus on the effect of state corporate income taxes on employment, worker, and firm mobility (see Ljungqvist and Smolyansky 2016; Serrato and Zidar 2016, 2018; Fajgelbaum et al. 2018; Giroud and Rauh 2019; Zidar 2019). We add to this important literature by showing the role played by companies in reallocating high-quality, productive jobs across states in response to personal tax innovations. We push the agenda forward by using "big data" on individual firms' descriptions of the *types of workers* they seek to hire and the *credentials* they require in order to assess the effect of taxes on jobs. Finally, we note that a related literature looks at the impact of personal taxes on millionaires, inventors, top athletes, and other highly achieved individuals (e.g., Young and Varner 2011, Kleven et al. 2013, Akcigit et al. 2016, Moretti and Wilson 2017, Schmidheiny and Slotwinski 2018). Our analysis, in contrast, considers the impact of taxes on workers across the *entire skill spectrum*, not only at the very top. It does so uniquely accounting for dimensions such as firm organizational form and interactions between technology and human capital.

2. Conceptual Framework

We develop a simple framework to guide our empirical tests (see Section A in the online appendix). The framework delivers intuition on how differences in state personal income taxes lead firms to change their hiring of skilled labor, shifting high-skill job openings toward low-tax states.

The setup and main mechanism of our model are as follows. A firm decides the hiring of new workers along the skill spectrum across two locations ("states") to maximize its production output. High-skill workers are more productive than low-skill ones. Workers of mass 1 are born for each skill level and can choose locations based on the job opportunities available, local tax rates, and idiosyncratic location preferences. Personal income taxes insert a wedge between the level of compensation paid by the firm and what is effectively earned by workers. At the beginning, both states use the same tax rate. When one state cuts taxes, workers in that state receive higher after-tax income, and the firm faces lower hiring costs. It thus becomes more appealing to both workers and the firm. In equilibrium, the firm assigns more jobs toward the low-tax state, offering lower pretax wages.

The aforementioned effect is particularly strong for high-skill workers, for whom taxes create a greater earning differential across states. As a result, worker skill composition differs across states, with the low-tax states attracting more skilled workers and jobs from the high-tax states. In other words, personal taxes lead to "upskilling" in the labor market of the low-tax state and a "brain drain" effect in the high-tax state.

Hypothesis 1. *Higher (lower) local income taxes lead to lower (high) skill requirements in local job postings.*

Our empirical tests will examine the equilibrium relation between the personal income tax rate in a state and the skill content of corporate job ads posted in that state. According to our model, we expect firms' new-hire skill requirements to be negatively associated with local personal income tax rates. We also expect this effect to be particularly strong for high-skill occupations.

Before proceeding to the empirical analysis, we provide a number of insights related to our model. To start, we note that job-related migration is common in the United States. Based on the Current Population Survey conducted by the census, job search accounts for approximately 20% of household relocation decisions. Our predictions are also consistent with prior studies documenting that elite employees (such as star scientists and soccer players) migrate because of tax reasons. In their framework, employers play a passive role in moderating migration decisions, whereas in our model, firms' production function and thus, wage setting are key determinants of job reallocation. Finally, our model yields implications for firms' investments that are complementary to high-quality human capital, such as expenditures in technology. We test such predictions in later analysis.

3. Data and Variable Definition

3.1. Data Sources

3.1.1. Job Postings. Our primary data source is a big data repository containing U.S. employers' job ads provided by BurningGlass Technologies. BurningGlass gathers information from online job ads 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 (Occupational Information Network (O*NET) job codes and Standard Occupational Classification (Standard Occupational Classification (SOC)) families). The database includes unique identifiers for each job posting, occupation, industry (North American Industry Classification System (NAICS)), and location (county and Metropolitan Statistical Area). It also contains the name of the employer posting the job and the associated time stamp.

In our firm-level analysis, we match BurningGlass employers to Compustat firms based on employer names. This effort allows us to estimate the role of publicly listed firms in shifting the hiring of high-skill jobs across different areas of the country. A more detailed description of the matching process is provided in Section B in the online appendix. Our sample of publicly listed firms includes 3,742 nonfinancial firms and 20,639 firm-year observations. They posted about 27 million job vacancy ads over our sample period.

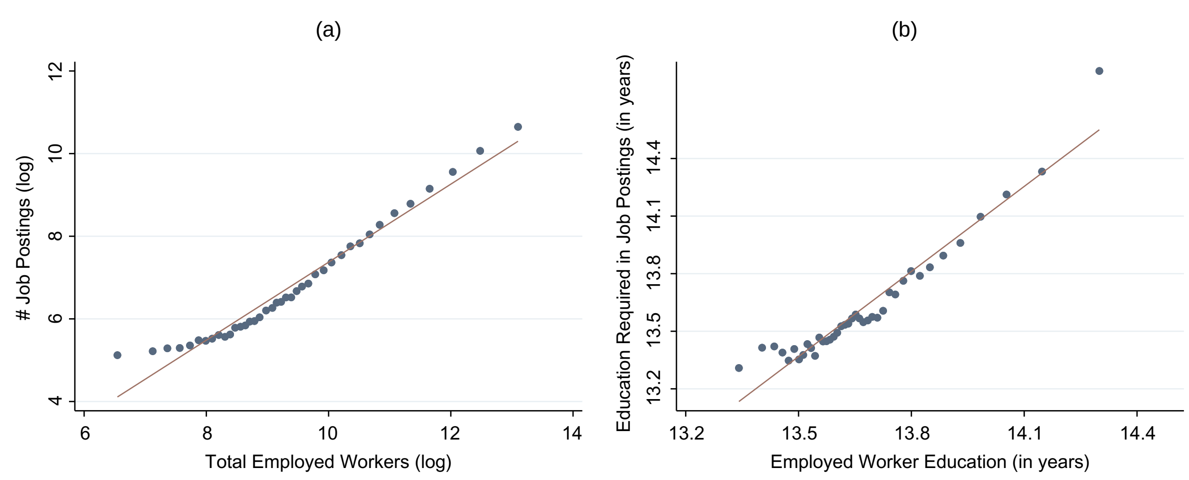
The most distinctive feature of the BurningGlass database is that it provides a detailed description of required skills listed in a job ad. In Figure C.1 in the online appendix, we provide an example to illustrate the skill requirements included in a job posting, which specifies the main responsibilities of the position as well as qualifications and experience expected. Using statistical natural language processing techniques, BurningGlass identifies and codifies required job credentials, such as the level of education needed to perform the job (e.g., years of received school education). It also includes the level of experience required in the same or similar line of work. Notably, it categorizes a number of qualitative skills and abilities associated with each 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 conducted by the Bureau of Labor Statistics, which focuses on the quantity of job openings.

Figure C.2 in the online appendix illustrates the distribution of BurningGlass job postings across major occupation groups. We compare such distribution with that from other data sources, including the Bureau of Labor Statistics' Occupational Employment Statistics data for employment stocks in panel (a) and the longitudinally linked Current Population Survey for new jobs in panel (b). Although BurningGlass provides comprehensive coverage across all major occupations, certain occupations, such as computer and mathematical occupation, management, and healthcare practitioners, have a larger representation. In contrast, BurningGlass underrepresents occupations including construction, transportation, and food preparation and serving. To ensure that the representativeness of BurningGlass data across occupation groups is not driving our conclusion, we explore within-occupation variations as part of our main analyses (Section 4.5).

We examine various measures of skill requirements in firms' job postings. We follow Hershbein and Kahn (2018) and consider the percentage of job postings containing education requirements (*Education*) and experience requirements (*Experience*) as well as cognitive skills (*Cognitive*). We also consider the percentage of postings requiring computer skills, either the general ability to operate a computer (*IT*) or specific software and programming knowledge (*Programming*). Education is a common measure of skill and sophistication of a worker. When available, we gather data on the years of education required and whether the job requires a high school or a bachelor and above degree. 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 decision-making, research, and analytical skills.[4] Those skills are needed in jobs involving model building, data analytics, management, and so forth. Programming skill requirements range from use of common software, such as Microsoft Office, to programming languages, such as Java and Python.

Although BurningGlass data reflect firms' published description of required local labor skills (workers who firms seek to hire), we verify whether this is informative of the skill level of workers that hold local jobs. We do so in Figure 1, relying on Census data (QWI). In panel (a), we examine the quantity of job postings and the number of employed workers, whereas in panel (b), we look at education required in local postings and the formal school education received by workers. Both panels depict a close correspondence between BurningGlass data and the actual employment of local workers and their skills.[5]

Figure 1. (Color online) Correspondence Between Job Ads (BurningGlass) and Census Employment (QWI)



Notes. Panel (a) shows the relation between the number of job ads posted in a county from BurningGlass data and the number of employed workers from QWI data in the same county and year. Both quantities are transformed to log terms. Panel (b) shows posted education requirements (in years) from BurningGlass data and the average education levels of employed workers in the same county (in years) computed from QWI data for those with high school or above education. The dots in each panel represent 40 equal-sized bins based on the number of employed workers and the average education level. (a) Number of job postings and QWI employment. (b) Education requirements and QWI worker education.

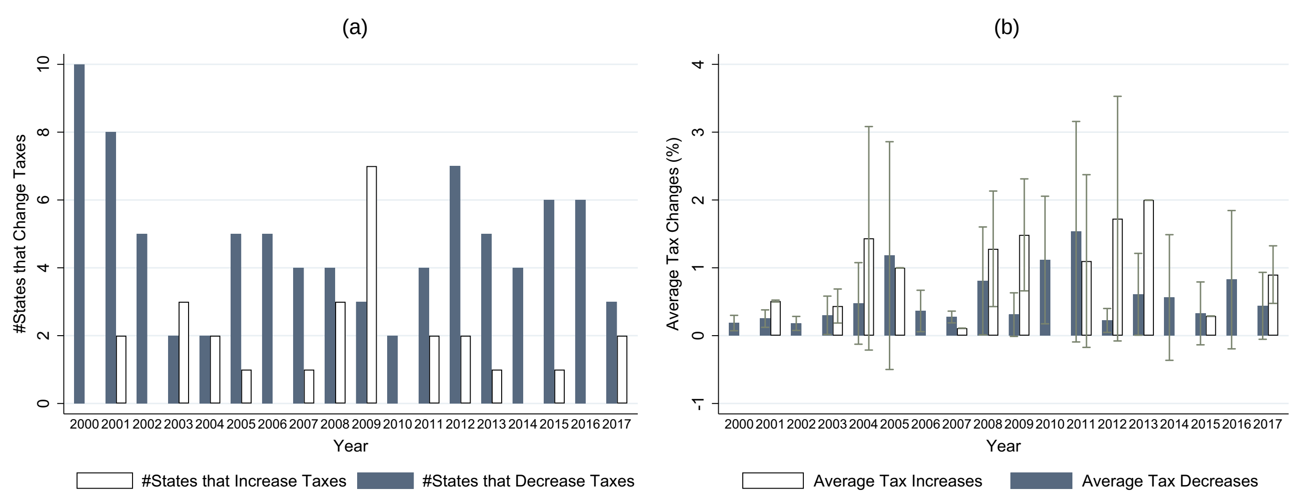
3.1.2. Personal and Other Local Taxes. Labor income is the most important factor determining the personal tax rates faced by American workers. Federal taxes follow a progressive system. State income tax systems, on the other hand, vary widely. The majority of states use progressive tax schemes. Nine states, including Washington, Florida, and Texas, do not tax individual incomes. Eight states, including Colorado, Illinois, and Indiana, apply a flat tax rate to all income levels. Individuals filing itemized deductions in their tax forms can claim a deduction of state and local taxes (SALT) toward federal income taxes. For every additional dollar increase in state and local taxes, a SALT deduction may 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 the SALT deduction than standard deductions.[6] However, these same individuals are often hit with the alternative minimum tax (AMT), which limits their ability to offset local personal taxes.

We use the TaxSim program supported by the National Bureau of Economic Research to identify the effective local 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 different income levels in a state-year based on state and federal tax codes, accounting for factors such as mortgage interest deductions, dividend income, and the crossdeduction between federal- and state-level taxes, among others. Although state statutory tax rates drive the variation in the total average tax rate, we note that our measure accounts for many complex interactions between state and federal taxes.[7] In other words, using TaxSim, we can design a personal income tax metric that captures the entire tax burden that workers face for jobs in different locations and jobs paying different wages.

