Investment Stimulus, Automation, and Skill Demand*

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Abstract

This paper studies how capital investment affects labor demand in the automation process at the firm level. Using the bonus depreciation policy in the recent U.S. tax reform as an exogenous variation in capital cost, we find that the policy-driven reduction in capital cost lowers labor demand while raising capital expenditure for machinery and equipment. Using detailed information on skill and patent compositions at the firm level, we also report that the reduction in labor demand concentrates in job positions with few software skills and firms with high automation-related technologies, supporting the displacement effect of automation. We illuminate the mechanisms and welfare implications behind the empirical results by introducing a model of automation based on the task-based framework. Linking the reduced-form estimates and the model, we recover capital-labor substitution elasticity by skill and technology levels and find that the task displacement effect of capital accounts for the parameter's heterogeneity. Our results support the public concern that automated capital could replace workers with few software skills and show that investment stimulus for machinery accelerates automation.

Keywords: bonus depreciation, automation, capital-labor substitution

JEL Codes: D22, H25, J23, J24, O33

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1 Introduction

"Human labor from time immemorial played the role of principal factor of production. There are reasons to believe that human labor will not retain this status in the future."

-Wassily Leontief

How automation affects labor demand has long interested policymakers and economists. Wassily Leontief expressed his concern in his essay in 1982 on the displacement effect of machines on human labor and wage inequality. Leontief's concern was not new in 1982, and he knew perfectly well that adopting advanced machines was one of the main drivers of economic growth. As we all know, however, the concerns about the previous waves of new machines have not come true.

This concern is growing again as automation technologies such as robots and artificial intelligence (AI) have expanded the coverage of capital in the production process in the 21st century. The last decades have witnessed new types of machines and software do the tasks that workers initially performed. At the same time, we have also seen that the workers complementing new machinery and equipment are more demanded by firms. Thus, the impact of capital investment could strikingly vary across different types of workers.

However, there is still little consensus on the causal effects of automation on labor demand because of several challenges: First, firms adjust both labor and capital inputs in response to technology or demand shocks, making it hard to identify the causal effects of capital investment on labor demand. The identification requires an exogenous shock to rule out other confounding forces. Second, it is hard to identify who is displaced or complemented by new capital inputs in a firm because this requires detailed information on the tasks and skills of workers in the firm. Third, how a firm adjusts labor inputs in response to capital investment also critically depends on the firm's technological capability for automation. Even if a firm would like to adopt automated capital substituting for particular tasks of workers, the firm cannot do that without sufficient technological capability. However, it is hard to observe such capacity for each firm.

We use several strategies to overcome these challenges: First, this study utilizes a novel strategy using the bonus depreciation policy of the Tax Cuts and Jobs Act in the U.S. as a quasi-experimental variation in the cost of capital. In 2017, the U.S. federal government introduced a bonus depreciation scheme as part of the Tax Cuts and Jobs Act (TCJA). Bonus depreciation is a form of investment stimulus to provide tax deductions for purchasing machinery and equipment and lowers the effective cost of capital. By comparing firms that benefit more from the policy to those that benefit less, we can identify an exogenous change

in capital investment for machinery and equipment. Second, this study constructs a unique firm-level data set by combining several data sources. Online job posting data provided by Lightcast is a database of a near-universe of online job vacancies and provides detailed skill requirements for each job position. So, we directly observe what kind of skills a job position in a firm has. Patent data provided by PatentsView includes detailed information on all patents published in the U.S. By conducting a text analysis on the descriptions of the patents, we capture the firm's technological capability for automation.

Using this unique setting, we first ask whether capital substitutes for human labor at the firm level through automation. Finding a firm-level causal effect is crucial to capture the automation process. Even if a decline in capital cost raises capital investment and lowers employment at some aggregate level, it does not necessarily mean a displacement effect of automation. This is because there could be a composition effect across industries having different labor input shares. Second, we investigate how the incidence of automation varies across skill groups. Answering the second question is vital because the government's investment stimulus for machinery could induce a welfare gap.

To answer these questions, we first construct a firm-level reduction in capital cost by utilizing two unique features of the bonus depreciation policy. First, bonus depreciation has heterogeneous effects across industries because each machinery and equipment has its schedule of tax deductions, and industries use different capital sets. Second, the policy also has heterogeneous effects across states because some states have pegged their bonus depreciation policy to the federal one, while other states do not allow bonus depreciation for state corporate taxation. We combine these two variations and the spatial and industrial distributions of a firm's establishments to construct a firm-level measure of the policy shock.

We estimate a series of event-study regressions of capital investment and labor demand with the firm-level policy shock. After the Tax Cuts and Jobs Act was approved, the effective capital cost decrease about 15%. During the two years after the policy change, the reduction in capital cost by bonus depreciation raised capital investment by 3.5% on average. We also find that only the eligible capital, machinery and equipment, responded to the policy change among various types of capital. During the same period, employment declined about 6.7% on average by the change in bonus depreciation. These results suggest that new machines embedding recent automation technologies and labor inputs are highly substitutable.

To investigate what type of workers are more vulnerable to automation, we analyze the heterogeneous effects of the decline in capital cost on labor demand across skill groups based on detailed skill requirements attached to the online job vacancies. We report that the decline in the number of job postings by bonus depreciation is concentrated in the job positions requiring few software skills. At the same time, there is no clear heterogeneous

pattern in the labor demand response across the classical skill measures, such as schooling and experience years. This heterogeneity is more striking for firms with higher automation-related technology measured by the number of robot-related patents. These results support the hypothesis that the decline in capital cost by bonus depreciation lowers labor demand through automation.

Following the sufficient statistics approach (Chetty, 2009; Kleven, 2020), we recover the capital-labor substitution elasticity across skill and technology levels from the reduced-form estimates. The substitution elasticity summarizes how a firm adjusts capital and labor inputs in response to automation. The estimated overall elasticity of substitution is 0.87, which is slightly less than one from the Cobb-Douglass production function or 0.9 from a meta-analysis by (Gechert et al., 2022). However, the group-level elasticity varies from 0.37 to 1.44 by skill level, indicating that the incidence of automation should highly differ across skill groups.

We then present a model of automation based on the task-based approach in the spirit of Acemoglu and Restrepo (2020) and Hubmer and Restrepo (2021). The model is helpful for a couple of reasons. First, the model clarifies the mechanisms behind the empirical results. Second, the model enables us to decompose the capital-labor substitution elasticity and to infer how much the automation channel can account for the parameter. Third, by connecting the elasticity of substitution and the welfare incidence of automation, we can infer whether automation can generate a welfare gap across different types of workers.

The model's insight is that a reduction in capital cost could induce firms to raise capital volume for the tasks that have been performed by capital (capital deepening) or adopt new machines to expand capital coverage for the tasks performed originally by workers (task displacement). The former raises the productivity of overall labor inputs, while the latter displaces workers performing automatable tasks. Extended from the literature, our model allows multiple labor groups to have different elasticity of substitution with capital based on the sets of skills. We also introduce the interaction between a firm's technological capability and a job position's skill level.

According to the model, our empirical results indicate that the task displacement effect dominates the productivity effect in the short run and that more tasks are reallocated from lower-skilled jobs to the capital. The decomposition exercise shows that the traditional substitution effect accounts for less than 10% of the elasticity and that task displacement results in a considerable difference in the elasticity across skill groups. The model also shows that the elasticity affects the welfare incidence of automation through the labor income share. So, we use our model to simulate the secular decline of labor income share and show that the heterogeneity in the elasticity of substitution accounts for the uneven trends in labor share

by skill group. This result indicates that assuming the homogeneous elasticity of substitution between capital and labor may obscure important welfare implications of issues in the labor market.

The findings of this study improve our understanding of the automation process in a couple of aspects. First, this paper shows that investment stimulus for machinery, such as bonus depreciation, can accelerate automation. Many countries, including China, South Korea, Singapore, and Indonesia, recently adopted similar policies. This study could give caution for adverse labor market effects of this kind of policy. Second, we show that the welfare incidence of automation depends on capital-labor substitution elasticity. Given the considerable variation in the estimate of the elasticity in the literature, it is crucial to estimate the parameter correctly based on an exogenous variation. Third, the heterogeneity in the substitution elasticity is enormous across skill groups by task reallocation. This heterogeneity could affect the incidence of other labor market issues, such as the decline of labor income share and monetary/fiscal policies.

The remainder of this paper unfolds as follows. We present the related literature and the contribution of our study to the existing literature in Section 2. We explain the background of the bonus depreciation policy in Section 3. Section 4 presents the sources of firm-level data and describes how to link the multiple data sets. Section 5 demonstrates our empirical design. Section 6 presents the estimation results and analyzes the mechanisms. In Section 7, we build a conceptual framework that explains the mechanism and welfare implications of automation. Section 8 conducts a quantitative analysis on the welfare incidence of automation. Section 9 concludes.

2 Literature Review

This study's main contribution to the existing literature is threefold. The first strand of papers investigates the effects of earlier bonus depreciation on capital investment and employment (House and Shapiro, 2008; Edgerton, 2010; Zwick and Mahon, 2017; Ohrn, 2019; Maffini, Xing, and Devereux, 2019; Garrett, Ohrn, and Suárez Serrato, 2020; Curtis et al., 2021). The bonus depreciation was temporarily implemented in the 2001 and 2008 recessions to stimulate the economy. Zwick and Mahon (2017) constructs the industry-level measures of the effectiveness of bonus depreciation based on tax return data and reports that the policy was effective as an investment stimulus. Some subsequent studies also report modest positive effects on employment as well as investment (Garrett, Ohrn, and Suárez Serrato, 2020; Curtis et al., 2021). However, these studies could not check whether the policy effects are related to the particular economic conditions during the recessions or the temporary

implementation of the policy.

This paper improves our understanding of the effects of bonus depreciation in several ways: First, this study first analyzes the effect of the recent bonus depreciation by TCJA on capital and labor inputs in a normal time. Our setting excludes the confounding forces from the uneven incidence of economic downturns across industries during the recessions compared to the previous results. A ten-year implementation of the bonus depreciation by TCJA also minimizes a firm's intertemporal incentive for capital investment, which could happen in the earlier periods because of the temporal implementations. Second, this paper constructs a firm-level cost reduction from bonus depreciation by combining the industry-level and state-level variations in the effectiveness of the policy. Compared to the literature depending on the industry-level variation, our setting makes it possible to control for other potentially confounding forces additionally.

