Economic Stimulus at the Expense of Routine-Task Jobs*

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Abstract

Do investment tax incentives improve job prospects for workers? Using two massive establishment-level datasets on occupational employment and computer investment, we study the causal effect of a major tax incentive for investment on labor outcomes. The incentive, Section 179, indirectly reduces the after-tax price of equipment investment for *eligible* firms (i.e., small businesses) but not for ineligible ones. Combining this heterogeneous treatment with the variation in states' adoption of the incentive for state taxes, we find that when states increase investment incentive, eligible firms increase their equipment investments but experience little change in total employment. A further investigation uncovers that these firms increase skilled employees immediately following the incentive, however, they reduce their routine-task employees over the following three years. Hence, investment policy affects workers of different skills not only in different directions, but also at different times.

Keywords: Routine-Biased Technological Change; Skill-Biased Technological Change; Investment Tax Incentives; Section 179; Small Businesses.

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1. Introduction

> "Our bill aimed to help small businesses invest, grow, and create jobs by providing needed tax relief and certainty. ... In light of the positive effects these provisions [permanent extension of Section 179 expensing] would have on small businesses, on jobs, and on our economy, I urge my colleagues to support the tax relief package."
>
> - Senator Susan Collins, co-sponsor of Small Business Tax Certainty and Growth Act of 2015 (Congressional Record, December 17, 2015)

Investment tax incentives are important tools for the governments to stimulate the economy. Despite these incentives being defined over investment, their main stated goal is usually to generate growth and boost job prospects.[1] While capital investment is generally considered to respond positively to these incentives (most recently, Zwick and Mahon (2017)), the evidence regarding labor market outcomes is limited and inconclusive. In this paper, we use confidential establishment-occupation level panel data to study the effect of investment tax incentives on labor outcomes. We find no effect on the total employment of firms. Yet, we uncover significant and heterogeneous effects on workers with different skills and performing different tasks, which can potentially promote further polarization of the labor pool. Our specific policy setting also offers an ideal experiment to examine and confirm machines' substitutability with routine-task labor, and their complementarity with skilled labor in the United States.

Specifically, we study the causal effect of Section 179 allowances on firm investment and employment. Section 179 of the Internal Revenue Code allows firms to expense limited amount of qualifying investments in equipment and software instantly rather than following the standard depreciation schedule. By shifting the timing of tax deductions to day zero, this incentive increases the present value of tax benefits, and it significantly reduces the immediate funding needs for investments. Importantly, Section 179 targets small businesses by imposing deduction limits and phaseout thresholds on firm investments, making large

[1]For instance, the federal tax law passed in 2003 is named "Jobs and Growth Tax Relief Reconciliation Act" and the 2010 law is named "Small Business Jobs and Credit Acts". Both laws had provisions that provide significant investment tax incentives.

firms essentially ineligible for this benefit.[2]

Since 2002, several federal acts have significantly increased the Section 179 deduction limits for federal taxes—from \$24,000 in 2002 to \$500,000 starting in 2010. While some states conform to the federal deduction limits and allow deductions to also increase for *state taxes*, others deviate. In this paper, we explore both the variation in states' treatment of Section 179 and the variation in firms' eligibility for Section 179 to identify the treatment effect of Section 179. By exploring these variations using a first-difference methodology with matching estimators, we examine the effect of changes in Section 179 deduction limits on firms' investment and employment outcomes.

We first examine firms' investment response to Section 179 using a private-sourced database from Harte-Hanks—Computer Intelligence Technology Database (CiTDB). This database provides annual data on the number of computers in over 500,000 establishments before 2010, and in 3.2 million establishments afterward. We find that a \$250,000 increase in state Section 179 limit, which is equivalent to the increase many states adopted in 2010, leads to 1.7% additional increase in computers for eligible establishments relative to their matched counterparties.[3] Our finding on (small) eligible firms is consistent with a recent study by Zwick and Mahon (2017), who find that much of the response of firm investment to federal bonus depreciation tax incentive is from small firms rather than large firms.[4]

We next present our main findings using confidential establishment-occupation level microdata from the Bureau of Labor Statistics (BLS). This database provides employment data for over 800 detailed occupations in 1.2 million establishments in the U.S. over three-year cycles. We find little effect of Section 179 on firm's total employment. Yet, we show that focusing solely on total employment is misguided, as there are heterogeneous effects on different segments of the labor market: Most importantly, eligible firms significantly reduce

[2] Deduction limit is the maximum deduction that a firm may claim in a year. If the firm's investment in a given year exceeds the phaseout threshold, Section 179 deduction is reduced by the amount exceeding the threshold. Our definition of eligible firms follows this feature closely and is detailed in Section 5.

[3] Additional evidence from examining a different dataset on small business's purchasing and leasing decisions on various types of capital (e.g., equipment, buildings, land, vehicles, etc.) reveals a consistent finding that only the decision on purchasing equipment responds positively to states' increase in Section 179 limits. See Section 5.3 for details.

[4] In addition, a growing body of work argues that smaller firms are more financially constrained and have higher discount rates for future cash flows. Hadlock and Pierce (2010) find that firm size is a particularly useful predictor of the firm's financial constraint. Farre-Mensa and Ljungqvist (2015) find that unlike public firms, small private firms are financially constrained. Such financial constraints make the tax deduction from Section 179 potentially more effective.

the number of workers who perform procedural and rule-based tasks, i.e., *routine* tasks, in response to an increase in state Section 179 limits. On the other hand, these firms increase the number of skilled workers who perform nonroutine tasks. A $250,000 increase in state limit leads to 6% decrease in routine-task employment in the three-year window after the policy change. The same policy shock leads to about 3.5% increase in skilled employment in the three year window around the policy change. We do not find any effect on nonroutine unskilled workers.[5] These different outcomes for the three distinct labor groups together form the insignificant effect of Section 179 incentive on firms' total employment.

These findings are consistent with two major hypotheses from the labor economics literature on routine-biased technological change (RBTC) and skill-biased technological change (SBTC). In a seminal paper, Autor, Levy, and Murnane (2003) hypothesize that computers substantially substitute for routine-task jobs, strongly complement abstract-task jobs, and have no direct relation to manual-task jobs. Indeed, in our setting, skilled workers perform mainly abstract tasks and nonroutine unskilled workers perform mainly manual tasks. While the implications of these hypotheses are wide-spread and far-reaching in many areas (e.g., Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014), Jaimovich and Siu (2014), Krusell, Ohanian, Rios-Rull, and Violante (2000)), we believe our setting, which explores policy shocks that indirectly reduce investment prices, offers an ideal experiment to examine and confirm the main predictions of these hypotheses in the U.S. economy.

In addition to the direction of the effects on heterogeneous labor outcomes, our tests also uncover a novel finding on the timing of these effects: Eligible firms increase their skilled workers shortly after the states increase the tax incentive; however, they reduce routine workers later, over the following three years. It is intuitive that firms need compatible skilled workers immediately when they purchase new equipment (Krusell et al. (2000)). The delayed reduction of routine workers potentially indicates a time-to-build feature (Kydland and Prescott (1982)), where installation of new capital takes multiple periods, or firms go through a transition period and reduce their routine workers only when their new equipment is ready for full scale production. The implication of this finding could be substantial: While the investment tax incentives may boost up skilled jobs immediately, the disruptive effect of these incentives on routine jobs may only show up a few years later.

[5] Examples of routine-task jobs include bank tellers, assembly line workers, travel agents, and tax preparers. Examples of nonroutine-task skilled jobs include managers, physicians, and civil engineers. Examples of nonroutine-task unskilled jobs include drivers, animal trainers, and janitors.

To formalize our testable hypotheses, we embed the above ingredients into a simple two-period model with taxes where firms optimally choose four factors of production, capital, skilled, routine, and nonroutine unskilled labor, to maximize firm value. We assume that capital and routine-task labor provide routine inputs to the production and are relative substitutes, and that skilled labor and capital are relative complements. Nonroutine unskilled labor neither substitutes, nor complements capital. A faster tax expensing increases firms' after-tax profits in the first period and reduces them in the second period. We show that faster expensing boosts up firms' investment, increases skilled labor, decreases routine-task labor, and has no effect on nonroutine unskilled labor. Discounting makes future deductions less valuable than current period deductions. If the discount rate is increased due to an additional channel, such as financing frictions, the effect of the tax incentive would be amplified.[6]

There are two main challenges to empirically identify the effect of investment tax incentives on investment and employment. First, federal investment tax incentives affect all firms at the same time. We thus use heterogeneous adoptions of Section 179 across states for *state taxes* to create a counterfactual for how firms' investment and employment would have evolved in the absence of the incentive. To construct closely-mirrored counterfactual, we run regressions with fixed effects that include a full interaction of 8 employment bins, over 300 NAICS 4-digit industry classifications, and 12 years.

The second empirical challenge is that factors that drive a state's policy choice on Section 179 may also drive the investment and employment decisions of establishments that operate in the state, leading to correlated state Section 179 policy and firm outcomes. We use a unique feature of Section 179 to address this concern: Only small businesses are eligible for the incentive. Specifically, we draw inferences from comparing the effect of states' increase in Section 179 limits among eligible firms with the effect among ineligible firms. Hence, any state-level factor that affects both eligible firms and ineligible firms in the state would be largely controlled for.

Our paper contributes to the growing literature that explores the effects of investment tax

[6]A simple costly external financing channel, similar to Kaplan and Zingales (1997), would lead to a higher effective discount rate. Another channel that potentially affects the firms' response to investment incentives is the presence of investment adjustment costs. Convex adjustment costs lead to gradual adjustment whereas non-convex costs lead to infrequent adjustment and lumpy investments. If Section 179 policy induces a firm across its adjustment threshold, firm investment may increase sharply (Winberry (2016)).

incentives. Most of the literature so far focused on the effect of tax incentives on investment.[7] Ohrn (2016) and Gaggl and Wright (2016) are the only two papers that explicitly study the effect of tax incentives on labor.[8] Ohrn (2016) studies the investment and total employment response to both bonus depreciation and Section 179 programs, and finds that employment does not respond to investment incentives. Gaggl and Wright (2016) study a small firm tax incentive episode from the U.K. for computer and communications equipment and find that the primary effect of these types of capital is to complement nonroutine work, which provides further support for our modeling assumptions.

Our findings also contribute to the literature on routine-biased technological change (RBTC) and skill-biased technological change (SBTC). The central theme of the RBTC literature is that technologies can directly replace routine-task jobs (see Autor, Levy, and Murnane (2003), Autor and Dorn (2013), Goos, Manning, and Salomons (2014), Acemoglu and Restrepo (2018), among others). Acemoglu and Autor (2011) extensively review this literature and show that such skill-replacing technologies are essential for explaining the changes in the distribution of employment over the last four decades, such as job polarization. The central theme of the SBTC literature is that technologies can directly complement skilled labor (see Goldin and Katz (1998), Krusell, Ohanian, Rios-Rull, and Violante (2000), among others). Our exploration of the investment tax policy shocks shows that when firms face cheaper access to technological equipment, they increase skilled employment and reduce routine-task employment, which is consistent with the central themes of both strands of literature.

Caution needs to be taken when interpreting our results beyond their current context. First, we refrain from generalizing our findings on offsetting employment effects observed in the treated firms to the entire economy. In particular, our setting does not capture the possible spillover effects from the eligible firms to their out-of-state suppliers. We thus interpret our findings on total employment as the outcome for eligible firms, and not as an equilibrium result for the whole economy. Second, while our findings show heterogeneous effects on firms' positions for routine-task and skilled jobs, because we do not observe the

[7]Summers (1981), Summers (1987), Cummins, Hassett, Hubbard, Hall, and Caballero (1994), Goolsbee (1998), Chirinko, Fazzari, and Meyer (1999) (among others) are some of the earlier contributors to the area. Post-2000 U.S. investment tax incentives are studied in House and Shapiro (2008), Edgerton (2010), Ohrn (2016), and Zwick and Mahon (2017).

[8]While not directly testing employment, Zwick and Mahon (2017) test the effect of bonus eligible investments on total payroll and find a positive effect.

subsequent outcomes for routine-task and skilled workers (e.g., job relocation), we refrain from drawing conclusions for individual or social welfare.

The paper is organized as follows. Section 2 presents a model to guide our empirical tests. Section 3 describes the policy background. Section 4 describes the data used in our empirical analysis and introduces our key measures. Section 5 presents our empirical results relating tax policy, investment, and labor outcomes. Section 6 concludes.

2. A Simple Model

We present a simple two-period model to derive the effect of investment tax incentives on firm's investment and labor decisions.