To pin down the relevant income level for our analysis, we first gather income data from the World Inequality Database (WID). According to the WID database, individuals at the 90th percentile earned an annual wage of approximately $101,000 in 2017, whereas individuals at the 10th percentile level made about $5,500. The income distribution becomes highly skewed as we approach the right tail, with individuals ranked at the 99.9th percentile making above $1.1 million in wage income. As a baseline, we take that a representative high-skill individual in our sample ranks at around the 90th percentile in the income distribution.[8] We assume away other forms of income so that the effective tax rates are determined by wage earnings and long-term capital gains.[9] In later analyses, we show that our results are robust to focusing on other comparable levels of income.

States differ substantially in how they modify personal income tax rates over time. Figure 2 tracks statutory changes in state personal taxes between 2000 and 2017. Panel (a) shows the number of states that changed their personal income tax rates in a year. Light columns represent the number of states that increased their personal taxes, and dark columns represent the number of states that cut taxes. Panel (b) shows the

Figure 2. (Color online) State Changes in Personal Income Taxes over Time



Notes. This figure shows the variation in top statutory 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, light columns indicate tax increases, and dark 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 vertical lines indicate the one-standard deviation range around the mean. (a) Number of states with personal tax changes. (b) Average personal tax changes (percentage).

average change in personal taxes across all states in a year, with light (dark) columns indicating the average increase (decrease) in rates. The figure makes it clear that states change personal taxes rather frequently. In 2000, 2001, and 2009 alone, 10 states altered their personal tax rates. Following the 2008–2009 crisis, state personal taxes experienced drastic changes, with 2010 and 2011 witnessing the most aggressive tax cuts and 2012 and 2013 seeing the largest increases. The average rate change in these years exceeded 1%, a substantial magnitude compared with the sample average of top-bracket state tax rates, 5.6%. The rich variation in personal income taxes across states and over recent years provides a good setting for our study. This variation is further amplified by cross-state differences in the way local and federal income taxes interact (e.g., treatment of SALT exemptions).

Aside from personal taxes, we also obtain information on state corporate income taxes, state sales taxes, and local property taxes.[10] We control for these other tax policies throughout our analysis. In Table 2 and Figure I.1 in the online appendix, we present evidence that changes in personal taxes in a state are not correlated with changes in other taxes, such as corporate income taxes.

3.1.3. IT Investment. We gather information on firms' investment in technology from the Ci Technology Database (CiTDB) from 2010 to 2017, a proprietary database that collects the quantities and types of technology investment conducted by firms at the establishment level (Zhang 2019). This database contains comprehensive, up-to-date information on several dimensions of firms' IT investment, including their acquisition of computers and detailed budgetary items such as those allocated for hardware, software, telecommunication, and other devices. It also contains firm identity together with the location and time of IT investment.

We compile a sample that includes all establishments of U.S. public firms covered by CiTDB. Using this sample, we examine a host of budgetary items that firms allocate in each of their establishments, including their overall IT budget (*IT Budget*) as well as itemized budgeting for hardware (*Hardware Budget*), software (*Software Budget*), and telecommunication expenditures (*Telecomm. Budget*). All variables are computed on a per-employee dollar basis and converted into log terms.

3.1.4. Other Data Sources. Our analysis accounts for a large array of state- and county-level covariates. Our tests control various taxes imposed by local governments (including corporate, sales, and property taxes). They also control for state-level policies, including unemployment insurance, number of tax incentives, and minimum wages. Taking into account that income tax revenues are used to fund fiscal spending, our tests also control for state government spending in health, education, public welfare, and infrastructure. All spending items are scaled by local Gross Domestic Product (GDP). We further include in the set of controls local demographic information, such as African American and Asian populations (as a percentage of total county population). These controls also include a measure of the projected education level of new hires that resembles a Bartik instrument mapping the education requirement at the national level into the local county. This measure is defined as the national average years of education across industries, weighted by the number of new hires employed by each industry in a county-year. It is designed to control for changes in local skill hiring driven by aggregate industry dynamics. For robustness, we test the sensitivity of our results to controlling for local economic conditions, proxied by state GDP, state government budget surplus (as a percentage of GDP), county housing price index, county median household income, and state-level consumer price index.[11]

Lastly, we gather information on firms' establishment-level location and employment count from the National Establishment Time Series (NETS) database produced by Walls & Associates. We also obtain the Census QWI data with total employment count by education achievement at the county-level for aggregate inference. We include a full set of variable definitions and data sources in Section D in the online appendix.

3.2. Sample

Studies on firms' reallocation of labor and capital often utilize an establishment-level sample (e.g., Giroud and Rauh 2019). We can approximate such granularity by aggregating firms' skill requirements at the county level. To do so, we compile a firm-county-year panel, in which each cell represents the average skill requirements across jobs posted by a firm in a county during a year. Those skill requirements are then correlated with the tax rates applicable to that county. For robustness, we repeat our analysis in a firm-state-year sample. Results are robust in this sample and are reported in Section H in the online appendix. In Section 7, we examine the effect of personal income taxes for job skill requirements by all businesses in a county, not just by public firms. We thus construct a county-year panel for that analysis. Finally, we utilize an establishment-level panel to examine firms' decision to invest in information technology.

Table E.1 in the online appendix presents summary statistics for the main variables in our analyses. Our key variable of interest is one minus personal taxes, $1 - \tau$. Workers at the 90th of the income distribution face a net-of-tax rate of 83.8% and a standard deviation of 1.9%. Summary statistics for job skill requirements suggest that nearly 50% of BurningGlass job postings contain education requirements, 44% contain experience requirements, and 26% (20%) require cognitive (programming) skills. Technology investment at the establishment level is calculated as log of per-employee spending. To interpret these statistics, the average establishment in our sample allocates around \$10,000 per employee for IT purchases each year, of which \$1,765 is allocated for hardware and over \$3,000 is for software purchases.

4. Main Results

4.1. Empirical Methodology

We examine firms' allocation of skill hiring across different locations in response to personal tax changes. This design fixes a public firm-county and examines whether the firm changes the skill profile of its job postings in states that have changed their personal income tax rates 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 the job postings by firm i in county c in year t. We then estimate the following model:

$$Y_{i,c,t} = \beta(1 - \tau_{c,t-1}) + Controls_{c,t-1} + \gamma_{i,c} + \mu_t + \epsilon_{i,c,t}, \tag{1}$$

where i represents a firm, c represents a county, and t represents a year. In Equation (1), $Y \in \{Education, Experience, Cognitive, IT, Programming\}$. The variable of interest is $1 - \tau_{c,t-1}$, the net-of-tax rate in a location in the previous year. We use a one-year lag to allow for a period of adjustment in firms' response. This delayed response is verified in the event study in Section 4.4.

We control for firm-county ($\gamma_{i,c}$) and year fixed effects (μ_t). Coefficient β in Equation (1) captures the extent to which firms change their skill hiring across counties at a given time as a function of local personal taxes. Some of our analyses further include firm-year fixed effects, which remove firms' time-evolving idiosyncratic characteristics. Standard errors are double clustered by firm and county.

We also consider an alternative specification using a firm-county-occupation-year panel. Occupation is defined at the two-digit SOC level to ensure that there are sufficient job postings in each grid. We adopt the following model:

$$Y_{i,c,o,t} = \beta(1 - \tau_{c,t-1}) + Controls_{c,t-1} + \gamma_{i,c,o} + \mu_t + \epsilon_{i,c,o,t}, \tag{2}$$

where o represents an occupation and $Y_{i,c,o,t}$ indicates the average skill requirements in job ads posted by firm i in county c for occupation category o during year t. This specification features firm-county-occupation fixed effects ($\gamma_{i,c,o}$), which allow us to track whether a firm changes its labor skill demand in a locality for a fixed job category and remove effects arising from changes in the occupation mix inside a firm.

4.2. Local Personal Income Taxes and Firms' Hiring of Skilled Labor

Table 1 presents the central results of this paper. We estimate Equation (1), which tracks the changes in skill hiring of public firms in a county after changes to local personal income tax rates. Each panel presents results for a specific labor skill requirement. We add control in stages to provide clarity to our results. First, we consider results only controlling for firm-county fixed effects, year fixed effects, and other tax policies in the same state together with local demographics (columns (1) and (2)). Next, we add controls for other nontax state-level policies, such as minimum wage and unemployment insurance (columns (3) and (4)). In the last step, we impose firm-year fixed effects to remove variation at the parent firm level (columns (5) and (6)). In each step, we compare the coefficients on personal taxes with and without local economic conditions as controls (included in columns (2), (4), and (6)). We carry the specification in column (3) through the rest of the paper.

Our results point to a significant upskilling effect. The coefficients for $1 - \tau$ are all positive, statistically significant, and economically meaningful. Results from column (3) of each panel suggest that a 1-percentage point increase in net-of-personal tax rate leads to an approximately 1.3-percentage point reduction in the job postings with explicit education and experience requirements. That net-of-tax rate increase triggers a similar increase in job ads requiring cognitive skills (1.3%), IT skills (2.0%), and programming skills (1.5%). The estimated magnitudes translate to tax elasticities of two to three for education and experience, four for cognitive, and around six for IT requirements. Our estimates change very little as we include local economic conditions as additional controls. They also remain stable when we remove or add controls for other state-level policies, suggesting that the concurrent changes in state-level policies included in the set of controls are unlikely to be determinant drivers of our effect. Finally, magnitudes drop slightly as we impose firm-year fixed effects, likely because that specification purges away the expansion or shrinkage of overall skill hiring at the corporation level.[12]

In Table F.1 in the online appendix, we also separately look at the quantity of job postings that contain a skill requirement and the quantity of postings that do not contain a skill requirement. We find that, as personal taxes decline, firms reduce the number of postings that do not contain skill requirements and simultaneously increase the number of postings that require worker skills. This result corroborates our findings on the skill compositions of job postings.

We note that our estimated job postings-tax sensitivities are generally larger than the employment-tax sensitivities documented in the literature. Several factors

Table 1. Requirements for Skills and Personal Taxes

Panel A: Education requirements						
Dependent variable: *Education*	(1)	(2)	(3)	(4)	(5)	(6)
1 − Personal Taxes	1.149***	1.811***	1.265***	1.571***	1.104***	1.316***
	(0.407)	(0.517)	(0.412)	(0.502)	(0.366)	(0.452)
Other taxes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Other policies			Yes	Yes	Yes	Yes
Economic conditions		Yes		Yes		Yes
Firm × year FE					Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,341,727	1,001,602	1,170,235	996,391	1,168,880	994,758
R^2	0.645	0.649	0.652	0.649	0.727	0.727

Panel B: Experience requirements						
Dependent variable: *Experience*	(1)	(2)	(3)	(4)	(5)	(6)
1 − Personal Taxes	1.342***	1.869***	1.397***	1.781***	0.929**	1.147**
	(0.432)	(0.533)	(0.436)	(0.521)	(0.388)	(0.454)
Other taxes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Other policies			Yes	Yes	Yes	Yes
Economic conditions		Yes		Yes		Yes
Firm × year FE					Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,341,727	1,001,602	1,170,235	996,391	1,168,880	994,758
R^2	0.584	0.592	0.594	0.592	0.674	0.674

Panel C: Cognitive requirements						
Dependent variable: *Cognitive*	(1)	(2)	(3)	(4)	(5)	(6)
1 − Personal Taxes	0.850**	1.566***	1.288***	1.757***	1.189***	1.643***
	(0.381)	(0.496)	(0.415)	(0.517)	(0.356)	(0.438)
Other taxes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Other policies			Yes	Yes	Yes	Yes
Economic conditions		Yes		Yes		Yes
Firm × year FE					Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,341,727	1,001,602	1,170,235	996,391	1,168,880	994,758
R^2	0.570	0.575	0.577	0.575	0.664	0.664

Panel D: IT requirements						
Dependent variable: *IT*	(1)	(2)	(3)	(4)	(5)	(6)
1 − Personal Taxes	1.515***	2.636***	2.059***	2.711***	1.937***	2.579***
	(0.408)	(0.559)	(0.458)	(0.570)	(0.403)	(0.483)
Other taxes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Other policies			Yes	Yes	Yes	Yes
Economic conditions		Yes		Yes		Yes
Firm × year FE					Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,341,727	1,001,602	1,170,235	996,391	1,168,880	994,758
R^2	0.605	0.610	0.611	0.610	0.683	0.684