This paper also builds on the fast-growing literature on automation. The seminal papers in the literature focus on the fact that computer capital has replaced labor performing routine tasks from the early 1980s, hollowing out the employment of middle-skilled jobs (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007; Acemoglu and Autor, 2011; Michaels, Natraj, and Van Reenen, 2014). As recent technologies have made significant progress in the field of automation, such as AIs and robots that can handle even non-routine tasks, more recent studies investigate the broader effects of those technologies in the labor market. Some of these papers find that adopting automation technologies could lower the employment of some subgroup of workers or any workers (Graetz and Michaels, 2018; Webb, 2019; Acemoglu and Restrepo, 2020; Stapleton, Copestake, and Pople, 2021; Acemoglu et al., 2022). Acemoglu and Restrepo (2020) construct exposure to robots at industry and commuting zone levels in the U.S. and report robust negative effects of robots on employment and wage during 1993-2007. Acemoglu et al. (2022) focus on AI, another archetype of the recent automation technologies. Using online job vacancies, the authors find that more exposure to AI is associated with the reduction in hiring in non-AI job positions at the establishment level over 2010-2018 in the U.S. On the contrary, some other papers find the positive effects of the recent technologies on employment in other contexts (Aghion et al., 2020; Alekseeva et al., 2021; Koch, Manuylov, and Smolka, 2021). Thus, there is little consensus on the causal effects of automated capital on labor demand.

This paper contributes to the literature by using an exogenous variation in capital cost to infer a firm-level causal effect of automation. The literature focuses on exogenous variations in technology adoption. This approach enforces to use a long-run variation because of the gradual change in nature, so the exclusion condition may not be satisfied. This approach makes it hard to distinguish the capital deepening and task displacement effects empirically.

Instead, the policy-driven cost variation makes it possible to have an explicit exclusion condition and to separate the capital deepening and task displacement effects. A firm-level analysis is crucial to capture the automation process. A negative effect of capital adoption on employment at some aggregate level cannot be directly considered labor displacement because there could be a composition effect across industries with different labor shares. The aggregation also contaminates automation effects with industry-specific or location-specific concurrent shocks. This study tries firm-level analysis by constructing firm-level shock based on the unique features of the bonus depreciation policy.

Our paper is also related to the literature estimating the capital-labor substitution elasticity. It is well known that obtaining the elasticity of substitution is difficult because the identification needs exogenous factor price movements (Diamond, McFadden, and Rodriguez, 1978). Some recent papers try to identify the elasticity of substitution by utilizing exogenous variations in long-run movements in the user cost of capital (Chirinko, Fazzari, and Meyer, 2011), the ratio between labor and materials prices (Doraszelski and Jaumandreu, 2018), and local wages (Raval, 2019). The studies on the capital-skill complementarity focus on the heterogeneity in the substitution elasticity and present that production workers are more substitutable with capital than non-production workers (Goldin and Katz, 1998; Krusell et al., 2000; Lindquist, 2005; Lewis, 2011; Curtis et al., 2021; Aum and Shin, 2022). Focusing on the recent technological progress in computer software, Aum and Shin (2022) report that software capital is more substitutable to both production and non-production workers than other types of capital.

We contribute to this literature by estimating the elasticity of substitution across firm and job characteristics with an exogenous variation in the cost of capital in the short run. The unique features of the bonus depreciation policy enable clear identification of the elasticity. Our detailed measures of skills and technologies also make it possible to investigate the heterogeneity in the elasticity in detail beyond the traditional classification of production and non-production workers. Our results provide consistent evidence with Aum and Shin (2022) in the sense that we report less reduction in labor demand for job positions with more software skills, which are more likely complementary to software capital, in response to a reduction in capital cost. On top of that, we also emphasize that the elasticity of substitution is larger for firms with higher technological capability.

3 Institutional Background

Governments worldwide have given businesses a tax incentive for investing in machinery and equipment by deducting the cost of newly purchased machinery and equipment from

their taxable income. However, firms cannot immediately deduct the total cost of newly purchased capital from their taxable income. In the U.S., the Modified Accelerated Cost Recovery System (MACRS) determines the tax deduction schedule for each type of qualified capital. In other words, when a firm buys machinery or equipment, the firm can get the tax deduction for that investment across years following the predetermined depreciation schedule. This policy is called "accelerated depreciation" in the sense that tax deduction is higher during the earlier years and is depreciated afterward.[1]

On top of the accelerated depreciation, "bonus depreciation", or Code Section 168(k) depreciation, allows firms to deduct a bonus percentage of the purchase price of eligible machinery and equipment right in the year it is purchased. So, firms can get the tax deductions much earlier than MACRS originally scheduled. For instance, if the bonus percentage rate is 50%, then a firm can deduct 50% of the purchase price of capital in the year of the purchase regardless of the predetermined schedule by MACRS. The remaining 50% of the purchase price is then deducted from taxable income following the original schedule. The categories of qualified bonus depreciation property by the Internal Revenue Service (IRS) are limited to (1) MACRS property with a depreciation period of 20 years or less, (2) computer software, and (3) Qualified improvement property (improvements to the interior of commercial buildings). To summarize, machinery, equipment, computers, software, and appliances generally qualify.

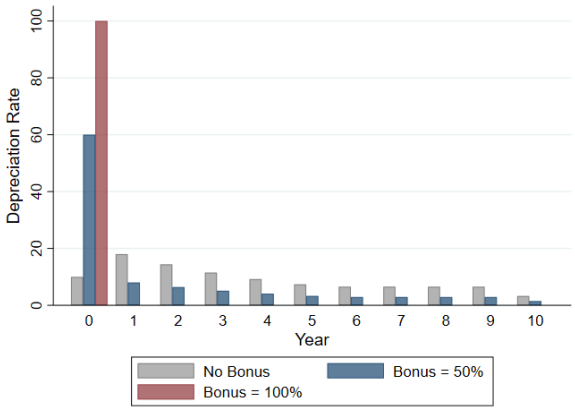
Figure 1a shows an example of the tax deduction schedule for a type of machine across different bonus depreciation rates. Let us say that a firm buys the machine in year 1. Without any bonus depreciation, the schedule of tax deductions follows the grey bars that MACRS predetermines. With 50% of the bonus depreciation rate (blue bars), 50% of the purchase price of the machine is deducted from taxable income in the first year, and the original tax deductions (grey bars) are halved. With a 100% bonus rate (red bar), the full cost of capital is deducted from taxable income in the first year regardless of the MACRS schedule. As shown in Table F.1, every machinery and equipment has its tax deduction schedule, and each industry uses a different set of machinery and equipment. Zwick and Mahon (2017) provides a 4-digit industry-level original tax deduction schedule and the net present value of the tax deductions based on corporate tax return data provided by the Statistics of Income (SOI) division of the IRS. We borrow their industry-level net present value of the original tax deductions to calculate the benefit of the bonus depreciation policy.

Figure 1b shows how the bonus depreciation policy has evolved in the U.S. The U.S. federal government first enacted federal bonus depreciation in 2001 at a rate of 30% by the

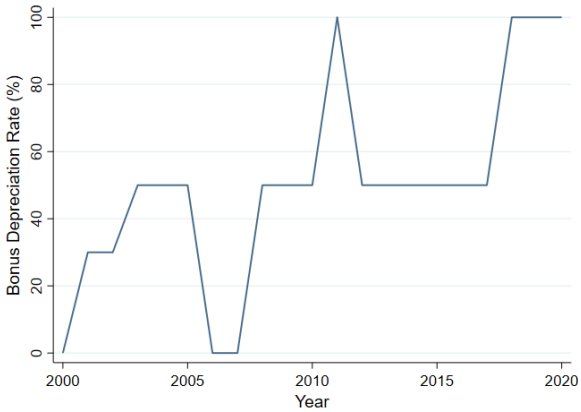
[1] Steinmüller, Thunecke, and Wamser (2019) reports that 41 countries use the accelerated depreciation policy to stimulate investment during 2004-2016.

Figure 1: Bonus Depreciation

(a) Example of Tax Deduction Schedule



(b) Trend in Bonus Depreciation Rate



Notes: Panel (a) shows an example of how bonus depreciation affects the tax deduction schedule for a type of equipment with 10 years of full depreciation. y-axis indicates the share of purchase price of machinery or equipment depreciated for tax deductions and x-axis indicates the year from the puchase. The schedule of tax deductions follows without any bonus rate (grey bars) is predetermined by MACRS. The other schedules are calculated by the Internal Revenue Service (IRS). Panel (b) reports the evolution of U.S. bonus depreciation rate provided by Tax Foundation.

Job Creation and Worker Assistance Act to stimulate the economy during the 2001 recession. The tax incentive was halted after the recession in 2005 until it resumed at the 50% rate in 2008 under the Economic Stimulus Act to counteract the Great Recession. Except for 2011, the bonus rate remained at 50% through 2017. In the third quarter of 2017, President Trump signed the first comprehensive reform of the U.S. tax code, the Tax Cuts and Jobs Act (TCJA). Major elements of the changes include reducing tax rates for businesses: (1) The government reduces the federal statutory corporate tax rate from 35% to 21%, (2) introduces a set of policies to reduce tax evasion of the U.S. multinationals (switch to territorial taxation of multinationals, deemed repatriation tax, etc.), and (3) increases bonus depreciation rate from 50% to 100%.

While any business entity can claim bonus depreciation, it is likely more helpful for large C-corporations because of another federal policy called Section 179 expensing. The Section 179 expensing is equivalent to a 100% bonus depreciation rate, but the tax deduction by Section 179 expensing is phased out above a certain threshold of capital expenditures.[2] It means that the Section 179 deduction is only available for small firms. Because the Section 179 expensing has been implemented since 1997, small firms which have been able to get a

[2]In 2017, the Section 179 deduction limit was $500,000, and the deduction decreases on dollar for dollar basis once total capital expenditure reaches $2,000,000.

tax deduction for the full cost of machinery and equipment immediately by the Section 179 allowance cannot benefit from the increase in bonus depreciation rate by TCJA.[3]

While this study focuses on the 100% bonus depreciation rate among the provisions of TCJA, it is important to clarify the relationship between the bonus depreciation policy and the other provisions of the tax reform for clear identification. First, the reduction in the federal corporate tax rate lowers the effectiveness of bonus depreciation in the sense that bonus depreciation intends to lower taxable income. Simply put, the amount of tax deductions is the multiplication of taxable income and corporate tax rate. However, bonus depreciation still gives a much larger incentive to invest in machinery and equipment than before the tax reform because the increase in bonus depreciation rate is larger than the decrease in the corporate income tax rate. To reflect the change in corporate tax rate along with the change in bonus depreciation rate, we define the effective bonus depreciation rate in Section 5.