Firms use four factors of production. Three of these are labor inputs, routine, skilled, and nonroutine unskilled labor (L_R, L_S, and L_{NU}), and the last factor is capital (K). Routine labor and capital, such as assembly line workers and robotic arms, perform routine tasks, whereas skilled labor, such as managers, perform abstract tasks that complement routine tasks in the production process. Autor, Levy, and Murnane (2003) emphasizes that nonroutine unskilled labor, such as janitors, perform manual tasks that have limited opportunity to complement or substitute capital. Following their lead, we assume that nonroutine unskilled labor does not interact with capital. Put together, firms produce output with these inputs using the following technology:[9]

$$Y = L_S^{\alpha} \left(L_R^{\mu} + K^{\mu}\right)^{\frac{\beta}{\mu}} + mL_{NU}^{\alpha+\beta},$$

where $\mu, \beta, \alpha \in (0, 1)$ and $\alpha + \beta < 1$.

The last inequality captures decreasing returns to scale, meaning that a proportional increase in productive inputs causes output to increase by a smaller proportion. The routine task inputs are aggregated using a constant elasticity of substitution (CES) aggregator, given by $\left(L_R^{\mu} + K^{\mu}\right)^{\frac{1}{\mu}}$ .The elasticity of substitution between routine labor and capital is given by $\frac{1}{1-\mu}$ and, by assumption, is greater than 1. The elasticity of substitution between skilled labor and aggregated routine task inputs is 1. Routine labor and capital are relative substitutes, whereas skilled labor and capital are relative complements. Firms are competitive and take

[9] Autor and Dorn (2013) use a similar specification for the goods sector aggregating routine, nonroutine labor and capital.

as given the prices of all inputs (wages, w_R, w_S, and w_{NU}, and purchase price of capital, P).

Capital is a long-term asset and depreciates at the rate of δ. The tax code allows the firm to deduct the cost of new investment from taxable income over time, however, depreciation tax schedule is decoupled from the economic depreciation rate. The firm is allowed to deduct η fraction of the new investment in the same period that investment is made, and the rest $(1-\eta)$ fraction is depreciated (expensed) in the next period. Variations in η capture the tax policy in this paper.

There are two periods. Firms start the first period with an existing capital stock K_1, hire labor, produce, make investments for the next period, and pay taxes. The resulting first period cash flow of the firms is given by:

$$D_1 \quad = \quad (1-\tau)\left(Y_1 - w_{R,1}L_{R,1} - w_{S,1}L_{S,1} - w_{NU,1}L_{NU,1}\right) - (1-\tau\eta)\, PI,$$

where τ is the marginal tax rate of the investors, I is firms' investment for next period, and $\tau\eta PI$ is the depreciation tax shield. Next period's capital K_2 is determined by the capital accumulation rule:

$$K_2 = (1-\delta)\, K_1 + I.$$

In the second period, firms produce and take the remaining depreciation tax shield. For simplicity we assume that the liquidation value of capital at the end of second period is zero.[10] The second period cash flow is given by:

$$D_2 = (1-\tau)\left(Y_2 - w_{R,2}L_{R,2} - w_{S,2}L_{S,2} - w_{NU,2}L_{NU,2}\right) + \tau\,(1-\eta)\, PI.$$

Firms make labor and investment decisions $(L_{R,1}, L_{S,1}, L_{NU,1}, I, L_{R,2}, L_{S,2}, L_{NU,2})$ to maximize the firm value V, which is the sum of period 1 cash flows and the present value of the period 2 cash flows:

$$\max_{\{L_{R,1},L_{S,1},L_{NU,1},I,L_{R,2},L_{S,2},L_{NU,2}\}} V = D_1 + \frac{D_2}{r}$$

where r is the rate firms use to discount future cash flows. The first order conditions with

[10]While we assume that the liquidation value of capital at the end of period 2 is zero, none of the results depend on this liquidation value, or the economic depreciation rate δ.

respect to L_R, L_S, L_{NU} and I give the optimality conditions:

$$
\begin{aligned}
w_R &= \beta L_S^{\alpha} L_R^{\mu-1} \left(L_R^{\mu} + K^{\mu}\right)^{\frac{\beta}{\mu}-1} && (1)\\
w_S &= \alpha L_S^{\alpha-1} \left(L_R^{\mu} + K^{\mu}\right)^{\frac{\beta}{\mu}} && (2)\\
w_{NU} &= (\alpha+\beta)\, L_{NU}^{\alpha+\beta-1} && (3)\\
(1-\tau\eta)\, Pr &= (1-\tau)\, \beta L_S^{\alpha} K^{\mu-1} \left(L_R^{\mu} + K^{\mu}\right)^{\frac{\beta}{\mu}-1} + \tau(1-\eta)P. && (4)
\end{aligned}
$$

Equations 1-3 show that the routine, skilled, and nonroutine unskilled wage rates are the marginal product of routine, skilled, and nonroutine unskilled labor, respectively. Equation 4 equates the marginal cost of investing, $(1-\tau\eta)\,P$, to the marginal benefit in the first period. All benefits, which are the after-tax marginal product of capital, and the tax benefit of the remaining depreciation deduction, happen in the second period and are discounted at the rate r.

We are interested in understanding the implications of depreciation tax policy, captured by η in this simple economy, on firms' investment and labor decisions. Higher η implies that a larger fraction of investment cost is deducted from taxable income in the period that the investment is made and mirrors the accelerated depreciation provisions in the tax code. Specifically, we are interested in solving for $\frac{dI}{d\eta}, \frac{dL_{R,2}}{d\eta}, \frac{dL_{S,2}}{d\eta}$ and $\frac{dL_{NU,2}}{d\eta}$ to understand how η affects investment and labor choices of the firms.[11]

Proposition 1 *Given $\frac{\beta}{\mu} < (1-\alpha)$, faster depreciation tax policy (higher η) leads to higher investment I and skilled employment L_S, and lower routine employment L_R. Depreciation tax policy does not affect nonroutine unskilled employment L_{NU}.*

Appendix A derives expressions for $\frac{dI_1}{d\eta}, \frac{dL_{R,2}}{d\eta}, \frac{dL_{S,2}}{d\eta}$ and $\frac{dL_{NU,2}}{d\eta}$ based on the first order conditions given in equations 1-4. We show that $\frac{dI_1}{d\eta} > 0, \frac{dL_{R,2}}{d\eta} < 0, \frac{dL_{S,2}}{d\eta} > 0, \frac{dL_{NU,2}}{d\eta} = 0$. Therefore, increasing tax incentive for investment (allowing faster tax deduction of investment) will boost investment I and skilled employment L_S, but dampen routine employment L_R. Tax incentive does not have an effect on nonroutine unskilled employment. The effect of η is conditional on firms' cost of capital. Because firms discount future deduction tax benefits at the rate of r (cost of capital), the higher cost of capital, the more appealing the

[11] Note that $L_{S,1}$ and $L_{R,1}$ will be determined only based on K_1, which is given.

investment tax incentive is. If the cost of capital is zero ($r = 1$), incentives do not have any effect on investment or labor choices.

While the model always generates positive response for capital and nonroutine labor to investment tax incentives, our result for $\frac{dL_R}{d\eta}$ (sensitivity of routine labor to the incentives) depends critically on an assumption on the parameter values, $\frac{\beta}{\mu} < (1-\alpha)$. This expression implies a relationship between returns to scale and the elasticity of substitution between capital and routine labor. When the returns to scale ($\alpha+\beta$) is high, the condition is satisfied with a higher elasticity of substitution (higher μ). Therefore, investment tax incentives lead to lower routine task labor if the returns to scale is relatively low, or the elasticity of substitution is sufficiently high. The interpretation of this condition is related to the dominance between income effect and substitution effect: The incentives which result in lower effective price of capital leads to both substitution of routine labor for capital (substitution effect), and expanding the scale of operations by increasing its inputs (income effect). The substitution effect dominates when the economy has sufficiently low returns to scale (which dampens the income effect), or when capital and routine labor are strong substitutes (which boosts the substitution effect).

In order to keep the model simple we refrained from including labor and capital adjustment frictions such as adjustment costs or time to build. Adding such frictions and more time periods would generate additional implications for the timing of effects on labor that we found in the data. For example, if installation of new capital takes multiple periods, the effects on labor can be delayed and can also vary across different types of labor.

3. Policy Background

3.1. Accelerated Depreciation as a Form of Investment Tax Incentive

Accelerated depreciation refers to the methods by which a company, for tax purposes, depreciates a fixed asset in such a way that the amount of depreciation taken each year is higher during the earlier years of that asset's ownership. In the United States, typically, businesses may deduct the cost of newly installed assets from their taxable income according to the Modified Accelerated Cost Recovery System (MACRS). MACRS specifies the life and depreciation method for each type of property and equipment. For instance, computers will be depreciated by 20% in year of purchase, and 32%, 19.2%, 11.5%, 11.5%, and 5.8% in the following five years, respectively.

Two sections of the Internal Revenue Code, Section 179 and Section 168, allow certain businesses to accelerate the deduction of certain investments further. Section 179 allows limited amount of qualified property to be 100% expensed immediately, whereas Section 168 allow certain proportion of bonus depreciation in the first year. Therefore, accelerated depreciation shifts the timing of deductions from later years to earlier years, without changing the total amount to be deducted.

There are three possible channels through which accelerated depreciation incentivizes investment. The first channel operates through the time value of money: Faster depreciation increases the present value of tax benefits. This effect can be especially pronounced if the firm's cost of capital is high. The second channel is due to financial frictions: Accelerated depreciation reduces the immediate funding needs for investments. If firms face financing constraints, freeing up funds can boost up investment. The last channel is due to the tax-minimization motive, advocated by Xu and Zwick (2018), who document that firms accelerate capital purchases near fiscal year-ends to minimize taxes. In the presence of accelerated depreciation, investment can potentially be an effective tax management tool for firms.

3.2. Eligibility for Section 179 Deduction

Section 179 of the Internal Revenue Code allows firms to expense limited amount of qualified investments instantly instead of following the baseline MACRS depreciation schedule. With few exceptions, qualified investments are limited to depreciable tangible assets such as machinery and equipment with a tax life of 3, 5, 7, 10, 15, or 20 years. Most structure investments do not qualify, such as buildings. The use of the Section 179 expensing is subject to three limitations. There is a *deduction limit*, which is the maximum deduction amount that can be allowed for instant expensing in a year. There is also a *phaseout threshold*. If in a given year the firm places in service more property than the phaseout threshold, 179 deduction is reduced dollar-for-dollar by the amount exceeding the limit. Finally, the income limitation bars the firm from claiming a Section 179 deduction greater than its taxable income. While firms in all lines of business and sizes have the option to elect 179 expensing, this incentive is application mostly to small businesses due to the deduction limits and phaseout thresholds.

Panel A of Figure 1 illustrates the marginal Section 179 tax benefits (i.e., reduction in present value of taxes) for every additional $1,000 equipment investment as a function of the firms' total equipment investment. For firms with equipment investment below the deduction limit, an extra $1,000 investment in equipment leads to $9.1 tax benefit (assuming state tax rate is 6.08%, the median state individual income tax rate in our sample, and discount rate is 10%), because each dollar of investment is expensed immediately rather than over time according to the MACRS. For firms with equipment investment above the deduction limit but below the phaseout threshold, an extra dollar of investment does not lead to any tax benefits, because this extra dollar cannot be expensed immediately and is subject to MACRS. Lastly, due to the dollar-for-dollar reduction in the 179 deduction when firms' equipment investment exceeds the phaseout threshold, an extra dollar of investment reduces the firms' Section 179 tax benefits until they reach zero, that is, until firms' investment reaches the sum of the phaseout threshold and the deduction limit.

Panel B of Figure 1 illustrates how the above-mentioned marginal tax benefits are affected by increases in Section 179 deduction limits and phaseout thresholds. Assume deduction limit and phaseout threshold increase from $250,000 to $500,000 and from $800,000 to $2,000,000, respectively,[12], firms that contemplate investment beyond $250,000 (old deduction) are encouraged to do so, since every extra dollar investment now leads to extra tax benefits. Moreover, firms with equipment investment beyond $800,000 (old phaseout threshold) are less concerned with their additional investments because they do not necessarily lead to reduction in tax benefits (thanks to the expansion of the new phaseout threshold). In contrast, firms with equipment investment exceeding $1,05 million (the sum of the old phaseout threshold and the old deduction limit) will not experience an increase in Section 179 tax benefits.[13] Therefore, Section 179 limit increases create nonnegative investment tax incentives for firms which invest less than the sum of the old phaseout threshold and the old deduction limit (old phaseout threshold + old deduction limit), and lead to no investment tax incentives for firms that invest more than this cutoff threshold.