Table 1. (Continued)

Panel E: Programming requirements						
Dependent variable: *Programming*	(1)	(2)	(3)	(4)	(5)	(6)
1 − Personal Taxes	1.061***	1.913***	1.475***	1.971***	1.355***	1.865***
	(0.382)	(0.520)	(0.415)	(0.519)	(0.355)	(0.432)
Other taxes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Other policies			Yes	Yes	Yes	Yes
Economic conditions		Yes		Yes		Yes
Firm × year FE					Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,341,727	1,001,602	1,170,235	996,391	1,168,880	994,758
R^2	0.602	0.605	0.605	0.605	0.667	0.668

Notes. This table examines the effect of personal taxes on firms' requirements for labor skill in a location. The dependent variable in each panel is the percentage of job postings requiring education (*Education*), experience (*Experience*), cognitive skills (*Cognitive*), general IT knowledge (*IT*), and programming knowledge of specific software (*Programming*). The unit of observation is a firm-county-year. *1 − Personal Taxes* is one minus the personal tax rates for individuals making 90th-percentile income, measured in the previous year. Control variables include other tax policies, including one minus corporate income tax rates, one minus sales taxes, one minus property taxes, and the number of tax incentives; other nontax policies, including state unemployment insurance, state minimum wage levels, and state government expenditures on health and hospitals, education, public welfare, and infrastructure; county-level demographic information, including the projected average education of new hires at the county level, the percentage of county population that is African American, and the percentage of county population that is Asian; and economic conditions, including the log of state GDP, state budget surplus, the log of county housing price index, the log of county median household income, and state consumer price index. Standard errors are double clustered by firm and county. FE, fixed effect.

**Significance at the 5% level; ***significance at the 1% level.

account for this. First, job postings represent changes and not the stock of employment counts. The same increase in the number of workers hired may represent a large percentage growth of newly hired workers but a small growth of total workers. Second, there are fewer frictions preventing firms from removing job postings compared with the frictions related to firing workers, making job postings more responsive to tax shocks than employment counts. Finally, some job ads may end up with no workers being hired, which means that firms may post more job ads than the number of workers hired, leading to higher estimated sensitivities. We supplement our main results using the Census QWI employment data in Section 7 and find smaller estimates that are closer to the employment-tax sensitivities in the literature.

We provide additional robustness checks for a few empirical choices made in the specification. In Section G in the online appendix, we compare the effect of lagged versus contemporaneous period tax rates. Using the contemporaneous personal net-of-tax rate produces results very similar to the lagged version. We also show that results do not change when we regress skill hiring on the log of net-of-tax rates or when we control for the supply of educated workers in an area. In Section H in the online appendix, we re-examine our baseline using the firm-state-year panel with standard errors double clustered at the firm and state level. Our baseline results remain robust to this alternative sample construction.

4.3. The Role of Other Local Tax Policies

In this subsection, we discuss the role of other local tax policies in moderating the effect of personal taxes on corporations' skill hiring. Aside from designing personal income taxes that could attract high-skill labor and incentivize corporations to post skilled jobs, local governments can also adjust other tax policies, including corporate income taxes, sales taxes, and real estate taxes, or implement tax incentives. One concern that arises from these simultaneous policy tools is that the effects from other tax policies could confound or amplify the personal tax effects we document.

We address this concern in two ways. To start, we examine how changes in various tax rates in a state, including personal, corporate, sales, and property taxes, are correlated. Results are reported in panel A of Table 2. Notably, although states often modify their personal and corporate income tax rates, they rarely move together. The in-state correlation between personal and corporate income tax changes is a statistically insignificant 0.01, likely because the two taxation schemes serve different policy objectives. Changes in personal taxes are not significantly related to changes in property taxes either, although they are negatively correlated with sales tax changes. We present more graphic evidence showing that changes in personal taxes are not clearly related to changes in other tax policies in Figure I.1 in the online appendix. These statistics help alleviate concerns that other tax policies could confound our inferences.

Table 2. Role of Other Tax Policies

Panel A: Correlation of tax policy changes

Correlation	*d(Personal taxes)*	*d(Corporate Taxes)*	*d(Sales Taxes)*	*d(Property Taxes)*
d(Personal Taxes)	1			
d(Corporate Taxes)	0.01	1		
d(Sales Taxes)	−0.15	0.08	1	
d(Property Taxes)	0.03	0.11	0.05	1

Panel B: Coefficients of control variables

	Education		*Experience*		*Cognitive*		*IT*		*Programming*	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1 − Personal Taxes	1.265***	1.571***	1.397***	1.781***	1.288***	1.757***	2.059***	2.711***	1.475***	1.971***
	(0.412)	(0.502)	(0.436)	(0.521)	(0.415)	(0.517)	(0.458)	(0.570)	(0.415)	(0.519)
1 − Corporate Taxes	−0.915***	−1.337***	−0.723***	−1.177***	−1.121***	−1.649***	−1.468***	−2.084***	−1.025***	−1.556***
	(0.271)	(0.332)	(0.268)	(0.320)	(0.288)	(0.356)	(0.322)	(0.396)	(0.291)	(0.358)
1 − Sales Taxes	−0.190	−0.300	−0.127	−0.073	−0.388	−0.689*	−0.547	−0.913*	−0.790*	−1.116**
	(0.388)	(0.423)	(0.401)	(0.453)	(0.369)	(0.402)	(0.448)	(0.491)	(0.442)	(0.490)
#Tax Incentives	−0.000	−0.000	−0.001	−0.001	−0.001**	−0.001	−0.002***	−0.002**	−0.002*	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1 − Property Taxes	1.230	0.854	0.886	1.179	1.703**	1.766**	3.559***	3.581***	2.893***	2.998***
	(0.985)	(1.084)	(0.986)	(1.042)	(0.818)	(0.810)	(0.914)	(1.018)	(0.814)	(0.987)
%African American	−0.004	−0.005**	−0.002	−0.003	−0.000	−0.000	−0.000	−0.001	−0.000	−0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
%Asian	0.014***	0.012***	0.014***	0.012***	0.003	0.002	0.005	0.003	0.004	0.003
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Industry Skill Demand	−0.038	−0.041	−0.046*	−0.049	−0.022	−0.033	−0.023	−0.035	−0.008	−0.019
	(0.025)	(0.029)	(0.027)	(0.032)	(0.019)	(0.023)	(0.017)	(0.023)	(0.011)	(0.014)
Minimum Wage	0.000	0.001	−0.004**	−0.005**	−0.004	−0.005*	−0.000	−0.002	−0.001	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
log(*Unemployment Insurance)*	0.006	0.003	0.003	0.001	0.017***	0.015***	0.013**	0.012**	0.007	0.005
	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)
Health Spending/GSP	−0.345	−0.280	−0.601	−0.765	−0.912*	−1.038*	−0.431	−0.836	0.048	−0.066
	(0.578)	(0.655)	(0.598)	(0.684)	(0.507)	(0.559)	(0.574)	(0.633)	(0.526)	(0.576)
Education Spending/GSP	−0.057	−0.390	0.082	−0.109	0.413	0.299	0.709	0.774	0.420	0.544
	(0.462)	(0.560)	(0.433)	(0.525)	(0.403)	(0.478)	(0.437)	(0.499)	(0.372)	(0.435)
Welfare Spending/GSP	0.211	−0.162	1.050***	0.843**	0.820***	0.630*	0.879**	1.045**	0.593*	0.795**
	(0.326)	(0.384)	(0.315)	(0.374)	(0.278)	(0.341)	(0.350)	(0.421)	(0.326)	(0.387)
Infrastructure Spending/GSP	1.428***	0.470	0.912	0.570	0.347	0.373	0.046	0.586	0.077	0.438
	(0.536)	(0.562)	(0.556)	(0.613)	(0.543)	(0.610)	(0.522)	(0.644)	(0.471)	(0.565)
log(*GSP)*		0.008		0.005		0.080***		0.105***		0.112***
		(0.036)		(0.037)		(0.031)		(0.034)		(0.030)
Budget Surplus/GSP		−0.000		−0.000		0.000		0.001**		0.000*
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
log(*HPI)*		−0.005		−0.004		−0.011		−0.009		−0.008
		(0.014)		(0.015)		(0.014)		(0.015)		(0.013)
log(*Median Household Income)*		0.020		0.013		0.004		−0.000		−0.015
		(0.020)		(0.020)		(0.015)		(0.019)		(0.018)
State CPI Index		0.000		−0.001		−0.001		0.000		0.000
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Firm × county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,170,235	996,391	1,170,235	996,391	1,170,235	996,391	1,170,235	996,391	1,170,235	996,391
R^2	0.652	0.649	0.594	0.592	0.577	0.575	0.611	0.610	0.605	0.605

Table 2. (Continued)

Panel B: Coefficients of control variables										
	Education		*Experience*		*Cognitive*		*IT*		*Programming*	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Magnitudes from one standard deviation										
1 – Personal Taxes	0.024	0.030	0.027	0.034	0.025	0.034	0.040	0.052	0.028	0.038
1 – Corporate Taxes	−0.019	−0.028	−0.015	−0.025	−0.024	−0.035	−0.031	−0.044	−0.022	−0.033
1 – Sales Taxes	−0.003	−0.005	−0.002	−0.001	−0.006	−0.011	−0.009	−0.014	−0.013	−0.018
1 – Property Taxes	0.007	0.005	0.005	0.007	0.009	0.010	0.020	0.020	0.016	0.017
#Tax Incentives	0.000	0.000	−0.004	−0.004	−0.004	−0.004	−0.008	−0.008	−0.008	−0.004

Notes. This table reports results related to the role of other tax policies as well as control variables from our baseline specifications. Panel A reports the correlation among annual changes in tax variables in a state. Panel B reports coefficients on control variables. The dependent variables are the percentage of job postings requiring education (*Education*), experience (*Experience*), cognitive skills (*Cognitive*), general IT knowledge (*IT*), and programming knowledge of specific software (*Programming*). The unit of observation is at the firm-county-year level. "Magnitude from one standard deviation" computes the magnitudes related to each of the tax policy variables based on one standard deviation of the variable times the corresponding coefficient. Standard errors are double clustered by firm and county. FE, fixed effect.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

Second, we look closely at the coefficients of other tax policies in our baseline regressions. This helps us understand how these tax policies influence the hiring of high-quality workers. In panel B of Table 2, we report the coefficients for all control variables in our baseline specification. We also report the economic magnitudes from each of the tax variables, which are computed by multiplying a one-standard deviation change in a tax policy with the corresponding coefficient. We find that the net of corporate taxes generates a negative, significant effect on corporate skill hiring. Although other tax policies, namely net of sales taxes, net of property taxes, and the number of tax incentives, also generate statistically significant loadings for some variables, the magnitudes of those effects are economically small.[13]

The negative coefficients on the net of corporate tax rates may seem puzzling at first. Yet, this can be explained in a framework where corporate taxes differentially affect the marginal value of hiring high- and low-skill workers. Consider the canonical setting where a worker of skill s generates surplus $f(s)$ for the firm, where $f(s)$ is the price of the goods multiplied by the marginal productivity minus the wage rate of worker type s. With corporate income tax being τ, the firm's hiring decision depends on $(1-\tau)f(s) > \rho$, where ρ is the opportunity cost of capital. In other words, a firm will hire/retain a worker if he generates an after-tax surplus that is greater than the opportunity cost of capital.

If $f(s)$ is a monotonic function of s, there exists s^* that satisfies $f(s^*) = \rho/(1-\tau)$. s^* represents the marginal worker type that the firm would hire. $f(s^*)$ increases with τ, suggesting that employers require the marginal worker to be more productive when corporate taxes are high. Suppose high-skill workers generate higher surplus for the firm than low-skill workers; that is, $f(s)$ increases with s. In this case, s^* increases with τ. A higher corporate income tax τ pushes the after-tax surplus of lower-skill workers below the cost of capital, reducing the incentive to hire low-skill workers. As a result, the firms' workforce composition will tilt toward high-skill workers. In other words, we should observe a negative correlation between the net of corporate taxes and worker skill. Our results are consistent with this hypothesis.