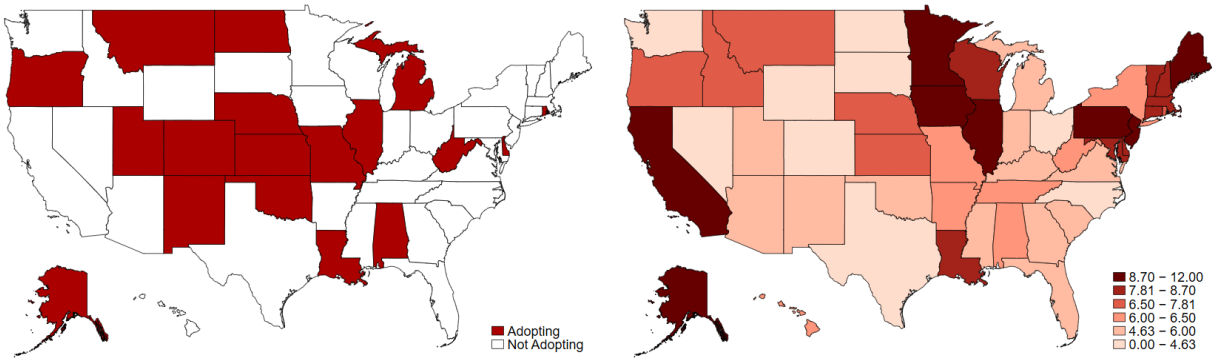
The provisions to reduce tax evasion of U.S. multinationals also could affect a firm's incentive to raise investment and to adjust labor along with bonus depreciation. It is well known that many U.S. multinationals such as Apple and Google reported a portion of their corporate taxes to tax heavens such as Ireland and Luxembourg to reduce their tax burden. The Global Intangible Low Tax Income (GILTI) provision halves the domestic tax rate on repatriated foreign-source income as a one-time incentive to report back their taxes in the U.S. The Base Erosion Anti-Abuse Tax (BEAT) provision imposes a minimum tax of 10% on multinational companies that make "base erosion payments" to foreign related parties. These provisions mean to prevent U.S. multinationals from avoiding domestic tax liability by shifting their profits out of the country.

Despite the other provisions of TCJA might also affect a firm's investment and employment decisions, the actual gains from bonus depreciation can be identified to a reasonably precise extent owing to a couple of features of the policy change. First, the 100% bonus depreciation rate was placed into service right after September 2017, while the other measures are generally effective from January 2018 or later. Some provisions, including capitalization of R%D expenditures, are effective from 2022. If the change in bonus depreciation has distinctive effects on investment and labor demand, the effects should also be captured in late 2017. Second, the provisions of TCJA affect separate items in a firm's tax report. How much a firm gets bonus depreciation can be directly captured by deferred tax liability from its balance sheet. Deferred tax liability reflects the gap between a firm's realized income and the taxable income because of inconsistency in the timing of taxation. So, if a firm gets a

[3]This study focuses on publicly traded firms because of data limitation, and Section 179 expensing and its relationship with bonus depreciation are not in our consideration.

Figure 2: State Bonus Conformity and State Corporate Tax Rates

(a) Conformity to Federal Bonus Depreciation **(b)** State Corporate Income Tax Rate



Notes: In Panel (a), the orange regions are the states pegging their bonus depreciation for state corporate taxation to the federal level in 2017. Conforming states are Alabama, Alaska, Colorado, Delaware, Illinois, Kansas, Louisiana, Michigan, Missouri, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, Oregon, Rhode Island, Utah, West Virginia. No state changed the conformity around during the period of interest. Panel (b) reports state corporate rates in 2017 provided by Tax Foundation.

tax deduction by claiming bonus depreciation, its taxable income declines, and its deferred tax liability should be negative. On the other hand, the provisions to reduce tax evasion should affect nonrecurring income taxes or foreign tax credits just for multinationals. We show that our firm-level measure of effective bonus depreciation only affects deferred tax liability in Section 6.

To construct the firm-level measure of effective bonus depreciation, it is also vital that the effect of bonus depreciation also varies across states though the policy itself is at the federal level. Some states have pegged their bonus depreciation to the federal level for state corporate taxation, while the other states do not allow bonus depreciation. So, the firms more exposed to the states with this policy conformity get a more significant incentive to raise capital investment. Figure 2a reports that 17 states in the continental U.S. conform to the federal bonus depreciation rate. If a state conforms to the federal bonus depreciation policy, then the state's corporate tax rate determines the additional effect of bonus depreciation owing to the conformity to the policy. Figure 2b report that some of the conformed states, such as Illinois and Alabama, also have relatively high state corporate tax rates. Firms that are more exposed to these states should be more affected by the change in bonus depreciation rate if all else is equal. The variations in the effectiveness of bonus depreciation across industries and states make it possible to construct a firm-level measure of the policy effect with the distribution of a firm's establishments across industries and states.

4 Firm Data

This section describes our firm-level data sets and how to combine them to investigate the effects of the change in bonus depreciation on capital investment and labor demand. Our empirical analysis draws on four main data sources: (1) Compustat North America Database; (2) Lightcast Online Job Posting Data; (3) Computer Intelligence Technology Database (CiTDB); and (4) PatentsView Database.

The primary measures of investment outcomes and tax information are derived from Compustat North America Database. Compustat gathers financial statements from firms that are traded publicly in the U.S. and provides a standardized set of income, different types of capital expenditures, employment, tax reports, and supplementary data items quarterly, though some variables are only reported annually. Our period of interest is from 2013 to 2019. We exclude all funds, trusts, and other financial vehicles (NAICS 525) from our sample. Considering that bonus depreciation only affects capital expenditure on machinery and equipment and that different provisions of the TCJA Act affect different items in the tax reports, financial statements from Compustat are valuable to cleanly identify the effect and mechanism of the policy.

A downside of the dataset is that it only covers publicly traded firms. Small, growing firms that do not appear in the dataset may be more likely to face financing constraints than publicly traded firms. On the other hand, they may be less likely to adopt automated machinery and equipment due to technological constraints. By excluding small and private firms, the results could understate or overstate the impact of bonus depreciation on investment and employment at the national level. To supplement our firm-level analysis with the narrowed firms, we also report the parallel results with the Occupational Employment and Wage Statistics (OEWS) in Appendix C.

We construct labor demand measures for years from 2013 to 2019 from the online job posting data of Lightcast, an employment analytic firm. Lightcast is a database of near-universe online job postings in the U.S. and provides detailed information on each job posting, including job title, standard occupation classification (SOC), name, location, and employer industry. More importantly, Lightcast collects detailed skill requirements of each job position, such as education, work experience, and a list of specific skills. The list of skills includes qualitative skills (such as communication skills, teamwork, and quality control) and specific software names (such as Python, Java, SQL, Tensor Flow, ND4J, etc.). Lightcast uses its algorithm to develop a robust skills taxonomy and classify a wide range of skills into several skill groups such as social, cognitive, management, and software skills.

It is worth noting some limitations of online job posting data. First, job vacancies posted

online may not well represent the overall employment distributions. This problem is shared by the other sources of job vacancies, such as the Job Openings and Labor Turnover Survey (JOLTS), and some studies report that job vacancies are skewed toward certain areas of the economy (Davis, Faberman, and Haltiwanger, 2013; Lazear and Spletzer, 2012). However, Lightcast is known to be consistent with these survey-based job vacancies. Hershbein and Kahn (2018) show that the national and industry trends of the number of online job postings from Lightcast closely track those of employment from the Current Population Survey (CPS) and Occupational Employment and Wage Statistics (OEWS), and job vacancies from JOLTS.

Second, the online job postings do not precisely show how the current employment of a firm changes. Posting job vacancies is just one way of adjusting labor inputs and a job vacancy is not necessarily filled. We will use Compustat's employment to investigate a firm's total labor inputs. Regarding the composition of labor inputs across skills and tasks, we assume that the composition change in employment comoves with that in online job vacancies. Thus, we utilize the job posting data to investigate the composition of a firm's skills and tasks rather than the total employment level.

Unfortunately, there is no simple way to link Compustat and Lightcast because there is no common firm identifier between the two datasets. Moreover, many firm names in the job posting data contain abbreviations or misspellings. For instance, a firm name "Micron Technology" can be expressed as "Micron," "Micron Tech," "Micron Incorporation," or "Micron Technology, Inc." in the job posting data. We use a fuzzy matching algorithm and employ another proprietary database called the Computer Intelligence Technology Database (CiTDB) to overcome this problem. CiTDB covers 3.2 million establishments since 2010 and provides a firm structure and address of each establishment. Specifically, there is a unique firm ID, and one can identify a firm's headquarters and branches and their addresses.

To link the firms in Compustat and the establishments from Lightcast, we first standardize their names using the algorithm provided by Wasi and Flaaen (2015). As an additional input for matching, we also construct a measure of industry linkage based on the input-output table. And then, we link Compustat and Lightcast using a fuzzy match based on the standardized names and industry linkage. Lastly, we compare the name and address of a matched establishment from Lightcast and that from CiTDB to ensure that the matched establishment is a branch of the matched firm from Compustat.[4] The detailed procedure of firm matching is described in Appendix A.

We also need to capture a firm's capability of automation to ensure that the effect of capital investment on labor demand is affected by automation. For doing this, we employ the

[4]It is computationally intractable to directly match the establishments from Lightcast and those from CiTDB.

PatentsView Database. It is a public database including all patents issued by the US Patent Trademark Office (USPTO) from 1975. The database provides a patent's title, description, inventor, assignee, classification, etc. Patents have long been used as a proxy for a firm's innovative activity and technology level. A growing number of papers recently utilize texts in patent titles and descriptions to investigate qualitative aspects of technology and innovation (Whalen et al., 2020; Dechezleprêtre et al., 2021; Kelly et al., 2021; Kogan et al., 2021; Mann and Püttmann, 2021). Kogan et al. (2021) show that the technological level in a field represented by the number of related patents is negatively associated with worse labor market outcomes for incumbent workers performing related tasks. Similarly, we hypothesize that a firm with technological constraints cannot adopt automated machinery even if the bonus depreciation policy lowers the cost of capital.