Following these features of Section 179, we define firms as **eligible** for Section 179 incentive if the firms' expected investment in equipment is below the sum of the phaseout

[12]This example mirrors the case of Section 179 increase in many states in 2010. See next subsection for details.

[13]Panel B of Figure 1 also illustrates that firms that invest more than the new phaseout threshold but less than the sum of the new phaseout threshold and the new deduction limit experience reductions in Section 179 deductions after the limit increases.

threshold and the deduction limit in the previous year—the cutoff threshold for eligibility.[14] We construct an ex-ante measure of establishments' expected equipment investment based on its employment and the equipment investment to employment ratio for the industry it belongs to.[15] Section 179 policy expansion will not create incentive to increase investment for firms with expected investment exceeding the cutoff amount.[16] In other words, those firms will be effectively *ineligible* for Section 179.

[FIGURE 1 ABOUT HERE]

3.3. Time-Series and Cross-Sectional Variations in State Section 179 Limits

Section 179 expensing began as a first year depreciation allowance with the Small Business Tax Revision Act of 1958 to reduce the tax burden on small business owners and stimulate small business investment. Before 2003, the incentive was not significant with deduction limit and phaseout limit as $24,000 and $200,000, respectively.[17] Since 2003, several acts have significantly increased the 179 deduction and phaseout limits for federal taxes, reaching $500,000 and $2,000,000, respectively, in 2010. Table 1 provides a timeline for the relevant legislations and changes to federal Section 179 limits.

[TABLE 1 ABOUT HERE]

[14] The specific changes in deduction limit and phaseout threshold in a given year may affect this cutoff threshold for that year. First, if the new phaseout threshold is lower than the sum of old phaseout threshold and old deduction limit, there will be no tax benefit beyond the new phaseout threshold. In this case, we set the cutoff thresholds as new phaseout threshold. Second, if the new deduction limit is higher than the sum of the old phaseout threshold and the old deduction limit, any investment below the new deduction limit leads to tax benefit. However, such large increase in deduction limit never happened in practice. We performed extensive sensitivity analysis with varying cutoff threshold for expected investment to define eligible firms and we confirmed that the results are robust to these perturbations in the cutoff threshold.

[15] We use BEA data to calculate the average equipment investment/employment ratio for each industry (at 3 digit NAICS level). Employment is full-time equivalent employees by industry and investment is investment in private equipment by industry. We smooth the ratio by taking the average of the last three years.

[16] For multi-establishment firms, some of the establishments we classify as "eligible" may actually be ineligible if total investment of the firm exceeds the cutoff amount. Our use of establishment-level employment counts instead of firm-level employment is mainly due to data limitation on firm employment. By using establishment-level employment, we potentially contaminate our sample of eligible establishments by including small establishments from large firms, making it more difficult for us to find any results among eligible firms. In untabulated results, we repeat the analyses by examining only single-unit businesses, which result in a much smaller sample, and find materially similar results.

[17] See Guenther (2015) for a detailed discussion of the Section 179 expensing and its legislative history.

Following Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA), the federal Section 179 deduction limit was increased from $24,000 to $100,000 for federal taxes. While all states conform to federal Section 179 limit before 2003, 28 states decided to keep conforming to the federal deduction limit by increase their Section 179 limit for state taxes as well, others deviate. Panel A of Figure 2 provides a map of states' adoption status of the new federal 179 limit in 2003. Panel B provides the map for 2014. Comparing Panel A and Panel B, we observe that states' adoption statuses are sticky, which implies that states' adoption decisions in 2003 largely shape the cross-sectional variations in the states' Section 179 limits for state taxes in the following many years. 12 states made non-revolving switches in their adoption statuses during 2003-2014, while 48 states kept their statuses largely persistent over time. Due to states' sticky adoption statuses, the time-series variation in states' Section 179 limits stems primarily from that the staggered increases in federal Section 179 limits affecting the adopting states and having no direct effect on the non-adopting states.

In Table 2, we examine whether states' changes in Section 179 limits are correlated with changes in states' other policies and business conditions that may potentially affect firms' investment and employment decisions. This exercise helps us understand the confounding factors, if any, to our main analyses so that we can better analyze and control for them. We run cross-sectional regressions of changes in state Section 179 limits on lagged changes in governor's political affiliation, changes in measures of states' fiscal health and economic indicators. Table 2 shows that states' increase in their Section 179 limits is accompanied by the adoption of tax bonus depreciation incentive, which targets mainly large businesses. State changes in Section 179 limits are not systematically related to any other political, fiscal, or economic conditions. Since these factors can still potentially affect investment and employment outcomes, we will add these time-varying controls to our regression specifications.

[FIGURE 2 ABOUT HERE]

[TABLE 2 ABOUT HERE]

3.4. Alternative Tax Incentive: Bonus Depreciation

There is another federal investment tax incentive, bonus depreciation, which was available between 2001-2004 and later starting in 2008. Bonus depreciation does not have any limits on investment size, however, it allows up to 50% additional depreciation, rather than 100% expensing allowed in Section 179.[18] Similar to Section 179, while some states conform to federal bonus depreciation for state taxes, others require adjustments. We primarily focus on Section 179 rather than bonus depreciation for several reasons. The first reason is the speed of deduction: For eligible firms Section 179 provides a more generous incentive, allowing firms to expense the entire investment in the first year. Second, the value of accelerated depreciation increases with the cost of capital of the firms, which rise with financing frictions, and the small firms that are eligible for Section 179 are most likely to be financially constrained. Section 179 deduction is claimed by roughly 6 million firms in 2014, which is more than twice as many as the number of firms claiming bonus deduction (Kitchen and Knittel (2016)). Our establishment-level datasets provide a good coverage of these firms that are likely to be eligible for Section 179. Finally, Section 179 federal limits have been raised from $24,000 to $500,000 in several increments during our sample period, which provides a nice variation and helps with identification in our tests. While we primarily focus on Section 179, as we discuss in Section 3.3, we find that state adoption of bonus depreciation and state Section 179 deduction limit increases are correlated. Therefore, we control for state bonus depreciation conformity in all our tests.

4. Data and Measurement

In this section we describe the data used in the paper and discuss the measurement of critical variables.

Investment data Our primary investment measure is derived from the Computer Intelligence Technology Database (CiTDB), which is a proprietary database that provides detailed information on information technology spending at the establishment level. This database is compiled from telephone surveys of the establishments, usually annually, and includes roughly 500,000 establishments before 2010, and 3.2 million establishments afterwards. The

[18] Bonus depreciation was 100% between 9/8/2010 and 12/31/2011.

database is used frequently to measure the impact of IT investments in management and informations systems literatures (Bryniolfsson and Hitt (2003); Tambe, Hitt, and Brynjolfsson (2012); Bloom, Garicano, Sadun, and Van Reenen (2014); and many others). While the database includes many different variables related to IT investments, the only variable that has been consistently surveyed over our sample period is the number of computers. We measure investment rate as the percent change in the number of computers that are put in service in an establishment.[19] The database also provides other establishment level information, such as the name, address, industry of the business and the number of employees.

We use an additional database of small businesses, Small Business Economic Trends survey compiled by the National Federation of Independent Business (NFIB), which is a survey of roughly 900 NFIB member businesses each month. The survey asks whether the firms invested in the past 6 months, along with the type of investment (equipment, vehicles, buildings or land purchase, building improvements, and whether the property is purchased or leased). This level of detail is useful since Section 179 applies primarily to equipment investment, while most other investment categories, such as leases, building and land purchases do not qualify for Section 179. Furthermore, unlike our other datasets, NFIB reports the form of business (C-corp, S-corp, proprietorship, partnership), which allows us to specifically target the state taxation of different business forms in our empirical tests.

Employment data and classification of occupations We construct measures related to employment from the microdata at the establishment-occupation level provided by the OES program of the Bureau of Labor Statistics (BLS). This dataset covers surveys that track employment by occupations in approximately 200,000 establishments every six months over three-year cycles. These data represent, on average, 62% of the non-farm employment in the U.S. The data use the OES taxonomy occupational classification with 828 detailed occupation definitions before 1999, and the Standard Occupational Classification (SOC) with 896 detailed occupation definitions thereafter. Besides occupational information, the microdata also cover establishments' location and industry affiliation, as well as their parent company's employer identification number (EIN), legal name, and trade name.

We classify employees in two dimensions. The first dimension measures the routineness of the tasks performed in occupations. The second dimension measures how much skill,

[19]We measure investment and employment growth rates by dividing the level change in variable by the average of the level of the variable before and after the change.

characterized by higher education or expertise level attained through related work experience, is required for each occupation.

We measure an establishment's routine-task and nonroutine-task employment following the methodology described in Zhang (2018), which is based on a commonly used procedure in the labor economics literature and is closest to Autor and Dorn (2013). The procedure starts by identifying occupations that can be classified as routine-task labor. Specifically, we use the Revised Fourth [1991] Edition of the U.S. Department of Labor's Dictionary of Occupational Titles (DOT) to obtain skill information of occupations classified at a very detailed level. For each DOT occupation, we select the occupation's required skill level in performing five categories of tasks: abstract analytic, abstract interactive, routine cognitive, routine manual and nonroutine manual tasks. We rescale these skill levels to be between 1 and 10. We then take the average of the routine cognitive and routine manual skill levels as the skill level required by the occupation in performing routine tasks. Similarly, we obtain the skill level required by each occupation in performing abstract tasks. We then aggregate the DOT occupations to the OES occupation level. The task skill measures for the OES occupations are the average of the skill measures for the corresponding DOT occupations following a weighting approach proposed by Autor, Levy, and Murnane (2003). Following Autor and Dorn (2013), we define the routine-task intensity (RTI) score for each OES occupation as

$$RTI_k = \ln\left(T_k^{Routine}\right) - \ln\left(T_k^{Abstract}\right) - \ln\left(T_k^{Manual}\right)$$

where $T_k^{Routine}$, $T_k^{Abstract}$, and T_k^{Manual} are the routine, abstract, and nonroutine manual task skill levels required by occupation k, respectively.

Routine-task labor is defined as follows: In each year, as suggested by the OES program, we select all workers in the OES sample in the current year as well as in the previous two years to represent the current year's total labor force. We then sort all workers in current year's labor force based on their occupations' RTI scores. We define workers as routine-task labor if their RTI scores fall in the top quintile of the distribution for that year. By classifying routine-task labor each year, this measure of routine-task labor accounts for technological evolution. In particular, it accounts for the fact that certain occupations that are not substitutable by machines in previous years become substitutable because their RTI rankings increase over time.

We also classify employees in skill dimension as skilled or unskilled labor. Skill can be attained through higher education or related work experience. We thus define skilled labor as employees with occupations that require at least 2 years of related work experience or a college degree, based on O*NET .[20] Based on this definition, roughly 40% of employees in OES are classified as skilled labor, and the remaining 60% are classified as unskilled labor.

Figure 3 provides a breakdown of OES employees, classified based on routineness and skill. The sizes of the nonroutine skilled workforce and nonroutine unskilled workforce are almost the same: Both account for roughly 40% of employment. Almost all of the remaining employees are classified as routine unskilled labor, which account for 18% of the workforce. Employees that are classified as routine and skilled account for only 1% of the workforce, which is consistent with the earlier findings in the labor economics literature that routine jobs are not high skilled jobs. Furthermore, the types of tasks performed by these routine skilled employees mirror the tasks performed by their routine unskilled peers, prompting us to combine these two groups into one "routine" entity.

A comparison of the characteristics of routine, nonroutine skilled, and nonroutine unskilled labor reveal stark differences in the types of tasks performed by these employees and their average compensation. Nonroutine skilled employees, such as managers and engineers, perform mostly abstract tasks and earn an average wage of $31 an hour. In contrast, nonroutine unskilled employees, such as drivers and janitors, perform mostly manual tasks and earn an average wage of $15 an hour. These differences are economically meaningful, and highlight the heterogeneity within the nonroutine workforce. Since nonroutine skilled employees account for 98% of the skilled workforce, for brevity, we refer to them as the "skilled" labor. Different from skilled labor and nonrouine unskilled labor, routine workers perform substantially more routine-task jobs, regardless the jobs been routine skilled or routine unskilled. These comparisons result in our three distinctive labor categories, **routine**, **skilled**, and **nonroutine unskilled** labor.

[FIGURE 3 ABOUT HERE]

[20] Most occupations that are classified as skilled require both higher education and work experience. Managers and mechanical engineers are a few examples to such occupations. However, there are some skilled occupations that rely on a college degree but no related work experience, such as chemists and computer engineers, and others that require work experience but no college degree, such as electricians and commercial pilots.