We note that the negative relation between *1 – Corporate Taxes* on worker skill in the local labor market is not unique to the job posting data. In later analyses that employ the QWI data (panel B of Table 8), we continue to find *1 – Corporate Taxes* to be negatively associated with the percentage of educated workers in a county. This result lends further credence to our finding that lower corporate taxes are associated with less local skill hiring.

4.4. Narrative Approach

We substantiate our inferences by using the narrative approach proposed by Romer and Romer (2010). This test design allows us to identify tax changes that are exogenous to short-term local economic conditions and trace out how the effects of the tax shocks evolve over time. The narrative approach has been used in numerous recent studies in the tax literature to verify the causality of tax policy changes (see Cloyne 2013, Mertens and Ravn 2013, Giroud and Rauh 2019, Zidar 2019).

We collect local narratives from politicians, journalists, and policy analysts regarding a state personal tax change and infer the underlying motives of the change. Under this approach, one classifies tax shocks that are not systematically correlated with factors affecting local output in the short or medium run as "exogenous," such as tax changes designed to promote taxpayer fairness or long-run growth or changes resulting from inherited budget deficits, which reflect past economic conditions. This stands in contrast to "endogenous" tax changes, which represent responses to changes in government spending or designed to offset factors that may change growth in the near future.

We focus on meaningful statutory tax changes that occurred during our sample period, defining "tax events" as cases where a state changed its top personal tax rate by at least 25 basis points that affect individuals at the 90th percentile in the income distribution. We do not consider changes that target the wealthiest individuals in a state nor changes that are soon followed by reversals.[14] In cases where a state gradually changed its tax rates (up or down) over a few years, only the first event is kept. We search on Google News and Factiva for news articles discussing each tax change, removing those classified as endogenous. Table J.1 in the online appendix lists the tax events we retain. We only observe a few exogenous tax increases clustered at the very beginning of our sample period. Our narrative-based analysis focuses on eight large exogenous tax cuts (we later present results for the three large tax hikes in our sample).

We adopt an event-study approach to estimate the effects of tax cuts using $[-3, +3]$ years around each event. The test uses a matched event sample, whereby for each state experiencing a tax cut (treated), we consider a group of control states that have not experienced any large statutory changes in personal tax rates (either increases or cuts) throughout our sample period. Residents ranked at the 90th-percentile income in those control states must not have experienced large changes in average tax rates (i.e., below the sample median for that event). With this matched sample, we estimate the following model:

$$Y_{e,i,c,t} = \sum_{m=-3}^{3} \beta_m \times Treatment_{e,i,c} \times 1_{t=T_e+m} + Controls_{e,c,t-1} + \gamma_{i,c} + \lambda_e + \theta_t + \epsilon_{e,c,t}, \quad (3)$$

where e indicates a tax shock event that occurs in year T_e; *Treatment* equals one for firm-counties in the state that cut personal taxes in event e and zero for firm-counties in the associated control states; and T_e is the year of the tax cut, and 1_t is an indicator for years in the event window. Our estimation controls for firm-county, event, and year fixed effects. The event fixed effects focus on the comparison of changes in firms' skill hiring between each treatment state and its matched control states.

Figure 3 shows the results from the analysis of exogenous tax cuts, with each panel depicting changes in one skill type. The dots represent coefficient estimates for β_m from Equation (3), and the vertical lines represent 90% confidence intervals. *Year* $-$ *1* is absorbed as the benchmark, so the coefficients in each plot show how skill requirements change relative to that year. The patterns in the figure reveal parallel trends where firms' job skill requirements do not exhibit significant changes prior to a tax change. Our paper's central inferences emerge from this test setting as well. During the one or two years following an exogenous personal income tax cut, the average local firm posts around 4%–5% more jobs containing education and experience requirements and 2%–3% more postings containing cognitive and computer programming skills. These estimates, especially those for education and experience, are larger compared with those from the base analysis. This is because of our focus on large, unprecedented tax shocks in the narrative analysis. In comparison, the baseline analysis reveals the effects of average tax changes and provides a more conservative estimate of the personal tax effects on firms' skill hiring.[15]

In Figure 4, we report the effect of tax increases using the narrative approach. In our sample period, there are only three exogenous tax increases (Connecticut and Illinois in 2011 and Maryland in 2012). These tax events are close to the beginning of our sample period, thus only allowing us to estimate the effect from $t-2$ onward. Using this contrasting, limited sample of tax hikes, we find that firms significantly reduce their requirements for worker education, experience, and cognitive skills in the treated states. They also seem to reduce IT and programming skill requirements, although the results are not statistically significant at the conventional levels. These findings are consistent with our baseline results, and more interestingly, they provide contrast to the evidence on tax cuts from Figure 3.

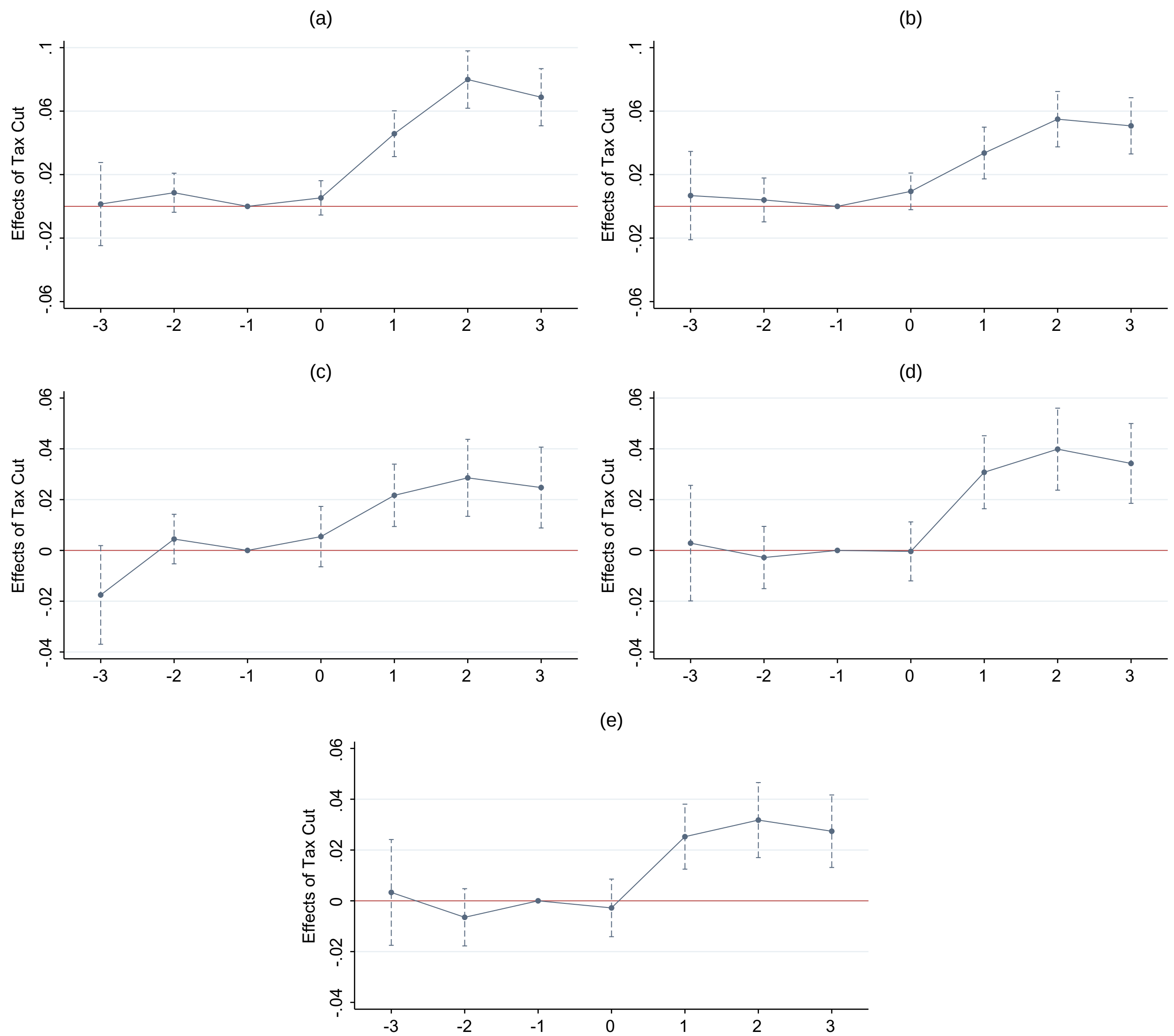
In Figure H.1 in the online appendix, we repeat the narrative analysis in a state-level sample. Specifically, for each event, we track firms' skill hiring in treated and control states and stack all events together. The resulting sample is an event-firm-state panel. We estimate our regressions while substituting firm-by-county fixed effects with firm-by-state fixed effects and double-clustered standard errors by firm and state. The analysis generates similar results.

Altogether, evidence from the narrative approach corroborates our argument that personal tax cuts generate an "upskilling" effect, incentivizing firms to hire more skilled labor in the local area.

4.5. Occupation-Level Evidence

We investigate the degree to which tax-induced skill changes in job postings occur within and across occupations. We perform this important analysis in three steps. We first augment the baseline approach with more refined occupation fixed effects. Next, we examine the differential upskilling effect across high-skill and low-skill occupations. Finally, we verify that results

Figure 3. (Color online) Narrative Approach: Tax Cuts

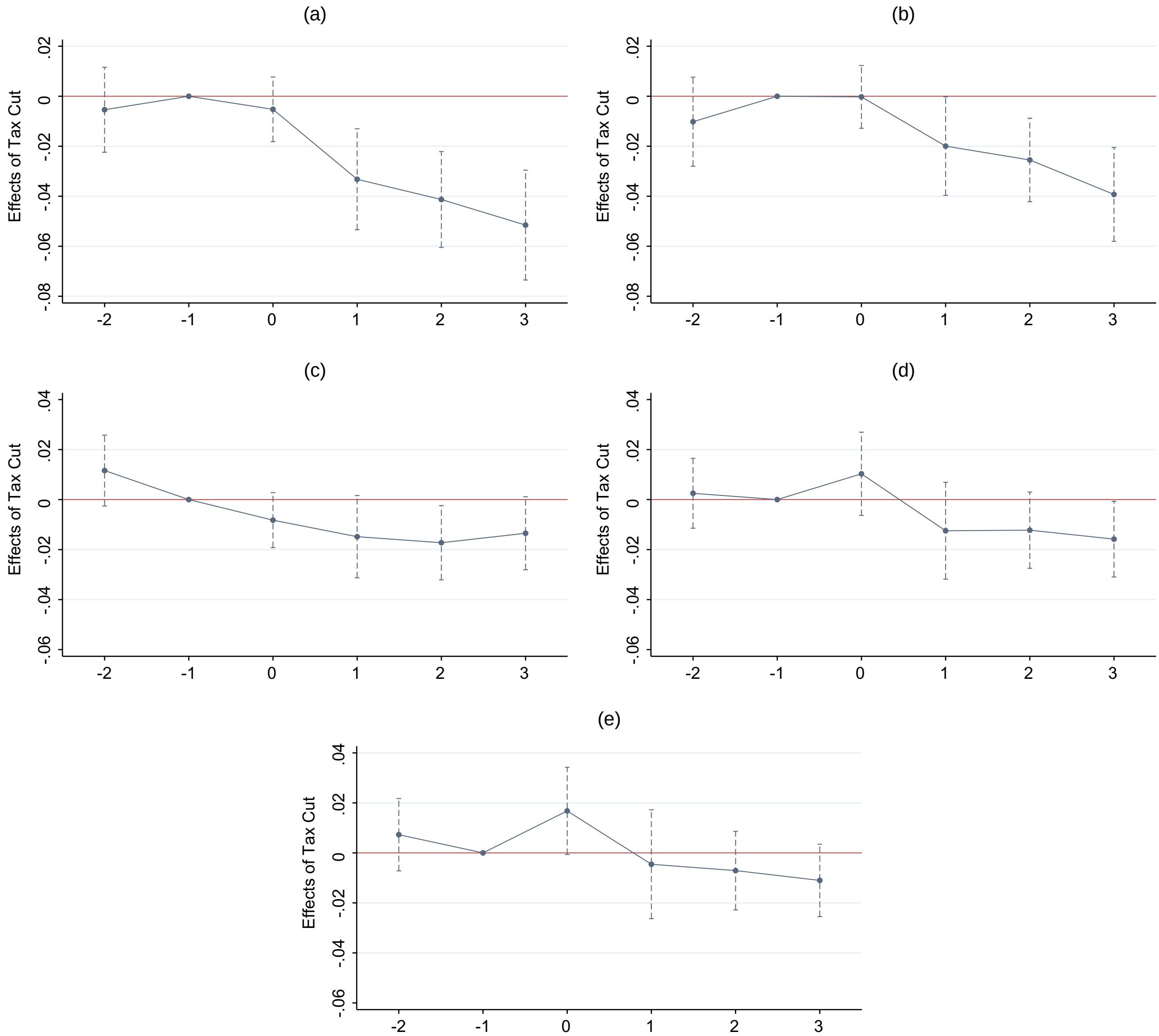


Notes. This figure shows the skill requirements contained in local job postings surrounding statutory changes affecting workers at the 90th income percentile. In each panel, the dots represent coefficient estimates of β_τ ($\tau \in [-3, 3]$) in Equation (3), and the intervals indicate 90% confidence intervals. The horizontal axis represents years relative to the year of the tax event, and the vertical axis represents the size of the coefficient. Year -1 is the benchmark. All tests include the same control as used in column (3) of Table 1. Standard errors are double clustered by firm and county. (a) Education. (b) Experience. (c) Cognitive skills. (d) IT skills. (e) Programming skills.

from the narrative approach persist in the occupation-level analysis.