We specifically focus on robot-related patents as a proxy for a firm's technological capability of automation. The literature considers AIs and robots as the archetypes of recent automation technology. However, robots are much more affected by bonus depreciation than AIs because robots have much longer depreciation schedules than computers or software. To construct firm-level robot-related patents, we first collect the patents having the lemmas[5] "robot" and "manipulator" (an obsolete word for robot) in the title or abstract among all utility patents from 1975 to 2019 (P_1). Then we collect all patents of the inventors of P_1 (P_2). Using a neural network-based model on titles and abstracts of all patents, we construct a semantic distance between each pair of all patents. For each $p \in P_2$, we collect the patents closer than the 10th percentile in terms of semantic distance (P_3).[6] We call the patent set P_3 as the robot-related patents.

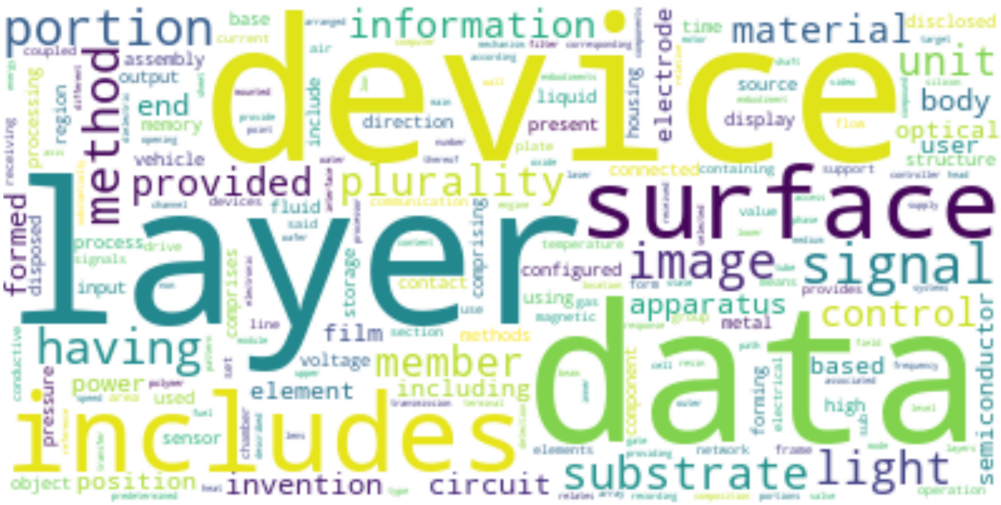
The key idea of this approach is that the inventors collected by the keyword searching use the other important keywords related to robots in all of their patents. This procedure is advantageous because we do not need to know expert knowledge on the field of interest or rely on a suspicious supervised algorithm. Rather, we depend on the experts' words and the semantic network of all published patents. Appendix B describes the detailed algorithm of patent classification. Figure 3 visualizes the keywords of the collected robot-related patents. The size of a word represents that word's importance in the patents' descriptions. "Device," "Layer," and "Data" are the main keywords of these patents. The top companies in the publication of the robot-related patents reported in Figure F.4 also indicate that the patent classification captures the common knowledge on technological capability for automation.

Table 1 reports summary statistics of the main variables for the matched sample of firms

[5] A lemma is the canonical form of a set of words or the headword in morphological analysis. For instance, "see" is the lemma for "saw", "seeing", and "seen". For simplicity, we also use "word" for lemma.

[6] The results are robust to the threshold of semantic distance for robot-related patents.

Figure 3: Keywords of Robot-related Patents



Notes: Token size is proportional to the value of information criterion called term frequency-inverse document frequenc (TF-IDF). Appendix B provides the detailed procedure to extract the keywords of robot-related patents.

before and after TCJA. The federal corporate tax rate and bonus depreciation rate are defined at the national level for each period and reflect the changes made by the tax reform. A comparison between the number of job postings and employment indicates that the sample firms hire a large portion of workers from online platforms. The financial information collected from Compustat shows that the sample firms are large in size, but the size highly varies within the sample. So, we normalize the dollar-dominated outcome variables by sales in the previous period in our main analysis.

5 Empirical Strategy

We utilize the change in bonus depreciation rate by TCJA as an exogenous variation in capital cost to investigate the causal effect of capital investment on labor demand across skills. Specifically, our research strategy compares the outcomes across firms that differentially benefited from the policy. In this section, we describe our firm-level policy shock and event-study framework.

Following the classical model of capital demand from Hall and Jorgenson (1967), we express the cost of capital in industry i at state s as:

$$R_{is} = \frac{1 - \alpha_i(\tau_{fed} + 1_s\tau_s)}{1 - (\tau_{fed} + \tau_s)}(r + \delta) \tag{1}$$

Table 1: Summary Table for Matched Firms

	Before TCJA			After TCJA		
	N	Mean	SD	N	Mean	SD
Federal Corporate Tax Rate	16,738	35.00	0.00	5,707	21.00	0.00
State Corporate Tax Rate	16,738	6.44	2.12	5,707	6.40	2.18
Bonus Depreciation Rate	16,738	50.00	0.00	5,707	100.00	0.00
Number of Job Postings	16,738	1,330	6,908	5,707	1,656	7,435
Employment	16,738	9,641	50,021	5,707	11,427	54,104
Sales (in M$)	16,738	3,708	16,085	5,707	4,751	19,261
Deferred Tax Liability (in M$)	16,738	514.8	2,686	5,707	599.0	12,273
Capital Expenditure (in M$)	16,738	277.3	1,351	5,707	295.8	1,255
Machinery and Equip. at Cost (in M$)	16,738	533.6	2,756	5,707	616.6	3,433
Leases at Cost (in M$)	16,738	50.66	373.5	5,707	125.0	795.3
Construction at Cost (in M$)	16,738	40.09	325.9	5,707	48.41	395.2
Natural Resources at Cost (in M$)	16,738	2.744	78.60	5,707	3.638	103.6
Other at Cost (in M$)	16,738	34.96	338.7	5,707	43.62	367.7
R&D Expenditure (in M$)	16,738	91.64	620.8	5,707	117.5	745.9
Number of Patents	16,738	266.8	2372.0	5,707	364.0	3211.0
Number of Robot Patents	16,738	38.68	374.2	5,707	52.56	504.6

Notes: The observations are at firm-by-year. The left-hand side of the table provides summary statistics for the matched firms before the tax reform (2013-2017), while the right-hand side provides those after the tax reform (2018-2019). Dollar values are deflated in 2017. Federal corporate tax rate and bonus depreciation rate are defined at national level for each period and state corporate tax rate for a firm is the weighted average across the firm's establishments.

where α_i is the present value of tax deduction schedule on one dollar of capital investment for industry i with bonus depreciation, r is the interest rate, δ is the capital depreciation rate, τ_{fed} is the federal corporate tax rate, τ_s is the state corporate tax rate in s, and 1_s is the indicator of conformity of state s to the bonus depreciation policy. The right-hand side is corresponding to the marginal cost of capital services in the first-order condition in a firm's maximization problem and the only difference from the usual user cost equation is tax deductions, here α_i times the corporate taxes.

The present value of tax deduction schedule on one dollar of capital investment with bonus depreciation is determined by bonus depreciation rate, θ, and the present value of tax deduction schedule without bonus depreciation, z_i, which is predetermined by MACRS:

$$\alpha_i = \theta + (1-\theta)z_i = \theta + (1-\theta)\left[D_{i0} + \sum_{t=1}^{T_i} \frac{D_{it}}{(1+r)^t}\right] \tag{2}$$

where D_{it} indicates the portion of tax deduction in year t after the purchase of capital and

T_i is the last period of the tax deduction schedule. $\{D_{it}, T_i\}$ determines the average present value of original tax deductions without bonus rate for machinery and equipment used in industry i, and it varies across 4-digit industries. We use 7% of interest rate to calculate z_i following the literature.[7] If industry a has a longer depreciation schedule than industry b on average, industry a benefits more from tax deductions per dollar of capital purchase and has lower z_i ($z_a < z_b$). Note that the bonus depreciation rate changes from 50% to 100% by TCJA so that α_i equals 1 for any industry after the tax reform. However, there is a heterogeneity in α_i before the tax reform ($\alpha_i = (1 + z_i)/2$) and $\Delta\alpha_i$ also varies across industries.

After the taxable income is determined by α_i, the corporate tax rate determines the effective rate of tax deduction $(1 - \alpha_i(\tau_{fed} + 1_s\tau_s))$. If state s conforms to the federal bonus depreciation policy ($1_s = 1$), the state corporate tax rate is also subject to the tax deduction. Suppose the state does not conform to the policy ($1_s = 0$). Then, only the federal corporate tax rate matters for bonus depreciation. Since the federal corporate tax rate also changes from 35% to 21% by TCJA, we also need to take into account this change to construct the measure of policy shock. To summarize, the reduction in taxable income by bonus depreciation varies across industries, and the corporate tax rate applying to the discounted taxable income varies across states.

From equation (1), the effect of bonus depreciation on the cost of capital in industry i at state s can be approximated as:

$$\frac{\partial \log R_{is}}{\partial \theta} \simeq -(1 - z_i)(\tau_{fed} + 1_s\tau_s) < 0. \tag{3}$$

The first parenthesis on the right-hand side reflects the industry-level variation in the tax deduction schedule by MACRS. When the bonus depreciation rate increases, the capital cost decreases more for the industries with a more extended schedule for tax deductions (lower z_i). The second parenthesis indicates the state-level variation in the corporate tax rate, and the cost of capital decreases more in the states with higher state tax rates and with the bonus conformity simultaneously.