Following the above categorization, we measure establishment j's routine employment, $L_{R,j,t}$, skilled employment, $L_{S,j,t}$, nonroutine unskilled employment, $L_{NU,j,t}$, and total employment, $L_{tot,j,t}$ in year t as:

$$\begin{aligned}
L_{tot,j,t} &= \sum_k emp_{j,k,t} \\
L_{R,j,t} &= \sum_k \mathbb{1}\left[RTI_k > RTI_t^{P80}\right] \times emp_{j,k,t} \\
L_{S,j,t} &= \sum_k \mathbb{1}\left[RTI_k \leq RTI_t^{P80}\right] \times \mathbb{1}\left[Skilled_k\right] \times emp_{j,k,t} \\
L_{NU,j,t} &= L_{tot,j,t} - L_{R,j,t} - L_{S,j,t}
\end{aligned}$$

where $\mathbb{1}$ is the index function, RTI_k is the RTI score of occupation k, RTI_t^{P80} is the 80th percentile of RTI scores for the labor force at year t, $Skilled_k$ is an indicator that takes the value of 1 if the occupation is categorized as a skilled occupation, and $emp_{j,k,t}$ is the number of employees of occupation k in establishment j at year t.[21]

Section 179 limits We hand-collected state Section 179 deduction limits and phaseout thresholds from CCH State Tax Handbooks, and supplemented the handbooks with state tax authorities' websites when needed.

State-level data We use various state level controls in our empirical tests. Similar to Section 179 limits, data on states' Section 168 bonus depreciation conformity is hand-collected from CCH State Tax Handbooks. The number of state job creation hiring credit programs is based on the data collected by and provided in Appendix Table 1 of Neumark and Grijalva (2013). The data ends in 2012. We extend the last year's credit counts to 2013 and 2014 in our tests. State unemployment rate is provided by the Bureau of Labor Statistics. State (real) GDP growth is downloaded from the Bureau of Economic Analysis website. State budget balance is compiled from the State Government Finances, U.S. Census Bureau. Budget surplus is measured as the difference between the "general revenue" and "general expenditure." The results of the gubernatorial elections is collected from the Congressional Quarterly Voting and Elections Collection. State corporate income tax rates are taken from the Tax

[21] In order to avoid double-counting the small routine skilled workforce in both routine and skilled groups, we condition skilled labor to be strictly nonroutine.

Foundation.[22] State individual income tax rates are obtained from the NBER database of marginal state income tax rates.[23]

5. Empirical Evidence

In this section we test the predictions of the simple model developed in section 2. The model predicts that increasing tax incentive for investment will boost up equipment investment and nonroutine employment, but reduce routine employment. We first compare the summary statistics from our datasets for the states that increase state Section 179 limits to the states that do not. Then we study the effect of changes in state Section 179 limits on investments. After confirming the effect of state policy changes on investment, we study their effect on labor (total, routine, and nonroutine-task) outcomes and discuss the results of our robustness analysis.

Section 179 deductions benefit firms by reducing their corporate income tax bills (for C-corporations), or individual income tax bills of the owners (for pass-through entities). Our main investment and employment datasets (except for the NFIB dataset) do not provide information on the form of business, so we do not know exactly which tax rates (corporate or individual) investors will be subject to. Therefore, we restrict our sample to states that either collect both corporate and individual income taxes or collect neither of them. We assign changes in state Section 179 deduction limits as zero for states that collect neither taxes.[24] We exclude states that collect corporate income tax, but do not collect individual income tax (Alaska and Florida) from our tests.

5.1. Summary Statistics

What are the characteristics of firms covered in our CiTBD and OES samples? To answer that question, Table 3 reports the OES and CiTDB sample statistics at the establishment-year level between 2003 and 2014. Our samples cover all establishments in OES and CiTDB datasets that have consecutive observations that allow computation of current and past employment or investment ratio. We require CiTDB firms to have at least two employees, and OES firms to have at least five employees to ensure that establishments have a reasonable

[22] https://taxfoundation.org/state-corporate-income-tax-rates

[23] Two states, New Hampshire and Tennessee, only tax interest and dividend income components of individual income. These rates are taken from the Tax Foundation.

[24] These states include Nevada, South Dakota, Texas, Washington and Wyoming.

distribution of routine and nonroutine-task employees. We confirm that our results are robust to these filters.[25] OES sample includes 332 thousand establishment-year observations. The average (median) number of total employees is 102 (25), routine employees is 21 (3), skilled employees is 39 (7), and nonroutine unskilled employees is 42 (9).

The CiTDB dataset is compiled from a somewhat different cross section of firms with slightly larger firms. The average (median) establishment has 158 (50) employees and 174 (43) computers. The sample includes roughly 355 thousand establishment-year observations.

5.2. Examining Pre-Trend of Investment and Employment Before 2003

We also compare the behavior of our key variables in states that increased their Section 179 limits in 2003, when the states start varying their Section 179 deduction limits, to states that did not, over the 2000-2003 period. Panel B of Table 3 reports the means and standard deviations of computer growth, routine, skilled, nonroutine unskilled, and total employment growth, and change in IT intensity (computers per employee) over the 2000-2003 period for the two groups of states classified based on 2003 limit change status. We find that these key variables behave very similarly in both groups prior to variations in Section 179 limit changes. The last column reports the t-statistics for the difference in means, which is indistinguishable from zero for all variables. This finding confirms that our treatment and control groups have similar trends in the absence of a treatment.

[TABLE 3 ABOUT HERE]

5.3. Investment Outcomes

Our first hypothesis is that an increase in state Section 179 limits will lead to additional investment (as measured by computer purchases) by eligible firms. We do not anticipate such an effect for the firms that are ineligible for the deduction.[26] This prediction is theoretically derived in Proposition 1. We test this hypothesis and report the results in Table 4.

[25] In addition, for the CiTDB sample, we exclude industries in which computer investment accounts for less than five percent of total investment in equipment and software to make sure that computer investment is a relevant investment category for the firms.

[26] Given that our model ignores any general equilibrium effects, we can only claim that we anticipate no direct effects of changes in Section 179 limits on ineligible establishments.

Specifically, we run the following regression:

$$\begin{aligned} Inv_{j,s,t} &= b_0 + b_1 \Delta Limit_{s,t} + b_2 Eligible_t + b_3 \Delta Limit_{s,t} \times Eligible_t \\ &\quad + b_4 \Delta X_{s,t} + b_5 Inv_{j,s,t-1} + Dummy_{EmpBin \times Ind \times Year} + \epsilon_{j,s,t}, \end{aligned} \tag{5}$$

where $Inv_{j,s,t}$ is the investment rate measured from the computer growth of firm j from year t to $t+1$ and $\Delta Limit_{s,t}$ is the change in state Section 179 limit from year $t-1$ to t in \$ millions.[27] $Eligible_t$ is a dummy variable that equals one for eligible firms defined as firms with expected equipment investments below the cutoff threshold for federal Section 179 (see more details in Section 3.2).

This specification deals with several endogeneity concerns. First, we control for changes in other *observable* time-varying investment opportunities in the state by adding changes in state characteristics and tax policies from year $t-1$ to t, $\Delta X_{s,t}$, as control variables.[28] Second, to control for *unobservable* time-varying investment opportunities in the states, we focus on the coefficient of the interaction term, b_3, to assess the effect of Section 179 on firm investment. In particular, by controlling for how investment in ineligible firms between treated and control states differ, we control for any unobservable time-varying state dynamics that affects all firms in the state. Third, to further ensure that we are comparing similar establishments across states, we control for a fixed effect of a full interaction of establishment-level employment bins, industry, and year, $Dummy_{EmpBin \times Ind \times Year}$. Lastly, to account for lumpy investment behaviors, we control for firm's computer investment in the previous year. In summary, if firms' investment respond to Section 179, we expect to find a positive estimate for b_3. We cluster standard errors at the state level.

Column 1 of Table 4 reports that computer investments of eligible firms go up in response to state Section 179 limit increases with a positive and significant coefficient for the interaction term. For eligible firms from a state that increases Section 179 state deduction

[27] CiTDB surveys the firms throughout the year, and reports computer holdings as of the day of the survey. Therefore, on average, computer holdings are reported as of the middle of the year. Changes to Section 179 limits tend to occur later in the year. In addition, Xu and Zwick (2018) document that investment spikes towards the end of the year, especially when it is motivated by tax considerations. Hence it is safe to assume that any computer investment following year t Section 179 limit changes will be reflected in year $t+1$ computer holdings in CiTDB.

[28] The state controls include changes in state hiring credits, adoption of bonus depreciation, budge surplus, gross state product, unemployment rate, individual income tax rate, corporate tax rate and democratic party dominance.

limit by $250,000—an amount by which many states increased in 2010, the point estimates imply 1.7% ($6.7 \times \$250,000/\$1,000,000$) higher computer investments annually compared to matching firms in states that do not increase their Section 179 deduction limits. Other state control variables have no effects and are omitted from the table.

In column 2 of Table 4 we replace the dependent variable with changes in IT intensity, which is the percent change in computers per employee. This regression tests whether Section 179 limit increases led firms to tilt their production inputs towards IT capital.[29] We find that eligible firms significantly increase their IT intensity in response to state Section 179 expansion.

[TABLE 4 ABOUT HERE]

We corroborate our findings on computer investments by providing additional evidence from a different dataset. While CiTDB allows us to measure computer investments, which qualify for Section 179 deductions, we are unsure how non-qualified investments differ in treated states and control states. In addition, to qualify for Section 179 deductions, capital needs to be purchased rather than leased. We thus explore these alternative investments using NFIB Small Business Economic Trends database.[30] Appendix Table B.1 shows that state Section 179 limit increases lead small businesses to increase qualified investments, such as equipment purchases, whereas there is no effect on any other investment category (notably, investments that do not qualify for Section 179, such as building improvements and land, and leases of any investment type). These results further strengthen our conclusions from CiTDB computer investment regressions that eligible firms increase qualified investments in response to state Section 179 limit increases.

5.4. Labor Outcomes

After confirming the effect of investment tax incentives on the investments of eligible firms, we turn to the labor outcomes. In this section we investigate the effects on total em-

[29] In the model, we did not derive any predictions for the ratio between capital and total labor. However, the model predicts opposite effects on routine versus skilled employment. If the differential effects on labor offset each other, we expect the IT intensity to increase in response to investment incentives.

[30] This database only covers businesses of NFIB members, which is a small business organization. Therefore, it is safe to assume that all businesses are eligible for Section 179 deduction. Also, firms are only surveyed once, so we cannot control for past investment in these tests. On the other hand, data includes the form of business (C-corp versus pass-through), which allows us to include states that collect corporate income tax, but do not collect individual income tax in the tests.

ployment, as well as the employment of routine-task, skilled, and nonroutine-task unskilled labor. Our model have separate and opposite predictions for the outcomes for routine-task and skilled labor, as derived in Proposition 1. We expect a negative effect on routine labor, and a positive effect on skilled labor, and no effect on nonroutine unskilled labor. The model does not make a prediction for total employment.

Since OES surveys each establishment once every three years, changes in employment are constructed as the growth rate from year t to year $t+3$. With each observation measuring multiple year employment changes, policy changes over several years can potentially affect these outcomes. In Tables 5-8, we run the following first-difference regressions by including changes in state Section 179 limits in the years t, $t+1$, $t+2$:

$$\begin{aligned} L_{j,s,t\to t+3} \quad = \quad & b_0 + \sum_{n=0}^{2}(b_{1,n}\Delta Limit_{s,t+n} + b_{2,n}Eligible_{t+n} + b_{3,n}\Delta Limit_{s,t+n} \times Eligible_{t+n}) \\ & + \sum_{n=0}^{2} b_{4,n}\Delta X_{s,t+n} + b_5\Delta L_{j,s,t-3\to t} + Dummy_{EmpBin\times Ind\times Year} + \epsilon_{j,s,t}, \end{aligned} \tag{6}$$

where $\Delta L_{j,s,t\to t+3}$ is the percent change in the number of employees (total, routine, skilled, nonroutine unskilled) from year t to $t+3$ and $\Delta L_{j,s,t-3\to t}$ controls for the past trend of the dependent variable. We include annual changes in state characteristics and tax policies in t, $t+1$, and $t+2$ to control for changes in other time-varying investment opportunities in the state. If eligible establishments respond to shocks, we expect to see some or all of $b_{3,0}$, $b_{3,1}$, and $b_{3,2}$ to be significant.