We start by estimating Equation (2) using a firm-county-occupation panel. The analysis repeats the baseline tests while imposing occupation-level fixed effects. Table 3 reports the results. The three panels report results with progressively stringent fixed effects. In panel A, we include occupation fixed effects. Tests in panel B further include occupation-by-year fixed effects, which remove confounding effects related to occupation-specific dynamics, such as changes in overall labor supply or the task content of the occupation. In panel C, we control for firm-county-occupation fixed effects. This set of fixed effects allows us to track the upskilling or downskilling of the same type of jobs by the same employer following changes in local personal tax rates while removing effects arising from changes in the composition of high-skill versus low-skill jobs inside the firm. Compared with results in column (3) of Table 1, estimates from our occupation-level analysis yield similar magnitudes as the baseline results. The stability of the estimates corroborates our argument that decreases (increases) in local personal taxes lead to an upskilling (downskilling) effect in local jobs. This result also alleviates the

Figure 4. (Color online) Narrative Approach: Tax Increases



Notes. This figure shows the skill requirements contained in local job postings surrounding statutory increases in personal income taxes affecting workers at the 90th income percentile. In each panel, the dots represent coefficient estimates of β_τ ($\tau \in [-2,3]$) in Equation (3) because we do not have data from $t-3$ for these events. The intervals indicate 90% confidence intervals. The horizontal axis represents years relative to the year of the tax event, and the vertical axis represents the size of the coefficient. Year $-$ 1 is the benchmark. All tests include the same control as used in column (3) of Table 1. Standard errors are double clustered by firm and county. (a) Education. (b) Experience. (c) Cognitive skills. (d) IT skills. (e) Programming skills.

concern that BurningGlass data may not capture as many low-skill jobs as they do high-skill ones.

In the next step, we examine the differential effect of personal taxes on firms' skill demand between job categories that require more or less labor skill. This empirical strategy benchmarks the changes in credentials required for performing high-skill jobs against those required for low-skill jobs in the same county. We expect that personal income taxes should generate a disproportionate effect on high-skill jobs for two reasons. First, those jobs command higher wages, and in monetary terms, personal taxes create a bigger wedge between wages paid by employers and those received by workers. Consequently, changes in personal taxes are likely to affect firms' labor costs related to high-skill occupations to a greater extent. Second, individuals qualified to perform those jobs tend to be highly educated and therefore, more mobile (e.g., Dahl 2002, Malamud and Wozniak 2012, Johnson and Schulhofer-Wohl 2019).

To test this conjecture, we divide the occupation groups into three categories based on the amount of

Table 3. Requirements of Skills and Personal Taxes: Occupation-Level Evidence

Panel A: Controlling for occupation fixed effects

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 − Personal Taxes	1.113***	1.402***	1.332***	2.184***	1.684***
	(0.406)	(0.426)	(0.454)	(0.511)	(0.458)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes
Observations	3,251,334	3,251,334	3,251,334	3,251,334	3,251,334
R^2	0.466	0.409	0.376	0.417	0.413

Panel B: Controlling for occupation-year fixed effects

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 − Personal Taxes	1.063***	1.353***	1.391***	2.245***	1.738***
	(0.401)	(0.414)	(0.434)	(0.491)	(0.438)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes
Occupation × year FE	Yes	Yes	Yes	Yes	Yes
Observations	3,251,334	3,251,334	3,251,334	3,251,334	3,251,334
R^2	0.468	0.412	0.380	0.422	0.418

Panel C: Controlling for firm-county-occupation fixed effects

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 − Personal Taxes	0.907**	1.207***	1.304***	1.974***	1.576***
	(0.371)	(0.388)	(0.444)	(0.506)	(0.453)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm × county × occupation FE	Yes	Yes	Yes	Yes	Yes
Observations	2,668,517	2,668,517	2,668,517	2,668,517	2,668,517
R^2	0.673	0.635	0.615	0.647	0.647

Notes. This table examines the effects of personal tax changes on firms' requirement for skill in a specific occupation. The dependent variables include the percentage of job postings requiring education (*Education*), experience (*Experience*), cognitive skills (*Cognitive*), general IT knowledge (*IT*), and programming knowledge of specific software (*Programming*). The unit of observation is at the firm-county-occupation-year level. Occupation is defined as a two-digit SOC code. In panel A, we control for occupation fixed effects. In panel B, we control for occupation-specific dynamics using occupation-year fixed effects. Panel C reports results from regressions with firm-county-occupation fixed effects. Control variables are the same as those used in column (3) of Table 1. Standard errors are double clustered by firm and county. FE, fixed effect.

**Significance at the 5% level; ***significance at the 1% level.

preparation required to perform the job. Information regarding job skill content comes from the O*NET program under the Department of Labor. The O*NET program collects survey evidence based on the level of education, on-the-job experience, and training required for each occupation category, and it compiles a "job zone" index that summarizes the level of labor skill required for each detailed occupation (categorized by six-digit SOC codes). We aggregate this index to the two-digit occupation group level using the weighted average value of job zones across all detailed occupations in a group. Weights are set based on the percentage of workers employed by each detailed occupation inside a broad group in the previous year. We then estimate the following model:

$$\begin{aligned} Y_{i,c,o,t} = {} & \beta_1(1-\tau_{c,t-1}) + \beta_2(1-\tau_{c,t-1}) \\ & \times \textit{Medium Skill Occupation} \\ & + \beta_3(1-\tau_{c,t-1}) \times \textit{High Skill Occupation} \\ & + \textit{Controls}_{c,t-1} + \gamma_{i,c,o} + \mu_t + \epsilon_{i,c,o,t}, \end{aligned} \quad (4)$$

where *Medium Skill Occupation* is an indicator for occupation groups whose average job zones are ranked at the middle tercile of the sample and *High Skill Occupation* indicates occupation groups with top-tercile job zone values. If the tax-induced upskilling is indeed more pronounced in high-skill occupations, we expect β_3 to be statistically significant with a positive sign.

Results from Table 4 conform to our conjecture. A reduction in personal income tax is associated with a weak upskilling effect on occupation groups that require little or moderate levels of preparation but leads to a strong upskilling effect on those demanding significant training or experience. Estimates remain similar even after we include county-year fixed effects (panel B), which absorb the noninteractive effect of $1-\tau$. In this specification, the coefficients suggest the incremental change in the credentials required for high-skill jobs relative to low-skill jobs following a tax change within the same firm in the same location and time.

We follow the narrative approach outlined in Section 4.4 to help substantiate these findings. Figure J.1 in the online appendix verifies that exogenous tax cuts lead to a within-occupation upskilling effect. We also repeat within-occupation analyses using the firm-state-year panel and present the results in Section H in the online appendix, including Table H.1 (panels B–F) and Figure H.2 in the online appendix. All within-occupation results hold robust.

5. Mechanisms

5.1. Firms' Reallocation of Skilled Job Hiring

We substantiate the inferences from our main tests by looking deeper into how firms reallocate skill hiring requirements within their boundaries (geographical location of operating establishments) following local tax changes. To identify tax-induced, within-firm hiring reallocation effects, we regress a firm's job skill requirements in a given state on the personal tax rate of that state as well as the personal taxes of all other states

Table 4. Differential Effects for High-Skill Occupations

Panel A: Effects on high-skill occupations					
Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 – Personal Taxes	0.262	0.561	0.367	1.117**	0.738*
	(0.381)	(0.411)	(0.437)	(0.493)	(0.427)
(1 – Personal Taxes) × Medium Skill Occupation	0.586***	0.568***	0.541***	0.727***	0.687***
	(0.173)	(0.154)	(0.146)	(0.143)	(0.102)
(1 – Personal Taxes) × High Skill Occupation	2.140***	2.182***	3.256***	2.879***	2.792***
	(0.361)	(0.344)	(0.337)	(0.304)	(0.244)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × county × occupation FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,667,411	2,667,411	2,667,411	2,667,411	2,667,411
R^2	0.673	0.636	0.616	0.647	0.647

Panel B: Controlling for county-year fixed effects					
Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
(1 – Personal Taxes) × Medium Skill Occupation	0.518***	0.556***	0.694***	0.734***	0.685***
	(0.186)	(0.165)	(0.149)	(0.140)	(0.098)
(1 – Personal Taxes) × High Skill Occupation	2.045***	2.122***	3.241***	2.649***	2.533***
	(0.340)	(0.339)	(0.320)	(0.289)	(0.228)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × county × occupation FE	Yes	Yes	Yes	Yes	Yes
County × year FE	Yes	Yes	Yes	Yes	Yes
Observations	2,666,188	2,666,188	2,666,188	2,666,188	2,666,188
R^2	0.678	0.641	0.622	0.654	0.654

Notes. This table examines the differential effects of personal tax changes on firms' requirement for high-skill and low-skill occupations. The dependent variables include the percentage of job postings requiring education (*Education*), experience (*Experience*), cognitive skills (*Cognitive*), general IT knowledge (*IT*), and programming knowledge of specific software (*Programming*). The unit of observation is at the firm-county-occupation-year level. Occupation is defined as a two-digit SOC code. *1 – Personal Taxes* is one minus the personal tax rates for individuals making 90th-percentile income, measured in the previous year. *Medium Skill Occupation* is an indicator for occupations whose weighted average job zone value falls in the middle tercile of the sample. *High Skill Occupation* indicates occupations whose average job zone value ranks at the top tercile of the sample. Weights are measured using the previous years' employment in each six-digit SOC code. Control variables are the same as those used in column (3) of Table 1. Standard errors are double clustered by firm and county. FE, fixed effect.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

Table 5. Reallocation of Skilled Worker Hiring

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 – Personal Taxes (Own State)	1.235***	1.006**	0.728**	1.713***	1.030***
	(0.422)	(0.421)	(0.334)	(0.335)	(0.285)
1 – Personal Taxes (Other States)	−0.494***	−0.394*	−0.513*	−0.464	−0.176
	(0.162)	(0.211)	(0.290)	(0.357)	(0.148)
Controls	Yes	Yes	Yes	Yes	Yes
Firm × county FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	587,041	587,041	587,041	587,041	587,041
R^2	0.647	0.575	0.596	0.608	0.599

Notes. This table shows the reallocation effect of personal taxes on firms' labor skill requirements. We estimate the effect of personal taxes in a given state and the effect of personal taxes in all other states where a firm has operations. *1 – Personal Taxes (Own State)* is one minus the personal tax rates for individuals making 90th-percentile income, measured in the previous year. *1 – Personal Taxes (Other States)* represents one minus the weighted average of the previous year's personal tax rates for individuals making 90th-percentile income in states other than *s* in which a firm has operations, with the weight being the firm's total employment (NETS) in each state. Control variables are the same as those used in column (3) of Table 1, and we additionally control for the weighted average of other states' corporate taxes, sales taxes, and tax incentives. Standard errors are double clustered by firm and county. FE, fixed effect.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

in which the firm operates. The regression specification is as follows:

$$Y_{i,c,t} = \beta(1-\tau_{s,t-1}) + \beta'(1-\tau_{-s,t-1}) + Controls_{c,t-1} + \phi_{i,c} + \tau_t + \epsilon_{i,c,t}, \qquad (5)$$

where *s* refers to the state where county *c* is located and –*s* indicates all other states where firm *i* has operations. The net-of-other-state-tax $1-\tau_{-s}$ is the weighted average of net-of-tax rate across all other states, where the weight is based on the firms' total employment in those states (employment counts come from NETS). The coefficient β' captures the hiring reallocation effect: changes in firm *i*'s skill requirements in state *s* in response to changes in personal income taxes in *other states* in which the firm operates.