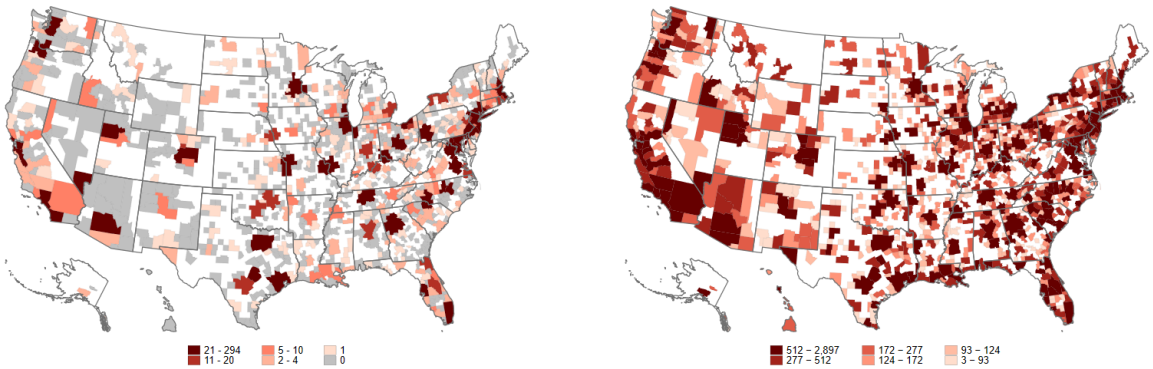
The publicly traded firms in our data set have multiple establishments across states, which could also be in different industries. It matters for corporate taxation because the U.S. state governments levy corporate taxes from a firm based on its employment, asset, and sales across states following tax apportionment rules, which estimate the corporation's economic activity share across states.[8] Figure 4 presents the location distributions of the firms in our

[7] Considering that the estimation sample includes just publicly traded firms, the potential disparity in r will not affect z_i much.

[8] Each state has its own apportionment rule and mostly puts different weights on three factors: payroll,

Figure 4: Location Distribution of Matched Firms

(a) Headquarters **(b)** Branches



Notes: Panel (a) reports the distribution of the headquarters of the U.S. publicly traded firms across core-based statistical areas (CBSAs). The white regions are rural areas that are not defined as a CBSA and the grey regions indicate the CBSAs with no headquarters. Panel (b) indicates the distribution of their establishments. The locations of the headquarters are based on the CBSA code from Compustat and those of the establishments are based on the CBSA code from Lightcast.

data set across core-based statistical areas (CBSAs). The headquarters concentrate in certain regions, such as California and the West Coast, and there are also many CBSAs with no headquarters, denoted by the grey regions. On the contrary, Figure 4b shows that branches are well dispersed across CBSAs with few grey areas, meaning that the effect of bonus depreciation change would not be driven by the concentration of the sample establishments in specific states.

Combining the distribution of a firm's establishments across states and industries and the effect of bonus depreciation on capital cost in equation (3), we define the effective bonus depreciation rate for a firm f in year t by:

$$bonus_{ft} = \left[\sum_{e \in E_f} \omega_e (1 - z_{i(e)})(\tau_{fed,t} + 1_{s(e)t}\tau_{s(e)t}) \right] \theta_t \tag{4}$$

where E_f represents the set of establishments of firm f and ω_e is the weight of establishment $e \in E_f$ within f. We use the share of job postings from e among the total number of job postings of f during the year before the tax reform as the weight. The number of job postings is the unique proxy in our data set to measure the shares of an establishment's economic activity, but it corresponds well to the basic idea of the tax apportionment rule to capture where a firm produces goods and services. The effect of bonus depreciation rate

property value, and sales.

on capital cost for industry i in state s is from equation (3). Subscript $i(e)$ corresponds to the 4-digit NAICS industry code of e and subscript $s(e)$ indicates the state where e locates. To summarize, we take the weighted average of the effect of the bonus depreciation rate on capital cost over the establishments of a firm and multiply it by the bonus depreciation rate in that year. Thus, this measure captures the effective bonus depreciation rate based on the distribution of a firm's establishments. Figure F.1 displays how the distribution of the effective bonus depreciation changes after TCJA. It increases by 15% after the tax reform, but the change amount highly varies across firms.

Then, the main specification of a firm-level event study takes the form of:

$$y_{ft} = \alpha_f + \delta_t + \sum_{k=2013Q1, k\neq 2017Q3}^{2019Q4} \beta_k \Delta bonus_f \cdot 1[t=k] + \gamma' X_{ft} + \epsilon_{ft} \tag{5}$$

where y_{ft} is an outcome such as logs or inverse hyperbolic sine transformations of investment and employment, α_f are firm fixed effects, δ_t are calendar quarter or year fixed effects, and X_{ft} is a time-varying set of controls that vary across specifications. $\Delta bonus_f$ is the change in the effective bonus depreciation rate by TCJA, and $1[t=k]$ is the indicator of each period k relative to the third quarter of 2017 when the tax reform was approved. We also divide $\Delta bonus_f$ by its average so that β_k can be interpreted as the average effect of the policy change. β_k captures the dynamic effects of the change in the effective bonus depreciation relative to the third quarter of 2017. We use the quarterly specification when the data is available to clearly show the timing of the effects, but difference-in-difference estimates in the results tables are based on the parallel annualized version to reduce measurement errors.

The identifying assumption to interpret β_k as the average treatment effect (ATE) is that the potential outcomes without the tax reform must be parallel for more-affected and less-affected firms by the change in bonus depreciation. In other words, the change in bonus rate must be orthogonal to the other unobservable shocks after controlling for the fixed effects and the covariates, and there must be no anticipatory effects. The parallel trends assumption is likely to hold for several reasons. First, the differences in z_i are predetermined by the federal tax system and are largely arbitrary because the depreciation schedule of specific equipment or machinery is determined not by its nature but by its use (Curtis et al., 2021). Second, the state-level conformity to the federal bonus depreciation has long been stable before the tax reform, and no state has changed its bonus depreciation conformity after the tax reform. Thus, it is not likely that a state's time-varying unobserved characteristics correlated with investment and employment affect bonus conformity. Third, the law passed so quickly that firms could not respond to the policy in advance (Wagner, Zeckhauser, and Ziegler, 2020).

Still, there could be other trends during the period that may correlate with the change in the effective bonus depreciation rate. To alleviate this concern, we report several robustness checks in Section 6.5.

It may be better to interpret the estimated β_k as intent-to-treat (ITT) in the sense that $\Delta bonus_f$ measures the exposure to the policy change based on the location and industry distributions of a firm's establishments before the policy change rather than its realized tax deduction by the change in effective bonus depreciation rate. However, even if one can observe the realized tax deduction, it is partially determined by capital expenditure on machinery and equipment. So, the estimated effect of tax deduction should be endogenous. The ideal way to identify the ATE of the change in the effective bonus rate would be using $\Delta bonus_f$ as an instrument for the realized tax deduction. While we cannot directly observe the realized tax deduction by bonus depreciation, the deferred tax liability can be used as a proxy for the tax deduction. Deferred tax liability reflects the gap between a firm's realized income and the taxable income because of inconsistency in the timing of taxation. So, if a firm gets tax deductions by bonus depreciation, the taxable income declines, and the deferred tax liability also goes down. We report the IV estimation results where $\Delta bonus_f$ is used as an instrument for deferred tax liability in Section 6.4.

6 Empirical Results

In this section, we report the estimates of the effects of the change in bonus depreciation on capital investment and labor demand. We find that the increase in the effective bonus depreciation rate by TCJA makes firms raise capital investment and reduce employment. The increase in bonus depreciation only raises the eligible capital expenditure on machinery and equipment. To see how firms change labor demand across tasks and skills, we also investigate the effect of the policy on the number of job postings by skill group. We find that the decrease in labor demand concentrates on job positions requiring few software skill levels among various skill measures. These capital investment and labor demand responses are driven by the firms having high automation technologies proxied by robot-related patents. Based on these results, we argue that the firm-level responses to the change in the effective bonus depreciation result from adopting automation technologies.

6.1 Firm-level Capital Investment Response

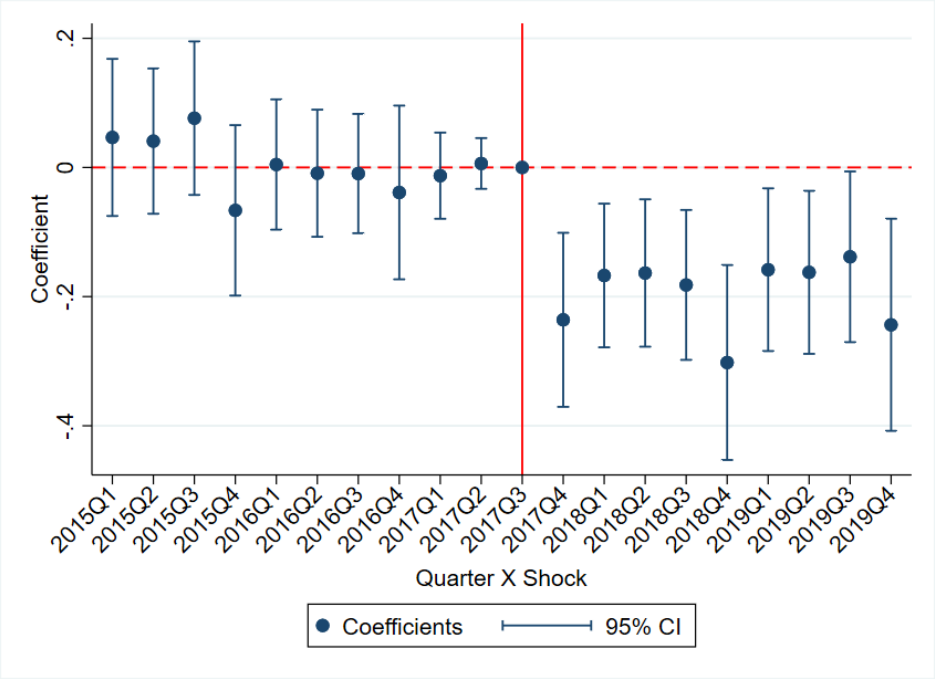
We begin by reporting the effect of the increase in the effective bonus depreciation on deferred tax liability (DTL). This result is the first-stage evidence in the sense that DTL mechanically

decreases when a firm gets tax deductions by claiming bonus depreciation. Specifically, DTL records taxes that are owed but are not due to be paid until a future date. It occurs due to a difference in timing between when the tax was accrued and when it is due to be paid. When a firm purchase capital, the purchase price is deducted from the firm's taxable income across years following the predetermined depreciation schedule, which generates the timing difference of taxation. If a firm gets tax deductions by bonus depreciation, its taxable income and DTL decline. DTL is merely an accounting rule to make financial statements consistent, but it hints at how much a firm benefits from the bonus depreciation.