Beyond the direction of the effects, we are also interested in the timing when Section 179 takes effect on firms' employment. In particular, $b_{3,0}$, $b_{3,1}$ and $b_{3,2}$ measure the effect of a policy change that happens in year t, $t+1$ and $t+2$ on an eligible firm's employment change from year t to $t+3$, respectively. Since the policy shock that happens in $t+2$ has shorter time to affect the employment outcome, we interpret $b_{3,2}$ as quick response, and $b_{3,0}$ as slow response.

Table 5 reports the effect of limit changes on total employment. All interaction terms are indistinguishable from zero, implying that state limit changes have no effect on total employment.

However, the findings change drastically when we look at different components of the labor market. Table 6 reports the results for routine-task labor. We find that $b_{3,0}$ is negative and highly significant in both univariate and multivariate specifications, implying that eligible firms respond to state incentives in investment by reducing routine-task labor, as predicted by the model. The findings also hint that the substitution effect takes place with a delay rather than immediately following the investment shock, since the longer term response is large and significant, whereas the short term responses are not. Following our example in investment regressions, a \$250,000 increase in state Section 179 deduction limit in year t corresponds to a 6% $(24.38 \times \$250,000/\$1,000,000)$reduction in routine-task employment in the 3 years from t to $t+3$.

Table 7 reports the results for skilled labor. The model predicts a positive effect for skilled labor, which we confirm in the following results. $b_{3,0}$, $b_{3,1}$, and $b_{3,2}$ are all positive and significant in univariate regressions, and the magnitude of the effect is also similar in all three regressions. The responses being significant and of similar magnitude regardless of whether the investment incentive happened in the first year, the second year, or the third year of the 3-year window over which the employment changes are measures indicates skilled employment respond to the incentive quickly. Multivariate regression further confirms this finding: In this setting, only $b_{3,1}$ and $b_{3,2}$ are significant. A \$250,000 increase in state Section 179 deduction limit in year $t+1$ or $t+2$ leads to about 3.4% increase in skilled labor from t to $t+3$.

Table 8 reports the results for nonroutine unskilled labor. The model does not predict an effect for this type of labor, which neither substitutes, nor complements capital. Consistent with this prediction, we find no effect of investment shocks on nonroutine skilled labor at any horizon.

[TABLE 5 ABOUT HERE]

[TABLE 6 ABOUT HERE]

[TABLE 7 ABOUT HERE]

[TABLE 8 ABOUT HERE]

How does compensation of employees (rather than the number of employees) respond to the investment policy shocks? To address this question, we replicate our main labor results using wage bills (wage times employment) instead of employment counts. Table 9 reports these results, which are generally similar to our employment results reported in Tables 5-8:

We find significant and negative response for routine-task employee wage bill, implying a reduction in the total compensation of routine-task employees. Similar to the employment results, this reduction in wage bill of routine labor takes place with a delay. We also find a sharp increase in the wage bill of skilled labor shortly after the investment shock. Like before, we find no effect on the wage bill of nonroutine unskilled labor. The effect on total wage bill of all employees is more nuanced. Consistent with the quick rise in skilled labor, wage bill initially rises, but the later decline of routine labor leads to a longer term decline in the total wage bill of eligible firms compared to ineligible firms when states increase their Section 179 deduction limits.

[TABLE 9 ABOUT HERE]

5.5. Robustness

We checked the robustness of our results to various regression specifications, control variables, and variable definitions. We report two main robustness checks here.

First, we add state fixed effects to the regressions. Our main empirical results are estimated from first-difference regressions to remove unobserved firm-specific fixed effects in levels. Any state fixed effects in the levels are also removed in this process. In addition, we control for contemporaneous changes in state political, economic, and other policy characteristics in all regressions to control for confounding effects on first differences. To control for any remaining unobserved time-invariant differences across states that might be correlated with state Section 179 deduction limit changes, we add state fixed effects to our main specifications, and report these results in Table 10. We confirm that specifications with state fixed effects yield almost the same results (on both point estimates and statistical significance) as our main specifications.

Second, we explore the effect of changes in Section 179 limit conditional on states' individual tax rates and corporate tax rates in Tables 11 and 12, respectively. Section 179 deductions benefit firms by reducing their corporate income tax bills (for C-corporations), or individual income tax bills of the owners (for pass-through entities). Marginal tax rates vary across states and over time, and the benefit of Section 179 deductions increase with the tax rates. In this analysis we interact our treatment variable, $\Delta \text{Limit}_{s,t}$ with the marginal state tax rates. We report the results for the individual income tax rates in Table 11, and the corporate income tax rates in Table 12. Both sets of results are similar to our baseline results: When states increase their Section 179 deduction limits, we find a strong negative delayed effect on the employment and wage bills for routine-task labor in eligible firms, but an immediate positive effect on their employment and wage bills for skilled labor.

[TABLE 10 ABOUT HERE]

[TABLE 11 ABOUT HERE]

[TABLE 12 ABOUT HERE]

6. Conclusion

This paper explores the implications of investment tax incentives for small firms on their investment and labor outcomes using detailed establishment-level datasets. We challenge the standard models with homogeneous capital and labor inputs, which would imply that both inputs should respond positively to investment tax incentives as long as labor complements capital. Earlier literature confirms the positive effect on investment, which we also confirm in our setting; yet, there is little and inconclusive evidence on the employment side.

We introduce heterogeneous labor inputs to study the labor outcomes. In particular, we adopt a hypothesis from the labor economics literature (Autor, Levy, and Murnane (2003)) that while skilled labor can be complemented by equipment capital, routine-task labor may be substitutable by equipment capital. Consistent with this hypothesis, we find that firms eligible for the investment tax incentives increase their skilled labor quickly and reduce their routine-task labor with a significant delay when responding to the incentives. Nonroutine unskilled labor, which neither substitutes nor complements capital, is not affected by the investment policy. Put together, there is little effect on the total employment of eligible firms.

We ask for caution when interpreting our results. First, while our work shows that tax policy has asymmetric effects on the employment of routine-task and skilled labor in the eligible firms, we refrain from extrapolating the effect to the total employment in the economy. General equilibrium effects of the tax policy, and its welfare implications are beyond the scope of this paper and are interesting for future research. Second, because we do not observe the subsequent outcomes for routine-task and skilled workers (e.g., job relocation), we refrain from drawing conclusions for individual or social welfare. Third, our identification relies on relatively small differences in tax policy across states with limited monetary effect on the firms' bottom lines. We find strong responses to these differences in tax policy, however, one should exercise caution when extrapolating the effects we find to larger changes in the policy.

Appendix

A. Proof of Proposition 1

In the following analysis, we suppress the second period index for notational simplicity unless otherwise indicated.

It is trivial to show that $\frac{dL_{NU}}{d\eta} = 0$. Equation 3 is the only first order condition that is relevant for L_{NU}. Since L_{NU} does not interact with K, η has no effect on dL_{NU}.

We derive the remaining expressions in three steps. We first examine the relation between K and L_R, and the relation between L_S and L_R. Then we calculate $\frac{dL_R}{d\eta}$, which measures the sensitivity of firm's routine employment to η. Lastly, we obtain the sign of $\frac{dK}{d\eta}$ and $\frac{dL_S}{d\eta}$.

Step 1: From equation 1 and 2, we have:

$$K = \left[\psi_1 L_R^{\frac{-\mu(1-\alpha)(1-\mu)}{\mu-\alpha\mu-\beta}} - L_R^{\mu}\right]^{\frac{1}{\mu}}, \tag{7}$$

and

$$L_S = \psi_2 L_R^{\frac{-(1-\mu)\beta}{\mu-\alpha\mu-\beta}}, \tag{8}$$

where

$$\psi_1 = \left[\left(\frac{\beta}{w_R}\right)^{1-\alpha}\left(\frac{\alpha}{w_S}\right)^{\alpha}\right]^{\frac{\mu}{\mu-\alpha\mu-\beta}}$$

and

$$\psi_2 = \left[\left(\frac{\beta}{w_R}\right)^{\beta}\left(\frac{\alpha}{w_S}\right)^{\mu-\beta}\right]^{\frac{\mu}{\mu-\alpha\mu-\beta}}.$$

Taking the derivative of K and L_S with respect to L_R,

$$\frac{dK}{dL_R} = -K^{1-\mu}\left[\psi_1 \frac{(1-\alpha)(1-\mu)}{\mu-\alpha\mu-\beta} L_R^{\frac{-\mu(1-\alpha)(1-\mu)}{\mu-\alpha\mu-\beta}-1} + L_R^{\mu-1}\right]$$

and

$$\frac{dL_S}{dL_R} = -\frac{(1-\mu)\beta}{\mu-\alpha\mu-\beta}\psi_2 L_R^{\frac{-(1-\mu)\beta}{\mu-\alpha\mu-\beta}-1}.$$

Given that $\psi_1 > 0$, $\psi_2 > 0$, and $\frac{\beta}{\mu} < 1-\alpha$, we have,

$$\frac{dK}{dL_R} < 0 \quad \text{and} \quad \frac{dL_S}{dL_R} < 0.$$

Step 2: Plugging K from equation 7 and L_S from equation 8 in the first order condition for I (equation 4):

$$(1-\tau\eta)\,Pr \quad = \quad (1-\tau)\,w_R\left[\psi_1 L_R^{\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}}-1\right]^{\frac{\mu-1}{\mu}}+\tau(1-\eta)P. \tag{9}$$

Implicitly differentiating equation 9 with respect to η yields:

$$\tau P\,(1-r)=(1-\tau)\,w_R\left[\begin{array}{c}\frac{\mu-1}{\mu}\left(\psi_1 L_R^{\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}}-1\right)^{-\frac{1}{\mu}}\\ \times\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}\psi_1 L_R^{\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}-1}\end{array}\right]\frac{dL_R}{d\eta} \tag{10}$$

To understand the sign of $\frac{dL_R}{d\eta}$, we have to understand the signs of the multiplicative components of equation 10. Since $r>1$ (the discount rate), the left hand side is negative. On the right hand side, $(1-\tau)\,w_R>0$, $\left(\psi_1 L_R^{\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}}-1\right)^{-\frac{1}{\mu}}=\frac{L_R}{K}>0$, $\psi_1>0$, $L_R^{\frac{-\mu(1-\alpha-\beta)}{\mu-\alpha\mu-\beta}-1}>0$, $\mu-\alpha\mu-\beta>0$. Two terms are negative: $\frac{\mu-1}{\mu}<0$ and $-\mu(1-\alpha-\beta)<0$. Equation will be satisfied if and only if $\frac{dL_R}{d\eta}<0$.

Step 3: From $\frac{dL_R}{d\eta}$, $\frac{dK}{dL_R}$, and $\frac{dL_S}{dL_R}$, we have:

$$\frac{dK}{d\eta}=\frac{dK}{dL_R}\frac{dL_R}{d\eta}>0, \tag{11}$$

and

$$\frac{dL_S}{d\eta}=\frac{dL_S}{dL_R}\frac{dL_R}{d\eta}>0. \tag{12}$$

B. Additional Table

Table B.1
Response of Small Business Investments to Changes in State Section 179 Deduction Limits

This table reports the effect of changes in state Section 179 deduction limits on small businesses' purchasing and leasing of different types of capital using data from the National Federation of Independent Business (NFIB). The dependent variable is a dummy variable that equals 100 if the small business purchased or leased a specific type of capital in the last six months. The key independent variable, $\Delta Limit$, is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from year $t-1$ to t, presented in millions. For C-corp (pass-through) businesses, the changes in state Section 179 limits and the changes in state adoption of bonus depreciation are set to zero if the states do not levy corporate (individual) income taxes; all states are included. The NFIB surveys small businesses monthly. We exclude surveys from the first quarter of each year to allow the survey results to reflect firms' responses to current year's changes in state Section 179 limits. Changes in state political, economic, and other policy characteristics from year $t-1$ to t are added to control for confounding effects. All regressions have fixed effects that include a full interaction of employment size bins, industry sector, pass-through dummy, and year. Businesses with less than three employees are excluded from the sample. Employment size bins are given in the NFIB data as (3, 5), (6, 9), (10, 14), (15, 19), (20, 39), (40, $+\infty$). Standard errors are clustered at the state level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Equipment		Furniture		Building Imp.		Land		Vehicle	
	Purch	Lease	Purch	Lease	Purch	Lease	Purch	Lease	Purch	Lease
ΔLimit_t	9.36***	−1.15	−0.10	−0.15	4.30	−0.37	2.07	0.33	5.05	−0.40
	(3.19)	(1.07)	(2.08)	(0.30)	(2.83)	(0.37)	(1.52)	(0.59)	(3.17)	(0.96)
Observations	90,529	90,529	90,529	90,529	90,529	90,529	90,529	90,529	90,529	90,529
Adjusted R^2	0.07	0.01	0.04	0.01	0.03	0.00	0.03	0.01	0.10	0.03

REFERENCES

Acemoglu, Daron, and David H. Autor, 2011, Skills, tasks and technologies: Implications for employment and earnings, *Handbook of Labor Economics* 4, 1043–1171.