Table 5 reports the results. The coefficient on $1-\tau_s$ remains positive across all dimensions of worker skill, whereas other states' taxes, $1-\tau_{-s}$, attract significantly negative coefficients. These results are new in highlighting the role of large firms in allocating high-skill jobs across states according to differential changes in local personal taxes. They demonstrate how firm internal networks propagate local shocks (see also Giroud and Mueller 2019). In particular, our results point to a corporate-led "brain drain" effect in high-tax states. On the flip side, corporations help transfer high-skill jobs and workers toward low-tax states. Given the importance of skilled labor in fostering economic growth, gaining high-skill job posts may generate persistent impacts on local economies in the United States.

5.2. Heterogeneity in Firm Responses

We study a number of characteristics that could influence firms' hiring responses to local personal tax innovations. This helps shed light on the economic frictions underlying our central results.

First, we look into the geographical diversity of firms' organizational structure, which could alter a firm's response to local tax policies in nontrivial ways. On the one hand, geographically diverse firms can diversify shocks from different states, thus exhibiting a muted response to a specific tax change. On the other hand, diverse firms may have an expansive footprint and have more room to reallocate across locations. We take these competing predictions to the data. Geographical diversity is measured by both the number of states where a firm posts job vacancies (*Number of States*) and the concentration of a firm's job postings across states (*HHI of States*). Concentration refers to the Herfindahl index based on the percentage of job postings allocated to each state by the firm in a given year. A higher number of states or lower Herfindahl–Hirschman index (HHI) value indicates that a firm has more geographically diverse operations.

Relatedly, we examine the differential response between firms in tradable and nontradable industries to changes in personal taxes. Firms in tradable industries tend to have more geographically concentrated operations, likely because of the benefits of geographical agglomeration (see Gervais and Jensen 2019). Accordingly, we expect our effects to be stronger in tradable industries.

Second, we examine the economic relevance of a locality for a firm. To start, we consider the employment share of a state for the firm of interest (*State Employment Share*). Employment share is calculated as the percentage of a firm's employees that work in a given state. Personal taxes in states with high employment shares should affect the firm's labor costs to a greater extent. Thus, we expect the effect of personal taxes to be more pronounced in those states.

Next, we investigate the differential responses of hiring in urban versus rural areas. The past decades have witnessed an increasing migration of skilled workers toward urban areas (see, e.g., Diamond 2016). We expect that following a tax cut, firms are more likely to increase the recruitment of high-skill workers in urban areas, where the supply of skilled workers is more plentiful.

Additionally, we consider the role of firm profitability. Profitability can be measured using both return on assets (*ROA*) and operating cash flow (*Cash Flow*). We conjecture that more profitable firms may be more resilient to changes in labor costs.

Finally, we compare high-growth and low-growth firms. Firms facing higher growth opportunities are likely to be more in need of high-skill workers and find it more efficient to relocate the hiring of those workers to low-tax areas. We measure growth using industry Q.

To test the predictions, we regress skill requirements on interactions between personal taxes and the mentioned characteristics. We estimate the following model:

$$\begin{aligned} Y_{i,c,t} = {} & \beta Personal\ Taxes_{c,t-1} + \delta Personal\ Taxes_{c,t-1} \\ & \times Characteristics_{i,t-1} + \theta Characteristics_{i,t-1} \\ & + Controls_{c,t-1} + \gamma_{i,c} + \mu_t + \epsilon_{i,c,t}, \end{aligned} \tag{6}$$

where *Characteristics* include *Number of States*, *HHI of States*, *Tradable*, *State Employment Share*, *Urban*, *ROA*, *Cash Flow*, and *Industry Q*. Similarly to Equation (1), the specification controls for firm-county ($\gamma_{i,c}$) and year fixed effects (μ_t), with standard errors double clustered by firm and county. Table 6 presents results from 40 alternative versions of Equation (6). To cut clutter, we only report the coefficients on interaction term of interest (δ) together with associated standard errors. The head of each row in the table shows the characteristic we focus on.

The first two interactions present results for firms' geographical diversity. We find that more diversified firms, which post jobs in many states and have a low cross-state concentration, are more resilient to local personal tax shocks. Consistently, firms in tradable industries are significantly more likely to relocate their skill hiring following tax changes.

At the same time, firms are more responsive to tax changes in states that are major employment locations. To interpret the economic magnitude of the interaction term, we use an interquartile change in state employment share (0.2). Let us use *Education* as an example. An interquartile change in state employment share corresponds to a change in the tax coefficient by around 0.8. This

Table 6. Heterogeneity in Firms' Response to Personal Taxes

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
(1 − Personal Taxes) × Number of States	−0.062***	−0.046***	−0.048***	−0.073***	−0.070***
	(0.013)	(0.013)	(0.010)	(0.011)	(0.009)
(1 − Personal Taxes) × HHI of States	2.292***	2.745***	2.299***	3.274***	3.551***
	(0.573)	(0.570)	(0.503)	(0.574)	(0.571)
(1 − Personal Taxes) × Tradable	4.310***	4.478***	2.536***	4.165***	3.651***
	(1.247)	(1.041)	(0.855)	(0.682)	(0.559)
(1 − Personal Taxes) × State Employment Share	4.237**	−1.802	2.984*	4.783***	5.300***
	(1.992)	(1.735)	(1.647)	(1.506)	(1.468)
(1 − Personal Taxes) × Urban	−0.038	−0.325	1.625**	2.153***	1.989***
	(0.707)	(0.593)	(0.662)	(0.570)	(0.371)
(1 − Personal Taxes) × Firm Profitability (ROA)	−2.409**	−2.536***	0.737	−1.465*	−1.433**
	(1.037)	(0.941)	(0.911)	(0.858)	(0.573)
(1 − Personal Taxes) × Firm Profitability (Cash Flow)	−3.106***	−2.271**	0.042	−2.487***	−2.221***
	(1.146)	(1.137)	(0.983)	(0.829)	(0.585)
(1 − Personal Taxes) × Industry Q	0.852***	0.622**	0.650**	0.817***	0.715***
	(0.279)	(0.286)	(0.269)	(0.229)	(0.181)

Notes. This table reports estimates of cross-sectional variations in multistate firms' responses to personal tax changes according to industry and firm characteristics. The unit of observation is at the firm-county-year level. We first examine the differential responses from firms with diverse and concentrated geographic operations. *Number of States* indicates the number of states where a firm posts job vacancy ads. *HHI of States* represents the Herfindahl index across all states where a firm generates job postings. We also examine firms in tradable and nontradable industries. Nontradable industries are defined as two-digit NAICS codes being in 44, 45, or 72. *Tradable* is an indicator for firm in other industries. We next consider the importance of a locality to the employer. *State Employment Share* is the percentage of employees of a firm who work in a given state. Employee counts come from NETS. *Urban* is an indicator for whether the local county is in an urban area. The definition of urban and rural areas comes from the U.S. Census. Furthermore, we examine the role of firm profitability, measured both by ROA and by cash flow (operating earnings before depreciation). Finally, we compare the response of high-growth and low-growth firms, whereby growth is measured by *Industry Q*, the average Tobin's *Q* of the firm's industry (SIC2). Control variables are the same as those used in column (3) of Table 1. Standard errors are double clustered by firm and county.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

suggests that, facing a 1-percentage point increase in personal taxes, firms adjust the education requirement in job postings in high-labor share states by about 0.8 percentage point more than in low-labor share states.

We also find that firms increase the hiring of skilled workers to a greater extent following personal tax cuts in urban than rural areas. The estimate on the interactive coefficient of *(1−Personal Taxes)×Urban* ranges from 1.625 for Cognitive to 1.989 for programming, accounting for majority of the average effect (see Table 1).

The next two interactions provide evidence related to profitability. Consistent with our predictions, profitable firms do not change skill hiring following personal tax hikes as much as nonprofitable firms. This result suggests that superior financial performance allows firms to hedge against fluctuations in labor costs. Finally, we note that high-growth firms are significantly more responsive to personal tax changes than low-growth firms. Taken together, results from the cross-sectional analyses reveal key mechanisms and frictions shaping firms' hiring responses to local personal taxes.

5.3. Personal Taxes at Other Income Levels

Our baseline tests revolve around personal tax rates levied on individuals whose income levels rank at the 90th percentile of the distribution. To verify that our tax effect is most relevant for skilled workers, we consider personal income taxes faced by workers making other levels of income, starting with the 10th percentile all the way through the 99.5th percentile of the income distribution.

In Figure 5, we present coefficients on personal taxes for various income levels together with their 90% confidence intervals. We do not find that changes to taxes affecting very low-income earners (10th-percentile income) affect local job skill postings because of several reasons. Notably, individuals at the 10th percentile of the income distribution are less likely to be highly skilled workers but are more likely to receive tax rebates. Tax rates applicable to those filers also exhibit less variation over time. As one moves up the income ladder, the negative effect of taxes on labor skill progressively intensifies, reaching its highest level at the 95th income percentile. At the 99th percentile, however, the effect of personal taxes on education requirements weakens. That effect vanishes at the 99.5th percentile of the income distribution. Individuals at this income level likely rely less on wage income. They are also less likely to rely on job postings to decide the place to work.

Overall, these findings are sensible for the population income range considered and imply that higher personal income taxes affect the job market prospects of local middle- and upper middle-class workers the most.

5.4. Local Personal Taxes and Wages

Our theoretical framework predicts that lower personal taxes reduce the labor costs faced by firms, more so for high-skill positions than for low-skill ones. In Section K in the online appendix, we use wages listed in job postings to verify this mechanism (Cohen et al. 2021). Although sparsely populated, these wage figures reveal the level of compensation needed to attract local workers. We provide both descriptive and statistical evidence regarding the relation between wages and personal taxes. Our results suggest that listed salaries generally increase with personal tax rates. Moreover, wages for higher skilled occupations are significantly more responsive to personal taxes than those for unskilled positions. These results help validate the mechanism that firms adjust skill requirements in response to changes in labor costs following personal tax innovations.