Table F.2 presents an example of the change in deferred tax liability in response to the change in the bonus depreciation schedule. Consider a type of equipment or machinery with a purchase price of $1,000 and a capital depreciation rate of 10% across ten years. For simplicity, suppose a 30% of the corporate tax rate. Then, $100 is counted as the cost of capital in the financial statements each year. Consider a straight-line depreciation method (column 4 in Table F.2) as an investment stimulus, which allows tax deductions for 20% of the purchase price for five years. By this rule, $60 is deducted from its taxable income each year during the five years, while only $30 should be deducted according to the accounting depreciation on the income statement. So, this gap ($30 - $60 = -$30) is recorded as DTL to make the calculation consistent. The gap in each year is accumulated as DTL until the accelerating depreciation ends (year 5), and then DTL increases by the same rate ($30 per year) until the capital is fully depreciated. Now consider the 100% bonus depreciation rate (column 6 in Table F.2). Then, the full cost of capital ($1,000) is deducted from the firm's taxable income in the year of purchase, and $270 (0.3×($100 - $1,000)=-$270) is recorded as DTL. So, the DTL of the 100% bonus depreciation rate is lower than that of the straight-line depreciation method until the fourth year, and they are the same afterward. This example shows that bonus depreciation mechanically lowers DTL for accounting purposes.

Figure 5 presents event study coefficients depicting the effect of the change in bonus depreciation on the log of DTL. Note that the coefficients can be interpreted as the average effect because $\Delta bonus_f$ in equation (5) is normalized by the average value. The figure shows that DTL declines about 17.4% on average by the bonus depreciation change right after the third quarter of 2017 when the TCJA was approved. It means that firms more affected by the increase in bonus depreciation rate experience larger cuts in their taxable income and deferred tax liability. Considering that the tax reform raises the effective bonus depreciation rate by 15% as shown in Table 1, the elasticity of DTL with respect to the bonus depreciation rate is around -1.16. Note that the bonus depreciation rate and the amount of capital expenditure determine the DTL change. The elasticity lower than -1 indicates that capital expenditure also changes in a way that DTL decreases more than the bonus

Figure 5: Dynamic Firm-level Response of Deferred Tax Liabilities (DTL)



Notes: The figure shows the dynamic response of the log of net deferred tax liabilities via the model of equation (5). The base period (2017Q3) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013Q1 to 2019Q4. Standard errors are clustered at the firm level and the confidence intervals are at 95% level.

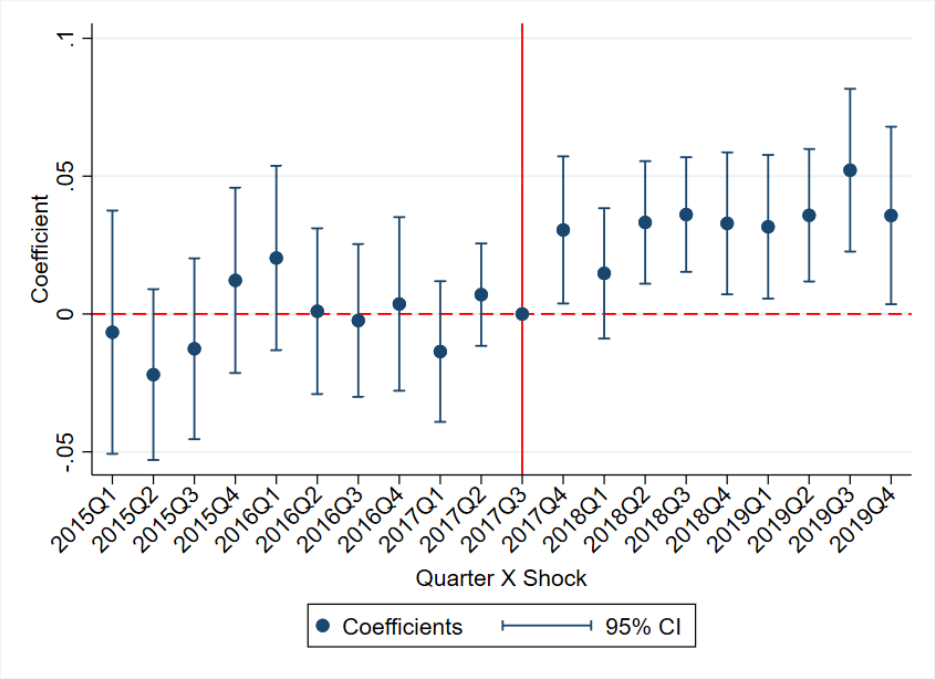
depreciation rate changes.[9] The lack of a pre-trend in the event study graph assures that the effect of the bonus depreciation change is not driven by preexisting differentials between more-affected and less-affected firms by the policy shock.

We move on to investigate the effect of the change in bonus depreciation on capital expenditure. We adjust capital expenditure by dividing it by sales in the previous period to take firm size into account. Since investment data can include spells of non-investment, we also take the inverse hyperbolic sine of the adjusted capital expenditure (i.e. $\ln\left(x + \sqrt{x^2+1}\right)$).[10] So, this outcome variable reflects both intensive and extensive margins of capital expenditure. Figure 6 shows that capital expenditure increases about 3.5% on average by the increase in bonus depreciation rate right after the tax reform, and the effect persists until the end of the period of interest. This result indicates that a firm more affected by the

[9] If a firm purchases the exact same set of capital and the capital prices do not change, then the elasticity should be -1.

[10] The inverse hyperbolic sine of a variable has similar values to that variable's log, but it can also be defined at zero. We also take the inverse hyperbolic sine of outcomes rather than taking a log whenever zero values are meaningful.

Figure 6: Dynamic Firm-level Response of Capital Expenditure



Notes: The figure shows the dynamic response of capital expenditure (CAPX) via the model of equation (5). The base period (2017Q3) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013Q1 to 2019Q4. Standard errors are clustered at firm level and the confidence intervals are at 95% level.

change in bonus depreciation raises capital investment more and confirms that the bonus depreciation policy is effective as an investment stimulus, which is also consistent with the findings of previous studies (House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2019; Curtis et al., 2021).[11]

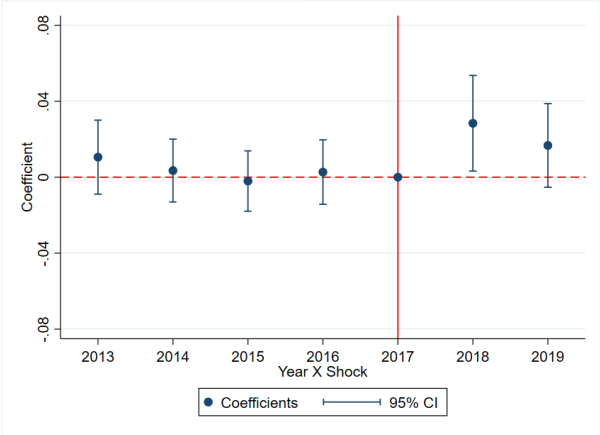
Note that only investment in machinery and equipment is eligible for the bonus depreciation policy. To see if the increase in capital investment is truly the response to the bonus depreciation, we investigate the effects of the policy change on different types of capital expenditures: Machinery and equipment at cost (FATE), Property, plant, and equipment leases at cost (FATL), Construction in progress at cost (FATB), and Other at cost (FATO).[12] We report the results at the annual level because these variables are not reported at the quarterly level. Figure 7a shows that the change in bonus depreciation raises capital expenditure on machinery and equipment as the policy intended. On the contrary, capital expenditure on equipment leases rises in 2018 but sharply declines in 2019 by the policy shock, as shown

[11]These papers focus on the periods from 2000 to 2011 when the bonus depreciation policy was temporarily implemented to counteract the recessions in 2001 and 2007.

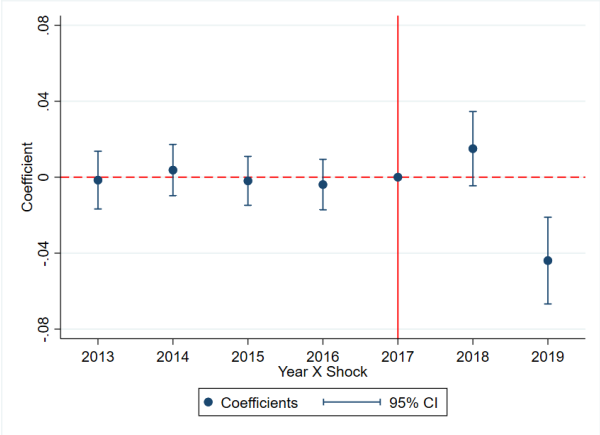
[12]We adjust the values by sales in the previous period and take the inverse hyperbolic sines of them.