Acemoglu, Daron, and Pascual Restrepo, 2018, Artificial intelligence, automation and work.

Autor, David H., and David Dorn, 2013, The growth of low-skill service jobs and the polarization of the US labor market, *American Economic Review* 103, 1553–1597.

Autor, David H., Frank Levy, and Richard J. Murnane, 2003, The skill content of recent technological change: An empirical exploration, *Quarterly Journal of Economics* 118, 1279–1333.

Bloom, Nicholas, Luis Garicano, Raffaella Sadun, and John Van Reenen, 2014, The distinct effects of information technology and communication technology on firm organization, *Management Science* 60, 2859–2885.

Brynjolfsson, Erik, and Lorin M Hitt, 2003, Computing productivity: Firm-level evidence, *Review of economics and statistics* 85, 793–808.

Chirinko, Robert S, Steven M Fazzari, and Andrew P Meyer, 1999, How responsive is business capital formation to its user cost?: An exploration with micro data, *Journal of public economics* 74, 53–80.

Cummins, Jason G, Kevin A Hassett, R Glenn Hubbard, Robert E Hall, and Ricardo J Caballero, 1994, A reconsideration of investment behavior using tax reforms as natural experiments, *Brookings papers on economic activity* 1994, 1–74.

Edgerton, Jesse, 2010, Investment incentives and corporate tax asymmetries, *Journal of Public Economics* 94, 936–952.

Farre-Mensa, Joan, and Alexander Ljungqvist, 2015, Do measures of financial constraints measure financial constraints?, *Review of Financial Studies* hhv052.

Gaggl, Paul, and Greg C Wright, 2016, A short-run view of what computers do: Evidence from a uk tax incentive .

Goldin, Claudia, and Lawrence F. Katz, 1998, The origins of technology-skill complementarity, *The Quarterly Journal of Economics* 113, 693–732.

Goolsbee, Austan, 1998, Taxes, organizational form, and the deadweight loss of the corporate income tax, *Journal of Public Economics* 69, 143–152.

Goos, Maarten, Alan Manning, and Anna Salomons, 2014, Explaining job polarization: Routine-biased technological change and offshoring, *American Economic Review* 104, 2509–2526.

Guenther, Gary, 2015, The section 179 and bonus depreciation expensing allowances: Current law and issues for the 114th congress, in *CRS Report prepared for Members and Committees of Congress*, 7–5700.

Hadlock, Charles J, and Joshua R Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the kz index, *Review of Financial studies* 23, 1909–1940.

House, Christopher L, and Matthew D Shapiro, 2008, Temporary investment tax incentives: theory with evidence from bonus depreciation, *The American Economic Review* 98, 737–768.

Jaimovich, Nir, and Henry E. Siu, 2014, The trend is the cycle: Job polarization and jobless recoveries, NBER working paper.

Kaplan, Steven N, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *The Quarterly Journal of Economics* 112, 169–215.

Kitchen, John, and Matthew Knittel, 2016, Business use of section 179 expensing and bonus depreciation, 2002-2014 .

Krusell, Per, Lee E. Ohanian, Jose-Victor Rios-Rull, and Giovanni L. Violante, 2000, Capital-skill complementarity and inequality: A macroeconomic analysis, *Econometrica* 68, 1029–1053.

Kydland, Finn E., and Edward C. Prescott, 1982, Time to build and aggregate fluctuations, *Econometrica* 50, 1345–1370.

Neumark, David, and Diego Grijalva, 2013, The employment effects of state hiring credits during and after the great recession .

Ohrn, Eric, 2016, Investment and employment responses to state adoption of federal accelerated depreciation policies .

Summers, Lawrence H, 1981, Capital taxation and accumulation in a life cycle growth model, *The American Economic Review* 71, 533–544.

Summers, Lawrence H, 1987, Investment incentives and the discounting of depreciation allowances, in *The effects of taxation on capital accumulation*, 295–304 (University of Chicago Press).

Tambe, Prasanna, Lorin M Hitt, and Erik Brynjolfsson, 2012, The extroverted firm: How external information practices affect innovation and productivity, *Management Science* 58, 843–859.

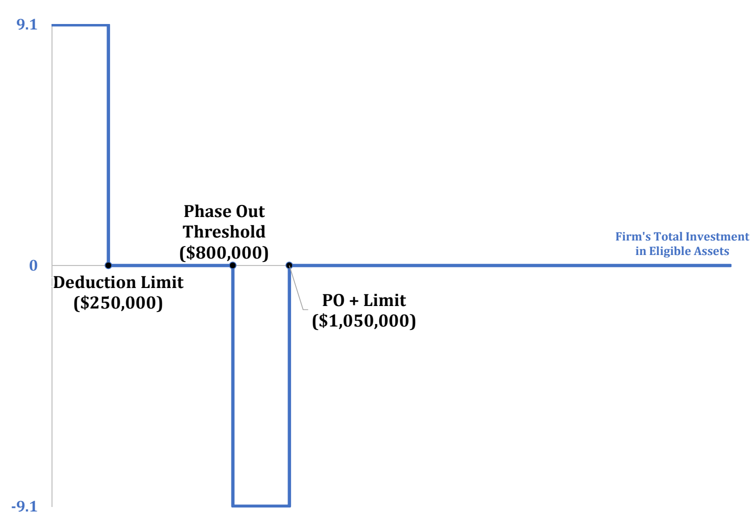
Winberry, Thomas, 2016, Lumpy investment, business cycles, and stimulus policy .

Xu, Qiping, and Eric Zwick, 2018, Kinky tax policy and abnormal investment behavior .

Zhang, Miao Ben, 2018, Labor-Technology Substitution: Implications for Asset Pricing, *Journal of Finance, Forthcoming* .

Zwick, Eric, and James Mahon, 2017, Tax policy and heterogeneous investment behavior, *The American Economic Review* 107, 217–248.

Panel A. Marginal Section 179 tax benefits as a function of firm investment



Panel B. Effect of changes in Section 179 on the marginal tax benefits

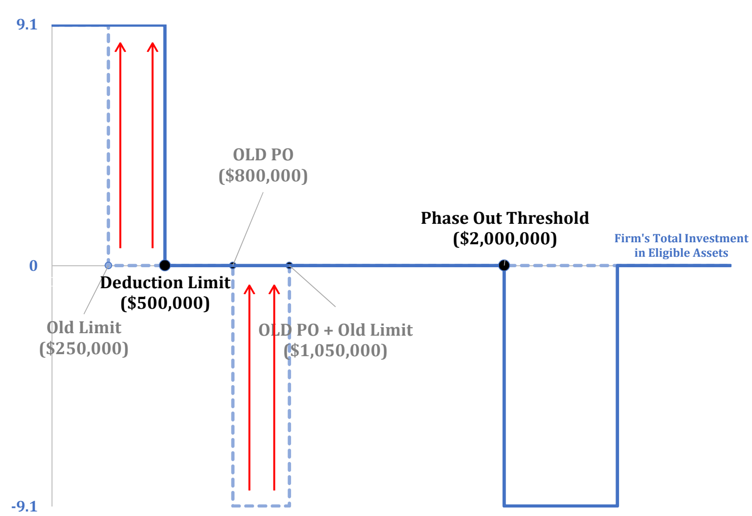
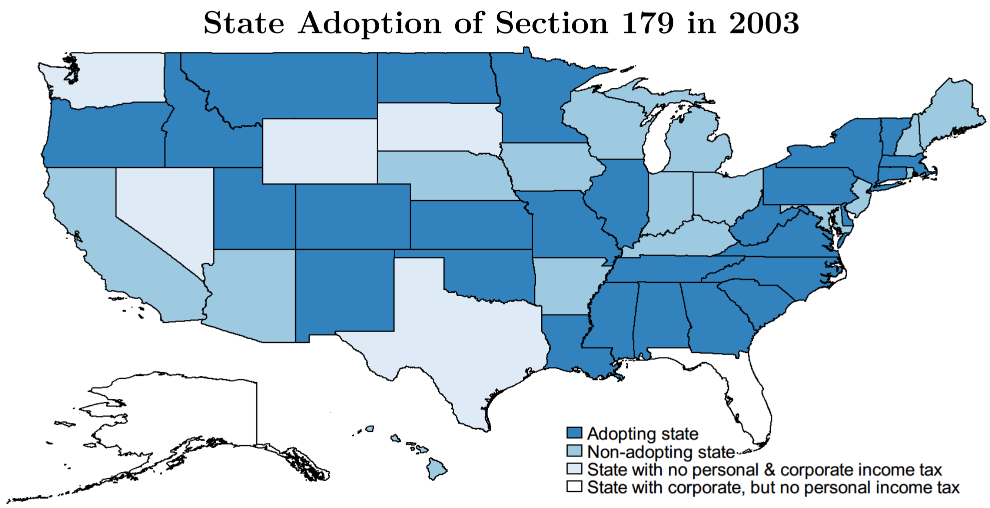


Figure 1. **Changes in Section 179 and firms' tax benefits.** Panel A illustrates the Section 179 tax benefit of additional $1,000 investment in qualified assets, conditional on the firm's total investment in qualified assets. The x-axis represents firm's total investment in qualified assets. The y-axis represents the reduction in the present value of state taxes due to an additional $1,000 qualified investment, such as computer investment, for a firm with a 10% discount rate, operating in the state with median income tax rate ($\tau_{state} = 6.08\%$). In the absence of Section 179, this exemplify asset is depreciated over 5-years following the MACRS. Panel B illustrates the changes in the above-mentioned tax benefits when the deduction limit and phaseout threshold of Section 179 increase from $250,000 to $500,000 and from $800,000 to $2,000,000, respectively.



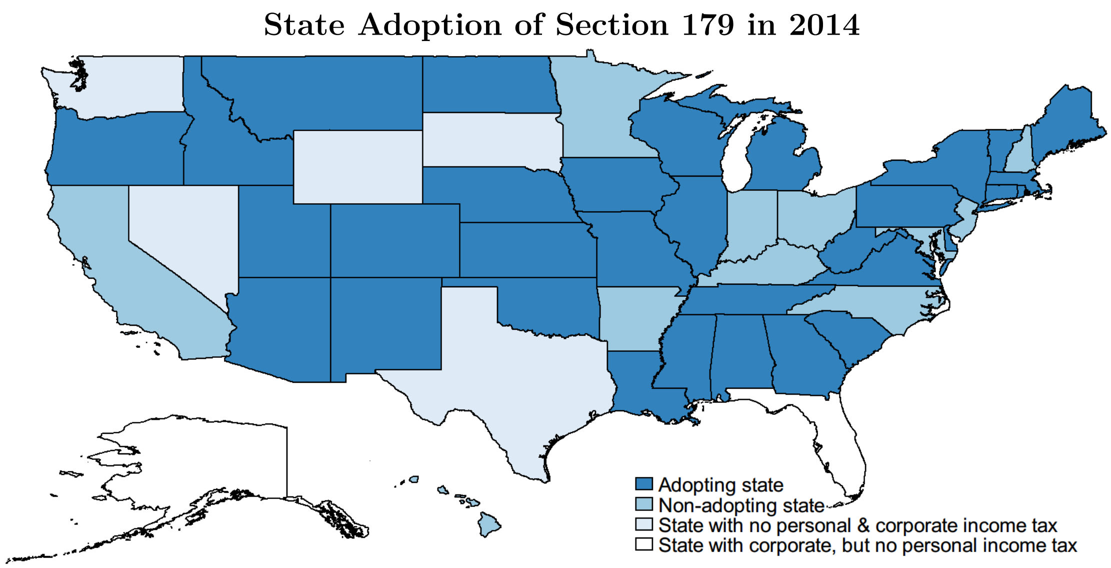


Figure 2. **State adoption of federal Section 179 deduction limits in 2003 and 2014.** This figure illustrates states' adoption of federal Section 179 deduction limits as of years 2003 and 2014. States that collect corporate income tax, but do not collect individual income tax are colored white. States that do not collect either individual or corporate income tax are shaded very light blue. Dark blue states adopt federal Section 179 deduction limits, whereas light blue states do not adopt federal limits.