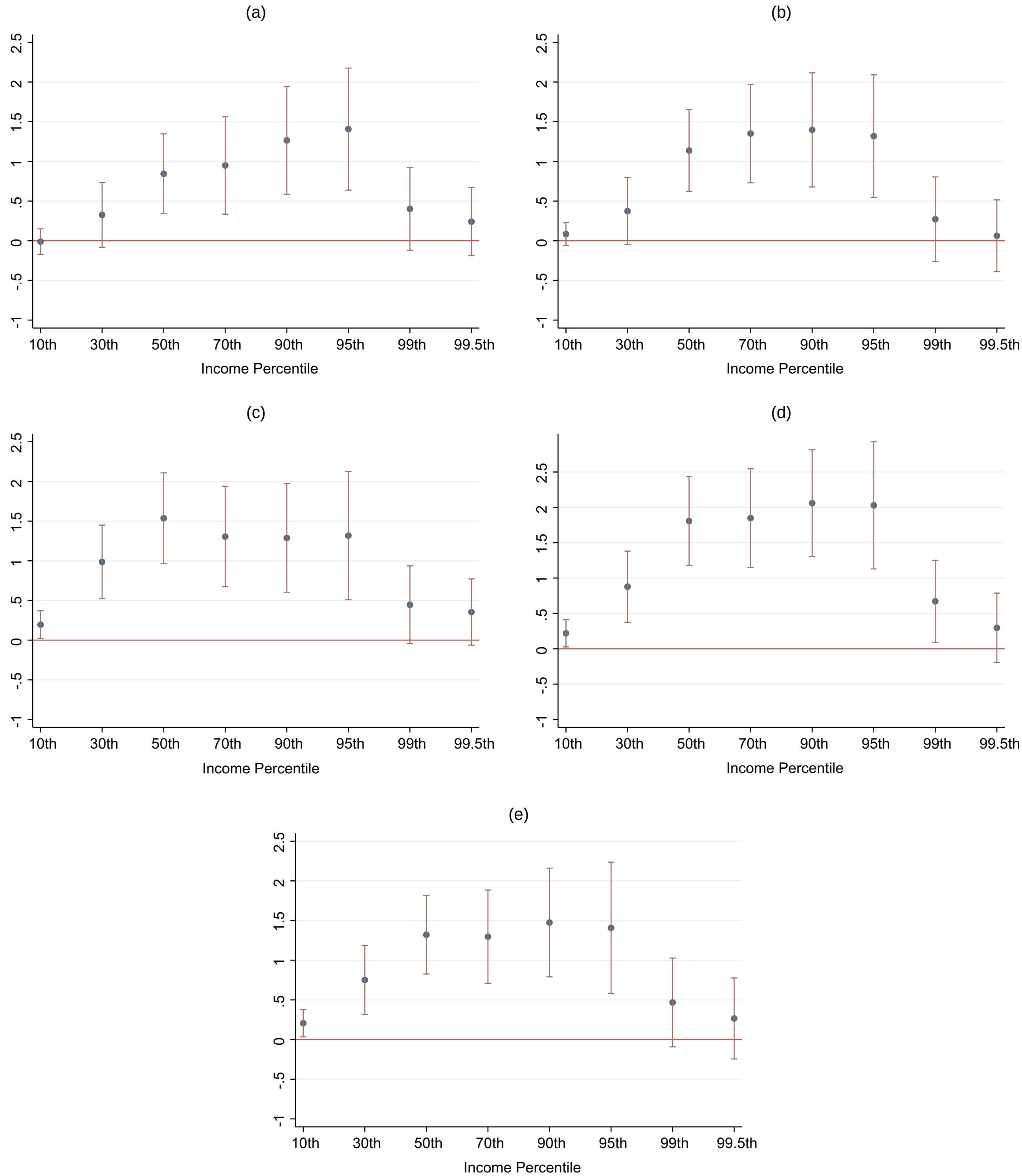
Our estimates of the wage-tax relationship allow us to make a back-of-the-envelope calculation regarding how much in labor costs firms can save by hiring skilled workers in a low-tax state. To start, we compute how much a personal tax cut ($\Delta\tau_{p,s}$) reduces firms' skilled labor costs: $\Delta LaborCost = \Delta\tau_{p,s} \times \hat{\beta}_\tau \times \overline{Wage_s} \times Workers_s \times (1 - \tau_{Federal} - \tau_{c,s})$, where s indicates a state, $\hat{\beta}_\tau$ is the estimated coefficient of log wages on personal taxes, $\overline{Wage_s}$ represents the average wage level of educated workers in state s, and $Workers_s$ represents the number of skilled workers employed by a firm in state s. Finally, $1 - \tau_{Federal} - \tau_{c,s}$ is the net of federal and state corporate tax rates.

Based on our wage regressions presented in Table K.1 in the online appendix, the sensitivity of wages to personal tax changes is −0.8 for high-skill occupations (the sum of the coefficient on the base group and the coefficient on the high-skill group in column (1)). We further collect information on average annual salaries from the Bureau of Labor Statistics ($48,529) as well as data on skilled employee counts of public firms in a state from NETS (1,427). Multiplying these numbers with the average net-of-corporate tax rates, we compute a net gain of relocating workers to a state with one-percentage point lower personal taxes to be $321,378 per year. Finally, applying a cost of capital of 10%, we find the present value of tax saving to be around $3.2 million. In other words, an average public firm can save up to $3.2 million in labor cost by relocating from one state to another where there is a one-percentage point differential in personal taxes.

6. Local Personal Taxes and IT Investment

As firms boost the hiring of high-skill workers in low-tax jurisdictions, they may also reallocate highly productive

Figure 5. (Color online) Coefficients for *1 – Personal Tax* Across Tax Brackets



Notes. This figure shows the effects of personal tax rates at different income brackets on the skill 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 90% confidence intervals for the estimates. (a) Education. (b) Experience. (c) Cognitive. (d) IT. (e) Programming.

physical assets, such as technology investment, toward those localities. Indeed, research on skill-technology complementarity posits that technological upgrades are coupled with greater reliance on high-skill workers (see, e.g., Autor et al. 2003, Autor and Dorn 2013).[16] This argument suggests that firms may increase their

Table 7. Technology Investment and Personal Taxes

Dependent variable: Log of per employee budget	(1) *IT Budget*	(2) *Hardware Budget*	(3) *Software Budget*	(4) *Telecomm. Budget*
1 − Personal Taxes	2.698**	2.295*	2.338*	2.385**
	(1.215)	(1.245)	(1.269)	(1.186)
1 − Corporate Taxes	−1.269**	−1.132*	−0.966	−0.587
	(0.640)	(0.654)	(0.694)	(0.600)
Controls	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes
Firm × year FE	Yes	Yes	Yes	Yes
Observations	2,303,631	2,303,631	2,303,631	2,303,631
R^2	0.875	0.884	0.891	0.858

Notes. This table examines the effect of personal tax changes on IT investment. The dependent variables include firms' budget items (in logarithm) for overall IT spending (*IT Budget*), hardware devices (*Hardware Budget*), computer software (*Software Budget*), and telecommunication services (*Telecomm. Budget*). All dependent variables are reported on a per-employee basis. We report coefficient estimates from Equation (7). The unit of observation is an establishment-year. Control variables are the same as those used in column (3) of Table 1. Standard errors are double clustered by firm and county. FE, fixed effect.

*Significance at the 10% level; **significance at the 5% level.

technology investment when lower personal taxes lead to reduced costs of human capital.

We evaluate the effect of personal taxes on public firms' IT investment at the establishment level using an establishment-level sample. We then estimate the following regression model:

$$\log(IT\ Spending)_{e,t} = \beta \log(1-\tau)_{c,t-1} + Controls_{c,t-1} + \psi_e + \mu_{i,t} + \epsilon_{e,t}, \tag{7}$$

where e represents an establishment of firm i. Firms' IT spending is measured in various ways, including an establishment's overall IT budget, budgets allocated to hardware and software purchases, and telecommunication services. All budgetary terms are measured on a log of per-employee basis. ψ_e represents establishment fixed effects. Standard errors are double clustered by firm and county. The results are presented in Table 7.

Our results indicate that personal income taxes significantly influence firms' technological investment in their local establishments. Indeed, the impact is observed across all related budgetary items (hardware, software, and telecommunication). The estimates suggest an elasticity of around two for overall IT investment with respect to personal income net-of-tax rates.[17]

In Table L.3 in the online appendix, we examine the changes in firms' IT investment following exogenous tax cuts using the narrative approach. To remain parallel with the skill hiring analysis, we aggregate IT spending to the firm-county level for this test. We find that firms' IT investment does not change prior to exogenous tax cuts but significantly increases in the year following those events.

Finally, we refine our narrative analysis on worker skill requirements and examine whether skill requirements increase more for firms that also expand their IT expenditures to a greater extent. Specifically, within each matched group of treated and control firms for a tax event, we partition firms into terciles based on how much they have increased their IT investment from two years prior to the event to two years after the event. The top-tercile (bottom-tercile) firms are labeled as "high-IT" ("low-IT") firms. We then track the changes in the skill hiring of high- and low-IT firms, respectively; in this analysis, we focus only on cognitive, IT, and programming skills because these skills are naturally complementary to information technology.[18] In contrast, we do not expect firms to differentially adjust their education and experience requirements, as those requirements correspond to general human capital and are not necessarily related to IT skills.

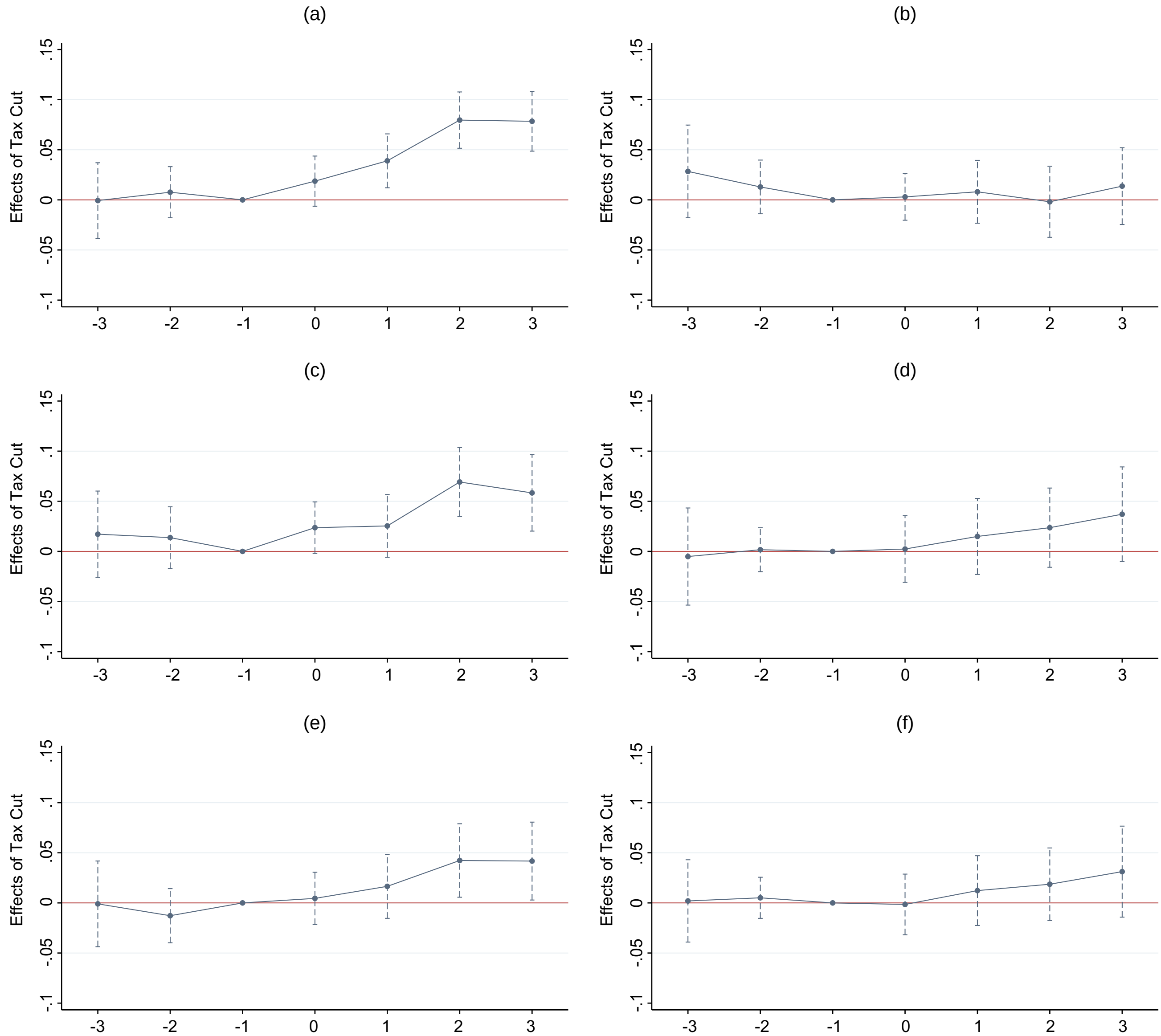
Figure 6 depicts the requirements for cognitive, IT, and programming skills for high-IT and low-IT firms around personal tax cuts. Consistent with our conjecture, high-IT firms significantly increase their skill requirements following tax cuts. In contrast, changes in these skill requirements are not statistically different from zero for low-IT firms.

Taken together, these results point to an unambiguous, positive effect of lower personal income tax rates on technology adoption. Firms not only shift their hiring of high-skill workers to low-tax states but also accelerate their technological upgrades in those states. As the growth in skilled jobs compounds with technological development, low personal income taxes are likely to contribute to a thriving local economy.