Figure 7: Dynamic Firm-level Response of Different Types of Capital Expenditure

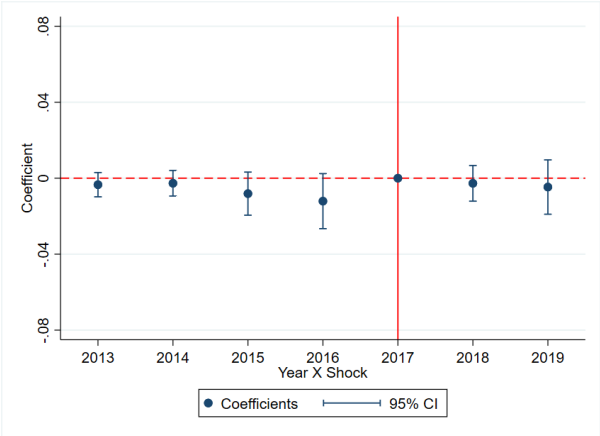
(a) Equipment & Machinery



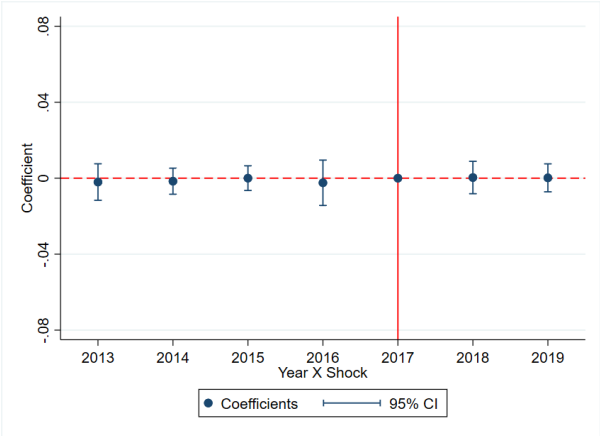
(b) Equipment & Machinery Lease



(c) Construction in Progress



(d) Other Costs

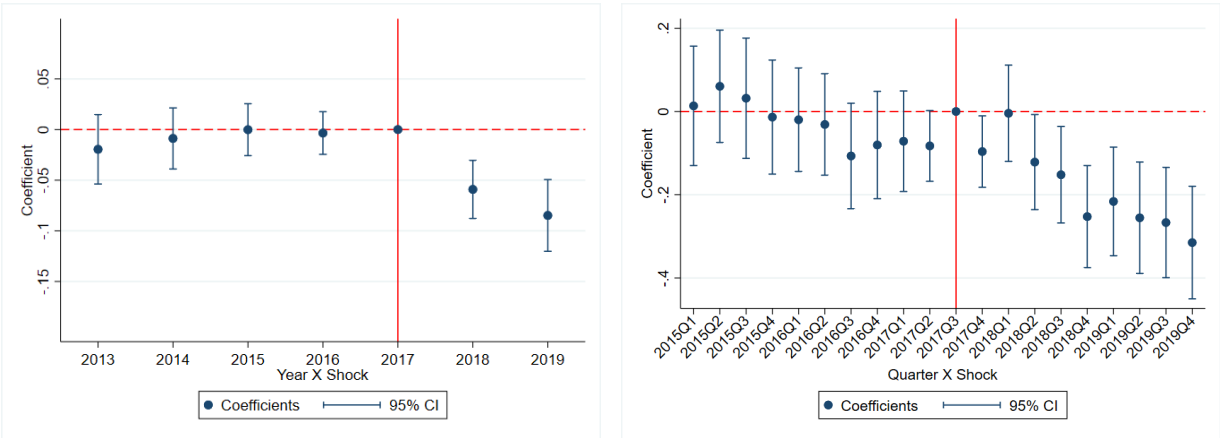


Notes: The figure shows the dynamic response of different types of capital expenditure at cost via the annualized version of the model of equation (5) because the outcome variables are reported only at yearly basis. The outcome variables are from Compustat (FATE, FATL, FATB, and FACO). The base year (2017) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013 to 2019. Standard errors are clustered at firm level and the confidence intervals are at 95% level.

in Figure 7b. This response is reasonable because some machinery and equipment could become affordable or more cost-effective with the tax deductions for some firms that previously leased the capital. The muted responses of construction in progress at cost (Figure 7c) and other expenses at cost (Figure 7d) make sure that the change in bonus depreciation only affects investment in the eligible capital of the policy and that the identification strategy works well to capture the causal effects of the policy.

Figure 8: Dynamic Firm-level Response of Labor Demand

(a) Employment **(b)** Number of Job Postings



Notes: The panel (a) shows the dynamic response of employment via the annualized version of the model of equation (5) because the outcome variable is reported only at yearly basis. The panel (b) shows the dynamic response of the number of online job postings via the model of equation (5). The base periods (2017Q3 in panel (a) and 2017 in panel (b)) correspond to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013 to 2019 in panel (a) and from 2013Q1 to 2019Q4 in panel (b). Standard errors are clustered at firm level and the confidence intervals are at 95% level.

6.2 Firm-level Labor Demand Response

The results in the previous subsection show that firms more affected by the increase in bonus depreciation rate raise capital investment in machinery and equipment more. Now we turn to the effect of the policy on firm-level labor demand. First, we investigate how much the policy affects employment and the number of online job postings. The number of online job postings directly reflects a firm's labor demand. The results of this analysis will answer whether the increased machinery and equipment displace workers by automation or raise labor demand as complementary factor inputs. Second, leveraging detailed information on skill requirements in the job posting data, we analyze a firm's labor composition change in response to the investment stimulus. This analysis shows how different types of workers are affected by the investment stimulus and the adoption of automated capital.

Figure 8a describes how the increase in the bonus depreciation rate affects firm-level employment after the enactment of the reform. The event study design is the annualized version of equation (5) and the outcome variable is the log of annual employment because employment is not reported quarterly in Compustat. The figure shows that employment decreases by about 6.7% on average in response to the change in bonus depreciation after the tax reform. In Figure 8b, we can also see that the number of online job postings

decreases by about 16.3% on average by the change in bonus depreciation. The absence of pre-trends in both figures indicates that the parallel trend assumption is valid. These results are consistent with the argument that the firms more affected by the reduction in capital cost replace workers with machinery.

Note that employment and online job postings come from different data sources. So, their similar patterns indicate that the two data sets are well matched. This consistency is essential considering that we use the fuzzy matching method depending just on a firm's name and industry. The more significant effect on the number of job postings is also reasonable because employment is a stock variable, while the number of job postings is a flow variable. Plus, firms do not necessarily fill all the posted vacancies. As a measure of the labor force, employment is more reasonable than the number of job postings. Still, the results of online job postings give additional information on a firm's behavior. First, the similar patterns between employment and job postings indicate that the changes in employment by bonus depreciation are mainly driven by labor demand shocks rather than labor supply shocks. Second, we can observe how a firm's skill and task compositions respond to the reduction in capital cost by investigating detailed skill requirements in the job posting data. So, we utilize the job posting data to investigate the composition of skills and tasks rather than the level of labor input.

Now we investigate the effect of the policy change on a firm's labor demand across skill groups. Analyzing skill demand is vital in the literature on automation because automation technologies are considered to facilitate replacing workers for specific skills and tasks with capital rather than all types of jobs. For instance, Autor, Levy, and Murnane (2003) argue that computerization makes capital substitutes for workers in performing routine tasks and Acemoglu, Lelarge, and Restrepo (2020) find that manufacturing firms adopting robot technologies reduce the share of production workers.

To identify what factors drive the heterogeneous response of labor demand to the increase in bonus depreciation, it is crucial to capture what tasks a job position does or what skills it has. Most of the previous papers on automation use occupation-level skill and task measures, for instance, from O*NET or the Dictionary of Occupational Titles (DOT). The implicit assumption behind these papers is that skills and tasks are mostly homogeneous within the same occupation code. However, some recent studies find that this is not the case. Autor and Handel (2013) provides evidence that job tasks hugely differ among workers within the same occupation and that this within-occupation variation is a crucial determinant of earnings. Using online job vacancy data, Marinescu and Wolthoff (2019) also report substantial heterogeneity in job titles and applicants within an occupation code. Hunt and Nunn (2022) find that the artificial way of occupation code reclassification mechanically

generates job polarization patterns found in the previous literature.

This heterogeneity of tasks and skills within an occupation results from the fact that occupation classification is much more ambiguous than product or industry classification. It is hard to identify the input and output of a specific job position in many cases. We may be able to define an occupation as a set of specific tasks and skills. However, there is no consensus and firms label the same job position with different job titles. Our idea on this issue is that tasks and skill requirements are much more homogeneous for a job title within a firm than across firms because the set of tasks and skills for a job position is determined in the context of the firm's production function. Thus, it would be more reasonable to classify job titles by skill level within a firm.

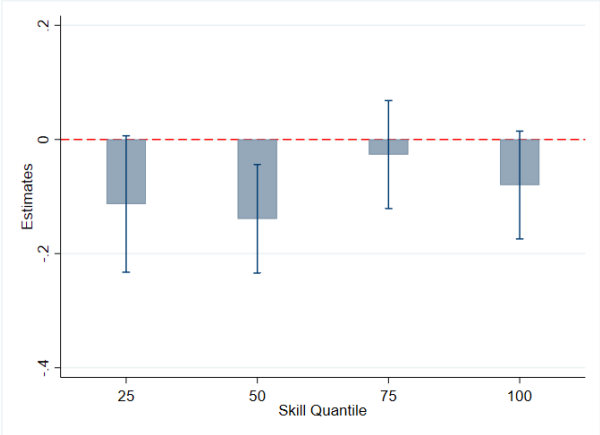
Figure F.2 presents the variances of skill requirements (schooling year, experience year, the numbers of any skills, software skills, cognitive skills, and social skills) from the job posting data within occupation (red histograms) and within firm-by-occupation (blue histograms) during 2013-2019. The values are demeaned, and zero indicates the average skill level within an occupation or a firm-by-occupation. For instance, the required schooling year is highly dispersed and left-skewed within an occupation, as shown in panel (a), which means that the job postings in the same occupation code require quite different schooling years across firms. On the contrary, the blue histogram in the same panel shows that the job postings in the same firm-by-occupation mostly require the same schooling year. The variance of schooling year within a firm-by-occupation is 36% of the variance within an occupation. The ratio of the variances is similar across skill measures, and job postings in the same firm-by-occupation mostly require the same skill levels. These results imply that firms use the same job title for positions with similar skills and tasks, even at different establishments. Thus, we define an occupation in a firm as a **job position** and classify them into quartiles for each skill measure based on the skill level within the firm before TCJA.

We report the difference-in-difference effect of the bonus depreciation change on the number of job postings by the skill quartiles in Figure 9. Panels (a) and (b) report the heterogeneous effects of bonus depreciation change on the number of job postings across the classical skill measures: schooling year and experience year. In general, the number of job postings more decreases for low-skilled positions by the change in bonus depreciation, but there is no clear and monotonic pattern. This means that the classical skill levels are not primary concerns when a firm changes labor demand in response to the reduction in capital cost.