Figure 3. **Characterictics of Occupations by Routineness and Skill.** This figure shows the characteristics of occupations categorized by routineness and skill. Definitions of routine and nonroutine occupations are provided in Section 4. Occupations that are classified as skilled require at least 2 years of related work experience or a college degree, based on O*Net. All the statistics are calculated each year over 2003-2014 and averaged based on the Occupational Employment Statistics (OES) data. Task intensities are calculated by the authors based on the Dictionary of Occupational Titles data and standardized to have zero mean and standard deviation of 1. We group routine-skilled and routine-unskilled occupations and classify them as *routine-task labor*. We classify nonroutine-skilled occupations as *skilled labor* and the rest as *nonroutine-task unskilled labor*.

Table 1
Timeline of Federal Section 179 Program

This table shows the timeline for the Section 179 federal deduction limits and the phase-out thresholds. Deduction limit is the maximum deduction that a firm may claim in a year. If the firm's investment in qualifying equipment and software in a given year exceeds the phaseout threshold, Section 179 deduction is reduced, dollar for dollar, by the amount exceeding the threshold.

Date Introduced	Date Enacted	Applied Period	Deduction Limit	Phase-out Threshold	Act
Baseline		≤2002	\$24,000	\$200,000	
2/27/2003	5/28/2003	2003-2005	\$100,000	\$400,000	Jobs and Growth Tax Relief Reconciliation Act
6/4/2004	10/22/2004	2006-2007	\$100,000	\$400,000	American Jobs Creation Act of 2004
1/17/2007	5/25/2007	2007	\$125,000	\$500,000	Small Business and Work Opportunity Tax Act of 2007
1/28/2008	2/13/2008	2008	\$250,000	\$800,000	Economic Stimulus Act of 2008
1/26/2009	2/17/2009	2009	\$250,000	\$800,000	American Recovery and Reinvestment Tax Act of 2009
6/12/2009	3/18/2010	2010	\$250,000	\$800,000	Hiring Incentives to Restore Employment Act
5/13/2010	9/27/2010	2010-2011	\$500,000	\$2,000,000	Small Business Jobs and Credit Act of 2010
7/24/2012	1/2/2013	2012-2013	\$500,000	\$2,000,000	American Taxpayer Relief Act of 2012
12/1/2014	12/19/2014	2014	\$500,000	\$2,000,000	Tax Increase Prevention Act of 2014

Table 2
Changes in State Section 179 Deduction Limits

This table relates lagged changes in states' economic and political characteristics to changes in state Section 179 deduction limits. *Hiring Credits* is the number of state job creation hiring credit programs. *Bonus Adoption* is a dummy variable that equals to 1 if the state adopts the federal bonus depreciation tax incentive. *Budget Surplus* is the state's budget surplus in $ millions (negative means budget deficit). *Democratic Dummy* is a dummy variable that equals to 1 if the state is governed by a Democratic governor. *State Indiv. Income Tax Rate* and *State Corp. Income Tax Rate* are the state's individual and corporate income tax rates, respectively. *GSP* is the real gross state product. All regressions have year fixed effects. States with zero individual and corporate income tax rate are included in the set of states that do not change state 179 deduction limits. States that collect corporate income tax, but do not collect individual income tax are excluded. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. Sample period is 2003-2014.

	Changes in State Section 179 Limit ($thousands)				
Lagged Changes in...	(1)	(2)	(3)	(4)	(5)
State Hiring Credits	−2.61				−1.62
	(5.40)				(5.35)
State Bonus Adoption	13.10***				11.86***
	(3.43)				(3.37)
State Budget Surplus		1.67			1.51
		(1.26)			(1.27)
State GSP		1.02			1.07
		(0.90)			(0.89)
State Unemployment			2.70		2.33
			(7.90)		(7.62)
State Indiv. Tax				−7.88	−7.35
				(7.95)	(7.80)
State Corp. Tax				6.46	6.14
				(4.96)	(4.71)
State Democratic Dummy				1.84	2.64
				(3.65)	(3.47)
Observations	576	576	576	576	576
Adjusted R^2	0.28	0.28	0.28	0.28	0.28

Table 3
Summary Statistics for Establishments

This table reports the summary statistics for employment and computers at the establishment level. Employment data is from the Occupational Employment Statistics database at the Bureau of Labor Statistics. L_{tot}, L_R, L_S, L_{NU} are the establishments' total employment, employment of routine-task labor, skilled labor, and nonroutine-task unskilled labor, respectively. Computer data is from the Computer Intelligence Technology Database (CiTDB). *Computer* is the total number of computers in the establishment. *IT Int.* is the IT intensity of establishment measured as the number of computers per employee. We require establishments to have consecutive observations that allow computation of current and past employment or investment ratio. We require establishments to have at least three employees. In the CiTDB sample, we exclude establishments from industries in which computer investment accounts for less than five percent of total investment in equipment. States that collect corporate income tax, but do not collect individual income tax are excluded. Panel A reports statistics over 2003-2014. Panel B reports the 3-year changes in establishments' computers and employment for states that adopt the federal Section 179 limits in 2003 and states that do not. The estimates are generated from a cross-sectional regression of the respective changes on the states' adoption status and a fixed effect of 8 employment bins interacted with NAICS 4-digit industry codes. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. t-statistics are based on standard errors clustered at the state level.

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min	P25	P50	P75	Max
CiTDB Sample (Obs = 354,566)							
L_{tot}	158.46	795.81	3	22	50	125	300100
$Computer$	173.98	1760.72	0	17	43	130	601990
$IT\ Int.$	1.26	2.34	0	0.56	0.98	1.46	505.33
OES Sample (Obs = 331,948)							
L_{tot}	101.70	393.36	3	11	25	74	40142
L_R	20.48	79.26	0	1	3	12	11003
L_S	39.28	249.82	0	2	7	21	38029
L_{NU}	41.95	146.37	0	3	9	30	12119

Panel B: 3-Year Growth Rates of Key Variables in Pre-Treatment Period (2000-2003)

	States that adopt federal Section 179 limits in 2003	States that do not adopt federal Section 179 limits in 2003	Difference in Mean	
	Mean	Mean	Difference	t-stats.
CiTDB Sample				
$\Delta Computer$	36.04	36.17	−0.13	−0.12
$\Delta Log(IT\ Int.)$	0.26	0.25	0.01	1.04
OES Sample				
ΔL_{tot}	0.65	1.32	−0.67	−0.65
ΔL_R	−1.27	−1.94	0.67	0.28
ΔL_S	−5.19	−1.11	−4.08	−1.67
ΔL_{NU}	9.01	7.26	1.75	1.23

Table 4
Response of Computer Investments to Changes in State Section 179 Deduction Limits

This table reports the effect of changes in state Section 179 deduction limits on establishments' investment in computers and on establishments' changes in IT intensity, using first-difference regressions in equation 5. *Computer Investment* is the growth rate of the number of computers in each establishment in year t calculated from the Computer Intelligence Technology Database (CiTDB). Δ *IT Intensity* is the change in the logarithm of the number of computers per worker. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies, contemporaneous changes in state political, economic, and other policy characteristics, and *Past Trend*, which is the establishment's computer investment or change in IT intensity in year $t-1$. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Computer Investments (1)	Δ IT Intensity (2)
$\Delta \text{Limit}_t \times \text{Eligible}_t$	6.70**	13.72***
	(2.88)	(4.09)
$\Delta \text{Limit179}_t$	0.50	−5.80
	(3.52)	(3.63)
Observations	353,912	342,420
Adjusted R^2	0.21	0.21

Table 5
Response of Total Employment to Changes in State Section 179 Deduction Limits

This table reports the effects of changes in state Section 179 deduction limits on establishments' total employment, using first-difference regressions in equation 6. The dependent variable is the three-year growth rate of the number of employees in each establishment from year t to $t+3$. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies for each year in t to $t+2$, contemporaneous changes in state political, economic, and other policy characteristics for each year in t to $t+2$, and *Past Trend*, which is the three-year growth rate of total employment in each establishment from year $t-3$ to t. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Δ Emp$^{Tot}_{t,t+3}$			
	(1)	(2)	(3)	(4)
ΔLimit$_t$ × Eligible$_t$	−1.57			−5.67
	(3.15)			(3.62)
ΔLimit$_{t+1}$ × Eligible$_{t+1}$		1.35		−5.32
		(4.00)		(4.41)
ΔLimit$_{t+2}$ × Eligible$_{t+2}$			3.64	4.00
			(3.98)	(3.85)
ΔLimit$_t$	2.66			5.63*
	(3.16)			(3.11)
ΔLimit$_{t+1}$		−0.07		5.90
		(4.48)		(4.72)
ΔLimit$_{t+2}$			−2.14	−2.91
			(3.14)	(3.03)
Observations	329,943	329,943	329,943	329,943
Adjusted R^2	0.08	0.09	0.10	0.11

Table 6
Response of Routine-Task Employment to Changes in State Section 179 Deduction Limits

This table reports the effects of changes in state Section 179 deduction limits on establishments' employment of routine-task labor, using first-difference regressions in equation 6. The dependent variable is the three-year growth rate of the number of routine-task employees in each establishment from year t to $t+3$. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies for each year in t to $t+2$, contemporaneous changes in state political, economic, and other policy characteristics for each year in t to $t+2$, and *Past Trend*, which is the three-year growth rate of routine-task employment in each establishment from year $t-3$ to t. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Δ Emp$^R_{t,t+3}$			
	(1)	(2)	(3)	(4)
ΔLimit$_t$ × Eligible$_t$	−21.16***			−24.38***
	(7.33)			(8.30)
ΔLimit$_{t+1}$ × Eligible$_{t+1}$		−2.75		−9.43
		(9.58)		(10.48)
ΔLimit$_{t+2}$ × Eligible$_{t+2}$			−3.61	0.56
			(9.94)	(10.45)
ΔLimit$_t$	4.21			5.83
	(9.11)			(9.49)
ΔLimit$_{t+1}$		−4.22		0.03
		(8.92)		(9.23)
ΔLimit$_{t+2}$			−3.15	−4.10
			(7.49)	(8.20)
Observations	269,784	269,784	269,784	269,784
Adjusted R^2	0.23	0.23	0.23	0.23

Table 7
Response of Skilled Employment to Changes in State Section 179 Deduction Limits

This table reports the effects of changes in state Section 179 deduction limits on establishments' employment of skilled labor, using first-difference regressions in equation 6. The dependent variable is the three-year growth rate of the number of skilled employees in each establishment from year t to $t+3$. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies for each year in t to $t+2$, contemporaneous changes in state political, economic, and other policy characteristics for each year in t to $t+2$, and *Past Trend*, which is the three-year growth rate of skilled employment in each establishment from year $t-3$ to t. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Δ Emp$^{S}_{t,t+3}$			
	(1)	(2)	(3)	(4)
ΔLimit$_t$ × Eligible$_t$	12.99**			8.54
	(6.07)			(6.57)
ΔLimit$_{t+1}$ × Eligible$_{t+1}$		18.16***		13.45*
		(6.47)		(6.75)
ΔLimit$_{t+2}$ × Eligible$_{t+2}$			15.99**	13.84*
			(7.31)	(7.28)
ΔLimit$_t$	−4.59			−1.34
	(6.80)			(7.07)
ΔLimit$_{t+1}$		−11.55*		−6.30
		(6.41)		(6.50)
ΔLimit$_{t+2}$			−7.23	−6.94
			(6.42)	(6.85)
Observations	302,873	302,873	302,873	302,873
Adjusted R^2	0.20	0.20	0.20	0.20

Table 8
Response of Nonroutine-task Unskilled Employment to Changes in State Section 179 Deduction Limits

This table reports the effects of changes in state Section 179 deduction limits on establishments' employment of nonroutine-task unskilled labor, using first-difference regressions in equation 6. The dependent variable is the three-year growth rate of the number of nonroutine-task unskilled employees in each establishment from year t to $t+3$. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies for each year in t to $t+2$, contemporaneous changes in state political, economic, and other policy characteristics for each year in t to $t+2$, and *Past Trend*, which is the three-year growth rate of nonroutine-task unskilled employment in each establishment from year $t-3$ to t. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Δ Emp$^{NU}_{t,t+3}$			
	(1)	(2)	(3)	(4)
ΔLimit$_t$ × Eligible$_t$	−1.83			−4.81
	(6.31)			(5.68)
ΔLimit$_{t+1}$ × Eligible$_{t+1}$		−2.61		−8.35
		(6.75)		(6.90)
ΔLimit$_{t+2}$ × Eligible$_{t+2}$			3.15	3.35
			(8.30)	(7.99)
ΔLimit$_t$	11.21*			13.07**
	(5.63)			(5.36)
ΔLimit$_{t+1}$		8.74		14.60**
		(6.04)		(6.12)
ΔLimit$_{t+2}$			1.57	−1.20
			(8.63)	(8.09)
Observations	304,617	304,617	304,617	304,617
Adjusted R^2	0.20	0.20	0.20	0.20