7. County-Level Evidence

In the last step of our analysis, we seek to understand whether changes in personal taxes shape the worker composition in a locality. We first examine the relationship between state personal taxes and skill requirements contained in all job ads in a county, not just ones posted by public firms.

Figure 6. (Color online) IT-Skill Complementarity: Narrative Approach



Notes. This figure shows how requirements for IT-related skills contained in job postings changed following tax cuts for firms that increased their IT expenditure to a greater or lesser extent. High-IT (low-IT) firms are those whose changes in IT expenses rank at the top (bottom) tercile within a matched group. In each panel, coefficient estimates of β_τ ($\tau \in [-3, 3]$) in Equation (3) are presented together with 90% confidence intervals. Year − 1 is the benchmark. All tests include the same control as used in column (3) of Table 2, as well as firm-county, year, and event fixed effects. Standard errors are double clustered by firm and county. (a) Cognitive, high-IT firms. (B) Cognitive, low-IT firms. (C) IT skills, high-IT firms. (D) IT skills, low-IT firms. (E) Programming skills, high-IT firms. (F) Programming skills, low-IT firms.

Supplementing the job posting data, we retrieve information on worker education attainment from the QWI data to study how personal income taxes influence the worker composition in the local labor markets.[19] During our sample period, the number of job postings and total employed workers in a county-year have a correlation of 0.94. Research using BurningGlass generally defines education requirements as whether workers need to have at least a high school degree (see, e.g., Deming and Kahn 2018, Hershbein and Kahn 2018). We apply this convention to the QWI data accordingly, defining educated workers to be those that have at least a high school degree.[20] We compute four variables to describe worker education in a county: the average years of education for employed workers (*Avg Education*), the percentage of employed workers with high school education or above (*%Educated Workers*), the log of the total number of employed workers with high school education or above (log(*Educated Workers*)), and the log of the total number of employed workers with no education or below high

Table 8. County-Level Results

Panel A: Job skill requirements in a county (BurningGlass)

Dependent variable	(1) *Education*	(2) *Experience*	(3) *Cognitive*	(4) *IT*	(5) *Programming*
1 − Personal Taxes	3.260***	2.582***	2.784***	3.046***	2.195***
	(0.510)	(0.424)	(0.298)	(0.313)	(0.261)
1 − Corporate Taxes	−1.174***	−1.438***	−1.186***	−1.257***	−0.836***
	(0.321)	(0.253)	(0.186)	(0.189)	(0.154)
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,888	23,888	23,888	23,888	23,888
R^2	0.506	0.486	0.572	0.618	0.633

Panel B: Worker education in a county (QWI)

Dependent variable	(1) *Avg Education*	(2) *%Educated Workers*	(3) log(*Educated Workers*)	(4) log(*Uneducated Workers*)
1 − Personal Taxes	0.842***	0.321***	1.041**	−0.422
	(0.293)	(0.052)	(0.505)	(0.566)
1 − Corporate Taxes	−0.075	−0.079**	−0.646*	−0.356
	(0.192)	(0.034)	(0.330)	(0.387)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	29,742	29,755	29,696	29,680
R^2	0.958	0.943	0.998	0.997

Notes. This table shows how the skill composition of workers in a county changes in response to personal tax changes. The unit of observation is a county-year. Panel A uses the BurningGlass data, where county-level skill requirements are computed using job postings by publicly traded and private employers. The dependent variables include the percentage of job postings requiring education (*Education*), experience (*Experience*), cognitive skills (*Cognitive*), general IT knowledge (*IT*), and programming knowledge of specific software (*Programming*). Panel B presents evidence using data from the QWI from the U.S. Census, and the dependent variables include the average years of education for employed workers (*Avg Education*), the percentage of employed workers with high school education or above (*%Educated Workers*), the log number of employed workers with high school education or above (log(*Educated Workers*)), and the log number of employed workers with below high school or no education (log(*Uneducated Workers*)). Control variables are the same as those used in column (3) of Table 1. Standard errors are clustered by county. FE, fixed effect.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

school education (log(*Uneducated Workers*)).[21] We estimate the following regression specification using a county-year sample:

$$Y_{c,t} = \beta(1 - \tau_{c,t-1}) + Controls_{c,t-1} + \gamma_c + \eta_t + \epsilon_{c,t}, \quad (8)$$

where $Y_{c,t}$ includes the percentage of postings listing a job skill in county c during year t. It also includes the four outcome variables from the QWI. We control for county fixed effects (γ_c) and year fixed effects (η_t). County fixed effects allow us to make inferences regarding in-county time-series variation in personal taxes and labor skills.

The results on job skill requirements are presented in panel A of Table 8. Coefficient estimates suggest that personal tax cuts are positively associated with county-level skill requirements. Specifically, a one-percentage point increase in $1 - \tau$ leads to an approximately three-percentage point increase in job ads featuring education, experience, cognitive, and IT prerequisites and a two-percentage point increase in programming skills. For a representative county-year in our sample with around 3,200 job postings, our estimates translate into approximately 100 jobs with education, cognitive, and IT skill requirements and 70–80 jobs with experience and programming requirements. In Section M in the online appendix, we enhance identification by comparing job postings in counties adjacent to state borders and find similar results as those obtained using the full sample.

Panel B of Table 8 presents the results using the QWI data. Coefficients estimates reveal consistent effects as those obtained from panel A. Personal tax cuts are positively associated with the average education and the percentage of educated worker in a county. Specifically, a 1-percentage point increase in *1 − Personal Taxes* leads to a 0.3-percentage point increase in *%Educated Workers* (column (2)), an approximately 1% increase in the quantity of skilled workers (column (3)), and a

0.4 (insignificant) decrease in the quantity of unskilled workers (column (4)). The results shown in columns (3) and (4) reveal that the growth in skilled workers is a stronger driver of the local skill composition in response to personal tax cuts compared with the decline in unskilled ones.

Across both panels, *1 – Corporate Taxes* generates consistently negative estimates on local educated workers. The aggregate evidence substantiates the estimates obtained using the BurningGlass job posting information where lower corporate taxes are positively associated with local skill hiring.

8. Concluding Remarks

This paper provides novel evidence on the effect of personal income taxes on firms' hiring of high-skill workers across U.S. states. Using unique data on firm job postings, we show that reductions in state-level personal income taxes leads firms to increase job skill requirements for local hires and reallocate high-skill jobs from other states. Tax-induced upskilling is accompanied by technology adoption. Our evidence also points to mechanisms underlying the personal tax effects on labor skills. We show that personal taxes add to the labor costs faced by firms, motivating firms to shift their skilled jobs from high-tax states toward low-tax states. The upskilling effects occur both within and across occupations, being concentrated among high-skill positions. They are also more pronounced in urban areas and tradable industries, but they are mitigated for geographically disperse firms.

In all, we show that large corporations play an active role in transferring skilled positions across states. This reallocation effect suggests a "brain drain" from high-tax regions of the country and an influx of skilled workers and jobs to low-tax jurisdictions. These effects are also associated with changes in corporate IT investment in the same direction across states. As local governments compete to attract talents and businesses, their personal income tax policies may shape the vibrancy of local labor markets and corporate organizational structures in the United States.

Although our findings reveal the effect of personal taxes on subsequent changes in local job skills, we caution the extrapolation of such inferences to long-run effects. As personal taxes are associated with shifts in fiscal policies and local labor market conditions, those factors may mitigate or amplify the effects of tax policies in the long run.

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Endnotes

[1] We showcase the information content of our data in Section 3, where we document a strong county-level relation between the education requirements featured in our job ads data and census data on local workers' education.

[2] They include corporate, property, and sales taxes; minimum wages; unemployment benefits; budgetary deficits; gross domestic product growth; population makeup; political party leanings; housing prices; and education and infrastructure spending (including transportation, public safety, and amenities). We also account for the expected education of new local hires via a Bartik instrument that maps the hiring of educated workers at the national level into a county.

[3] This is a canonical approach used to assign causal effects of tax policies (see, e.g., Cloyne 2013, Mertens and Ravn 2013, Giroud and Rauh 2019, Zidar 2019). Additional details are provided in Section 4.4 and Section E in the online appendix.

[4] Specifically, we consider a job to require cognitive skills if the skill description includes "research," "analy," "decision," "solving," "math," "statistic," or "thinking" (Hershbein and Kahn 2018).

[5] Although the variation in BurningGlass job postings closely approximates that of employed workers, we do not observe the number of workers hired in each job category. It is possible that some job postings result in no hire, whereas others result in multiple hires. The difference between job postings and employed workers could create noise in our estimation, but it is unclear how it could bias the estimation between tax rates and the composition of postings.

[6] 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: Internal Revenue Services Statistics of Income Tax Stats). SALT deduction was capped at \$10,000 by the Tax Cuts and Jobs Act passed in December 2007, and this change does not affect our sample period.

[7] 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.

[8] Based on 2017 BurningGlass data, workers in positions such as software engineer, project manager, and pharmacist have annual salaries of around \$100,000; positions such as supervisors, technicians, and IT staff pay around \$50,000. Examples of wage distributions for these skilled positions are shown in Figure C.3 in the online appendix.

[9] We follow Moretti and Wilson (2017) and make the following assumptions; the taxpayer is a married joint filer, had zero dependent exemptions, had zero childcare expenses, had no other sources of income, and had zero itemized deductions other than the deduction for state income tax payments calculated by TaxSim.

[10] Corporate income taxes and sales taxes are from the University of Michigan tax database, the tax foundation, and the Book of the States. Property tax data are from the American Community Survey (ACS). We exclude the following state-years because of 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 before 2012, and Nevada after 2015.

[11] State-level GDP data come from the Bureau of Economic Analysis, whereas unemployment insurance information is from the Department of Labor. Information on state budgetary surplus and minimum wages is from the Institute for Public Policy and Social Research. Home Price Index (HPI) is obtained from the Federal Housing Finance Agency. Local demographic information comes from the ACS. State-level consumer price index is from Hazell et al. (2022).

[12] Our empirical approach differs from the generalized difference-in-difference setup discussed in recent work by Goodman-Bacon (2021) and Callaway and Sant'Anna (2021). This is because personal taxes might change continuously and can move up and down in the same state during our sample period. Nonetheless, we address concerns related to heterogeneous treatment timing in Section 4.4, where we compare states with large tax shocks with matched control states that never experience tax shocks in our sample period.

[13] We further examine the interactive effects of personal income taxes and the aggregate tax burdens from other tax policies on local firms' skill hiring in Table I.1 in the online appendix. We test the effect of personal taxes on firm skill hiring in states with high, medium, and low tax burden from other sources. We do not find a clear interactive effect between personal and other types of taxes. This suggests that other tax policies do not amplify or weaken the influence of personal taxes on firm skill hiring.

[14] We do not consider the tax reform in Maryland in 2011, which applied to the top 1% income earners, and the tax cut in Illinois in 2015, which was reverted in 2017.

[15] In Table J.2 in the online appendix, we re-estimate our baseline regressions after excluding the eight states that have experienced exogenous tax cuts in our narrative analysis. Our estimates remain unchanged.

[16] In Table L.1 in the online appendix, we show that more skill requirements in firms' job ads correspond to higher IT budgets, supporting the complementarity between firms' IT investment and skill requirements in our sample.

[17] We find a negative but weakly significant coefficient on *1 – Corporate Taxes* for IT investment in general. This could be explained by the technology-human capital complementarity, as *1 – Corporate Taxes* also generates a negative coefficient on skill hiring (see Table 1). In Table L.2 in the online appendix, we present estimates for all control variables for firms' IT investment.

[18] Recall that cognitive skills refer to the ability to perform modeling, mathematics, and data analytics tasks, which often require IT equipment.

[19] Data underlying the QWI come from the Longitudinal Employer-Household Dynamics-linked employer-employee microdata. These data cover 95% of the private sector jobs in the United States.

[20] Studies in labor economics also use high school degree as a cutoff for worker skill. See, for example, Ciccone and Peri (2005) and Goldin and Katz (2010)

[21] When calculating the average education years, we assign the following education years based on the education categories: 9 years for no education or below high school, 12 years for high school degrees, 14 years for associate degrees, and 16 years for bachelor degrees.

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