Table 9
Response of Wage Bills to Changes in State Section 179 Deduction Limits

This table reports the effects of changes in state Section 179 deduction limits on establishments' wage bills for all employees, routine-task employees, skilled employees, and nonroutine unskilled employees, respectively, using first-difference regressions in equation 6. The dependent variable is the three-year growth rate of the wage bill metric in each establishment from year t to $t+3$. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies for each year in t to $t+2$, contemporaneous changes in state political, economic, and other policy characteristics for each year in t to $t+2$, and *Past Trend*, which is the three-year growth rate of the wage bill for the corresponding type of employees in each establishment from year $t-3$ to t. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	$\Delta\text{WageBill}^{Tot}_{t,t+3}$	$\Delta\text{WageBill}^{R}_{t,t+3}$	$\Delta\text{WageBill}^{S}_{t,t+3}$	$\Delta\text{WageBill}^{NU}_{t,t+3}$
	(1)	(2)	(3)	(4)
$\Delta\text{Limit}_t \times \text{Eligible}_t$	-7.83^{**}	-25.47^{***}	4.17	-6.18
	(3.68)	(8.38)	(6.37)	(6.02)
$\Delta\text{Limit}_{t+1} \times \text{Eligible}_{t+1}$	-1.96	-5.95	9.89	-6.71
	(4.98)	(10.89)	(6.62)	(7.55)
$\Delta\text{Limit}_{t+2} \times \text{Eligible}_{t+2}$	9.40^{**}	3.05	18.55^{***}	7.91
	(3.68)	(9.73)	(6.35)	(7.93)
ΔLimit_t	9.20^{**}	5.66	3.52	15.24^{**}
	(3.67)	(9.57)	(6.67)	(5.76)
ΔLimit_{t+1}	2.98	-5.40	-2.44	13.27^{*}
	(4.89)	(9.45)	(6.56)	(6.62)
ΔLimit_{t+2}	-7.66^{**}	-6.59	-11.31^{*}	-5.54
	(2.94)	(7.79)	(5.98)	(8.23)
Observations	329,943	269,784	302,873	304,617
Adjusted R^2	0.11	0.23	0.19	0.20

Table 10
Main Results with State Fixed Effects

This table reports the effects of changes in state Section 179 deduction limits on computer investments and employment metrics by adding state fixed effects to the first-difference regressions in equations 5 and 6. The dependent variables are annual investment measures and three-year growth rate of the employment metrics in each establishment. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies, contemporaneous changes in state political, economic, and other policy characteristics, and *Past Trend*, which are the lagged annual investment measures and lagged three-year growth rate of the employment metrics in each establishment. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Panel A: Investment Regressions	
	Computer Investments (1)	Δ IT Intensity (2)
$\Delta \text{Limit}_t \times \text{Eligible}_t$	7.07**	13.54***
	(2.87)	(4.12)
ΔLimit_t	−0.72	−6.16
	(3.58)	(3.96)
Observations	353,912	342,420
Adjusted R^2	0.21	0.21

	Panel B: Employment Regressions				Panel C: Wage Bill Regressions			
	Tot (1)	R (2)	S (3)	NU (4)	Tot (5)	R (6)	S (7)	NU (8)
$\Delta \text{Limit}_t \times \text{Eligible}_t$	−5.55	−26.46***	8.37	−3.06	−8.10**	−28.07***	3.89	−4.75
	(3.63)	(8.32)	(6.71)	(5.65)	(3.76)	(8.50)	(6.50)	(5.96)
$\Delta \text{Limit}_{t+1} \times \text{Eligible}_{t+1}$	−5.63	−11.02	12.99*	−7.05	−2.35	−8.03	9.28	−5.59
	(4.34)	(10.68)	(6.70)	(6.70)	(4.95)	(11.11)	(6.59)	(7.29)
$\Delta \text{Limit}_{t+2} \times \text{Eligible}_{t+2}$	4.09	0.49	13.81*	4.47	9.56**	2.51	18.61***	8.92
	(3.89)	(10.25)	(7.11)	(7.73)	(3.77)	(9.59)	(6.30)	(7.60)
ΔLimit_t	4.71	14.28	−5.65	6.89	6.91*	14.23	−1.52	7.99
	(2.94)	(11.08)	(6.92)	(5.35)	(3.70)	(11.22)	(6.04)	(5.76)
$\Delta \text{Limit}_{t+1}$	5.69	6.96	−9.27	9.59	1.23	1.41	−5.68	7.07
	(4.98)	(10.94)	(6.57)	(6.27)	(5.52)	(11.62)	(6.58)	(6.73)
$\Delta \text{Limit}_{t+2}$	−3.00	−1.05	−9.57	−3.64	−9.25***	−3.84	−14.18**	−9.10
	(3.25)	(8.01)	(6.96)	(7.16)	(3.41)	(7.58)	(6.88)	(7.29)
Observations	329,943	269,784	302,873	304,617	329,943	269,784	302,873	304,617
Adjusted R^2	0.11	0.23	0.21	0.20	0.11	0.23	0.20	0.20

Table 11
Responses of Investment and Employment to the Interaction of State Deduction Limit Changes and State Individual Income Tax Rates

This table reports the effects of changes in state Section 179 deduction limits, interacting with marginal state individual income tax rates, on computer investments and employment metrics using first-difference regressions in equations 5 and 6. The dependent variables are annual investment measures and three-year growth rate of the employment metrics in each establishment. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. τ_t^i is the marginal state individual income tax rates in year t. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies, contemporaneous changes in state political, economic, and other policy characteristics, and *Past Trend*, which are the lagged annual investment measures and lagged three-year growth rate of the employment metrics in each establishment. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Panel A: Investment Regressions	
	Computer Investments (1)	Δ IT Intensity (2)
$\Delta\text{Limit}_t \times \tau_t^i \times \text{Eligible}_t$	1.04**	1.97***
	(0.49)	(0.62)
$\Delta\text{Limit}_t \times \tau_t^i$	0.12	−0.86*
	(0.66)	(0.46)
Observations	353,912	342,420
Adjusted R^2	0.21	0.21

	Panel B: Employment Regressions				Panel C: Wage Bill Regressions			
	Tot (1)	R (2)	S (3)	NU (4)	Tot (5)	R (6)	S (7)	NU (8)
$\Delta\text{Limit}_t \times \tau_t^i \times \text{Eligible}_t$	−0.72	−3.16**	1.42	−0.91	−0.93*	−3.10**	0.82	−1.06
	(0.50)	(1.24)	(1.06)	(0.87)	(0.56)	(1.23)	(1.01)	(0.94)
$\Delta\text{Limit}_{t+1} \times \tau_{t+1}^i \times \text{Eligible}_{t+1}$	−1.10*	−1.52	1.93*	−2.14**	−0.81	−0.93	1.13	−2.09*
	(0.63)	(1.55)	(0.96)	(0.97)	(0.69)	(1.56)	(0.93)	(1.05)
$\Delta\text{Limit}_{t+2} \times \tau_{t+2}^i \times \text{Eligible}_{t+2}$	0.74	−0.23	2.40**	0.43	1.40**	0.12	2.96***	1.02
	(0.54)	(1.66)	(1.15)	(1.14)	(0.52)	(1.54)	(1.08)	(1.09)
$\Delta\text{Limit}_t \times \tau_t^i$	0.77*	0.81	0.23	1.89**	1.20**	0.64	0.87	2.24**
	(0.43)	(1.52)	(1.15)	(0.78)	(0.50)	(1.48)	(1.07)	(0.85)
$\Delta\text{Limit}_{t+1} \times \tau_{t+1}^i$	1.15*	0.58	−0.85	2.87***	0.84	−0.28	−0.11	2.84***
	(0.65)	(1.39)	(0.91)	(0.91)	(0.65)	(1.40)	(0.86)	(0.97)
$\Delta\text{Limit}_{t+2} \times \tau_{t+2}^i$	−0.67	−0.53	−1.67	0.03	−1.31***	−0.94	−2.25**	−0.63
	(0.48)	(1.27)	(1.19)	(1.14)	(0.46)	(1.21)	(1.10)	(1.12)
Observations	329,943	269,784	302,873	304,617	329,943	269,784	302,873	304,617
Adjusted R^2	0.11	0.23	0.20	0.20	0.11	0.23	0.19	0.20

Table 12
Responses of Investment and Employment to the Interaction of State Deduction Limit Changes and State Corporate Income Tax Rates

This table reports the effects of changes in state Section 179 deduction limits, interacting with marginal state corporate income tax rates, on computer investments and employment metrics using first-difference regressions in equations 5 and 6. The dependent variables are annual investment measures and three-year growth rate of the employment metrics in each establishment. $\Delta Limit_t$ is the change in the maximum Section 179 deduction that a firm may claim in a year from the state taxes from $t-1$ to t, presented in millions. τ_t^c is the marginal state corporate income tax rates in year t. $Eligible_t$ is a dummy variable that equals to 1 if the firm is eligible for the federal Section 179 in year t (see definition of eligibility in Section 3.2). For brevity, we do not report the follow variables which are also included in the regression: The standalone eligibility dummies, contemporaneous changes in state political, economic, and other policy characteristics, and *Past Trend*, which are the lagged annual investment measures and lagged three-year growth rate of the employment metrics in each establishment. All regressions have fixed effects that include a full interaction of 8 employment bins, NAICS 4-digit industry codes and year. Employment bins are defined as (1, 4), (5, 9), (10, 14), (15, 24), (25, 49), (50, 99), (100, 199), and above 200. Standard errors are clustered at the state level and reported in parentheses. * , ** , and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is 2003-2014.

	Panel A: Investment Regressions	
	Computer Investments (1)	Δ IT Intensity (2)
$\Delta \text{Limit}_t \times \tau_t^c \times \text{Eligible}_t$	0.79^{**}	1.80^{***}
	(0.38)	(0.49)
$\Delta \text{Limit}_t \times \tau_t^c$	-0.04	-1.06^{**}
	(0.41)	(0.41)
Observations	353,912	342,420
Adjusted R^2	0.21	0.21

	Panel B: Employment Regressions				Panel C: Wage Bill Regressions			
	Tot (1)	R (2)	S (3)	NU (4)	Tot (5)	R (6)	S (7)	NU (8)
$\Delta \text{Limit}_t \times \tau_t^c \times \text{Eligible}_t$	-0.71^{*}	-3.07^{**}	1.54^{*}	-0.86	-0.83^{**}	-3.19^{**}	0.95	-0.88
	(0.37)	(1.30)	(0.82)	(0.75)	(0.40)	(1.28)	(0.79)	(0.74)
$\Delta \text{Limit}_{t+1} \times \tau_{t+1}^c \times \text{Eligible}_{t+1}$	-0.70	-1.60	2.17^{**}	-1.18	-0.21	-1.21	1.69^{*}	-1.07
	(0.50)	(1.36)	(0.94)	(0.77)	(0.57)	(1.42)	(0.87)	(0.85)
$\Delta \text{Limit}_{t+2} \times \tau_{t+2}^c \times \text{Eligible}_{t+2}$	0.62	-0.01	2.10^{**}	0.08	1.20^{***}	0.20	2.48^{***}	0.54
	(0.48)	(1.59)	(0.89)	(0.88)	(0.44)	(1.49)	(0.82)	(0.80)
$\Delta \text{Limit}_t \times \tau_t^c$	0.70^{*}	1.15	-0.42	1.64^{**}	1.07^{***}	1.15	0.27	1.88^{**}
	(0.35)	(1.20)	(0.88)	(0.65)	(0.39)	(1.19)	(0.80)	(0.70)
$\Delta \text{Limit}_{t+1} \times \tau_{t+1}^c$	0.93^{*}	0.73	-0.62	1.87^{**}	0.59	0.15	-0.01	1.79^{**}
	(0.53)	(1.25)	(0.75)	(0.74)	(0.54)	(1.34)	(0.73)	(0.81)
$\Delta \text{Limit}_{t+2} \times \tau_{t+2}^c$	-0.25	-0.21	-0.86	0.31	-0.67	-0.36	-1.08	-0.08
	(0.44)	(1.23)	(0.82)	(0.81)	(0.43)	(1.24)	(0.77)	(0.76)
Observations	329,943	269,784	302,873	304,617	329,943	269,784	302,873	304,617
Adjusted R^2	0.11	0.23	0.20	0.20	0.11	0.23	0.19	0.20