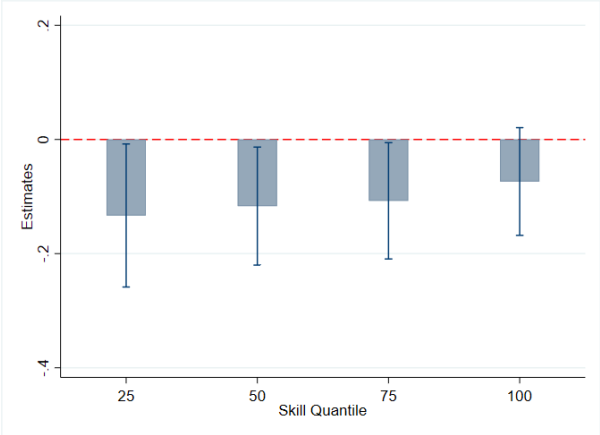
Panels (c) and (d) report the parallel estimates across the number of any skills and the number of software skills. In panel (c), we can see a slightly increasing pattern in the estimated effect as the number of any skills increases. There is a clearer pattern when we classify the jobs based on software skills among all skill requirements. The number of job

Figure 9: Firm-level Response of Job Postings across Skill Levels

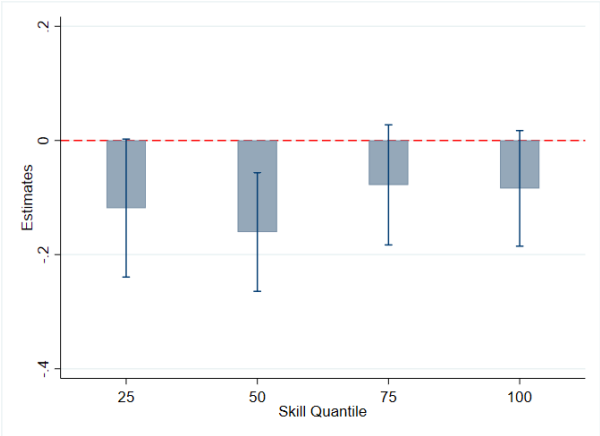
(a) Schooling Years



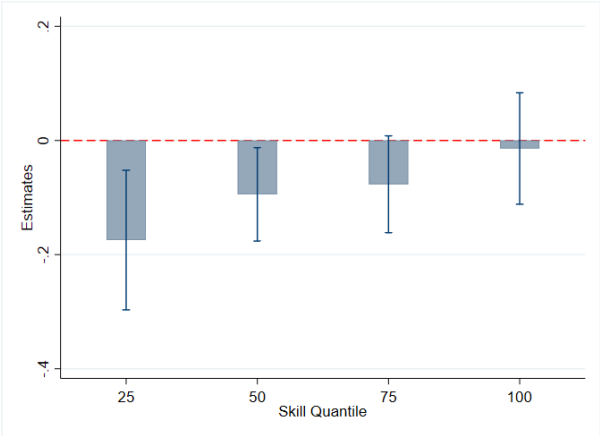
(b) Experience Years



(c) Number of Skills



(d) Number of Software Skills



Notes: Each figure shows the difference-in-difference estimates of the number of job postings across skill groups based on a skill measure. For each skill measure, we calculate the average skill level of a job (firm-by-occupation pair) before the tax reform and classify the jobs into quartiles based on the relative skill level within the firm and aggregate them at firm-skill group-quarter level. The point estimates are the coefficients of $\Delta bonus_f \cdot 1[t > 2017Q3]$ in the difference-in-difference version of equation (5). Standard errors are clustered at firm level and the confidence intervals are at 95% level.

postings in the first quartile of software skill level declines 18% in response to the increase in bonus depreciation rate, and the policy effect monotonically increases as the software skill level increases. We also check the parallel estimates with different types of skills such as cognitive, social, and management skills, but they do not show any clear and monotonic pattern as shown in Figure F.3. Table F.3 reports the difference-in-difference effect of the bonus depreciation change on average skill requirements within a firm. The software skill level is the only skill measure that experiences upskilling in response to the policy change.

Thus, the results indicate that the firms more affected by the change in bonus depreciation downsize job positions requiring fewer software skills.

6.3 Mechanism: Automation

So far, we present that firms more affected by the increase in bonus depreciation rate disproportionately raise capital expenditure on machinery and equipment and reduce employment, especially for job positions requiring few software skills. However, the previous results do not show whether these responses are related to automation. In this section, we investigate the heterogeneity in the policy effects by a firm's technology level. The literature on automation argues that firms with technological constraints cannot adopt capital to automate tasks performed by workers even if a policy change lowers the cost of capital (Acemoglu and Restrepo, 2020). If we find a sharper decrease in labor demand in response to the policy change for firms with higher automation technologies, that would be evidence that the bonus depreciation policy lowers labor demand through the automation process.

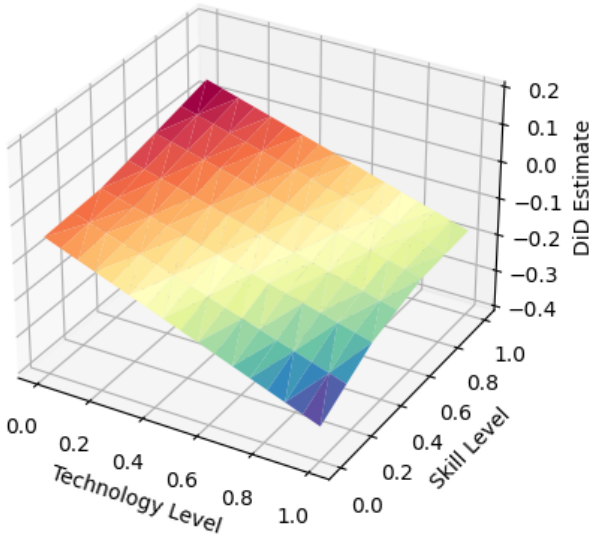
For doing this, we focus on a firm's adoption of robot technologies. Why do robots matter? The literature considers AIs and robots as the archetypes of recent automation technology. At the same time, robots are much more affected by bonus depreciation because robots have much longer depreciation schedules than computers or software. To capture the level of automation technologies, we collect robot-related patents of each firm using a neural-network-based NLP algorithm as explained in Section B since patents have long been used as a proxy for a firm's technology level in the literature. Figure F.4 presents top 20 U.S. firms in the number of robot-related patents. The fact that IBM has the largest number of robot patents indicates that the NLP-based classification of patents works well. The figure also shows that robot-related patents are not solely concentrated in specific industries.

Table 2: Difference-in-Difference Estimates of Main Outcomes by Robot Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(Capx)	Log(Emp)	Log(Post)	Log(Post_{Q1})	Log(Post_{Q2})	Log(Post_{Q3})	Log(Post_{Q4})
Panel A: By Number of Robot-related Patents							
Post$\times\Delta bonus_f$	0.035***	-0.068***	-0.140***	-0.153***	-0.083**	-0.069*	-0.018
	(0.009)	(0.016)	(0.052)	(0.053)	(0.035)	(0.037)	(0.031)
Post$\times\Delta bonus_f\times$ Robot Patents	0.003**	-0.017***	-0.054***	-0.044***	-0.036***	-0.032***	-0.020
	(0.002)	(0.006)	(0.009)	(0.011)	(0.011)	(0.009)	(0.014)
Panel B: By Number of Robot-related Patent Claims							
Post$\times\Delta bonus_f$	0.036***	-0.069***	-0.141***	-0.154***	-0.083**	-0.069*	-0.017
	(0.009)	(0.016)	(0.052)	(0.053)	(0.035)	(0.037)	(0.031)
Post$\times\Delta bonus_f\times$ Robot Patents	0.004***	-0.017***	-0.053***	-0.044***	-0.032**	-0.029**	-0.016
	(0.001)	(0.005)	(0.012)	(0.011)	(0.015)	(0.012)	(0.016)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y
Observations	20,957	20,038	20,957	20,957	20,957	20,957	20,957

Notes: Observations are at the firm-year level. 2018 and 2019 are defined as the post-policy years. The covariates include firm fixed-effects, year fixed-effects, firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

Figure 10: Firm-level Response of Job Postings by Skill and Technology Levels

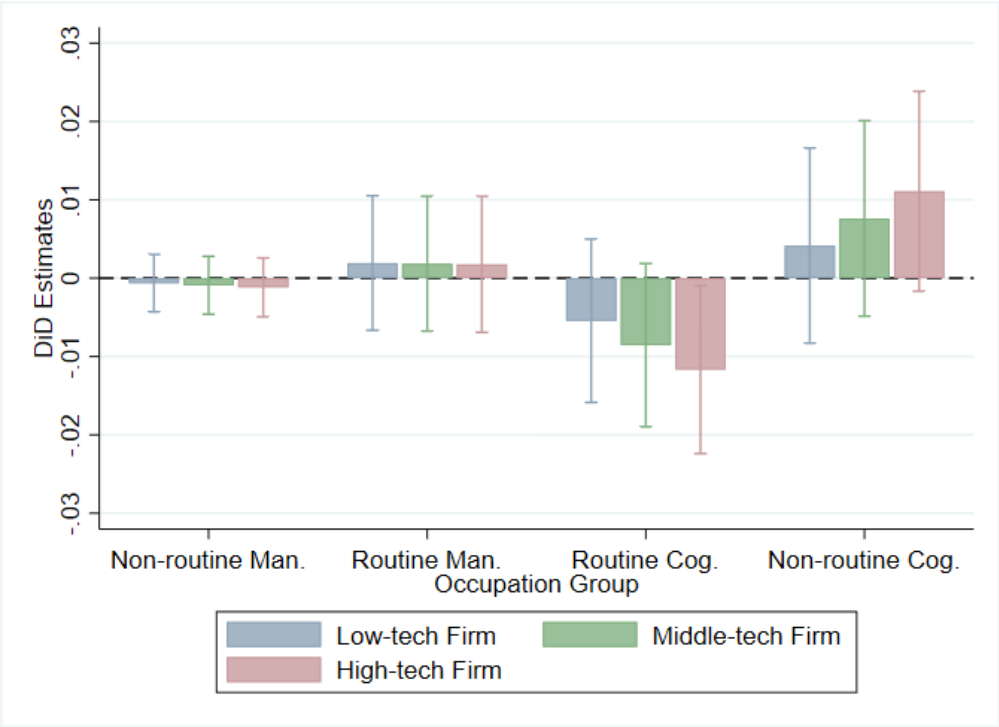


Notes: The figure shows the response of the number of job postings across software skill levels and the number of robot-related patents via the difference-in-difference version of the model of equation (5). We combine the estimation results on columns 4 to 7 in Table 2 and interpolate the estimates between skill levels. We transform each measure from 0 (lowest) to 1 (highest). Standard errors are clustered at firm level and the confidence intervals are at 95% level.

Table 2 reports the difference-in-difference effects of bonus depreciation change on the main outcomes by the number of robot-related patents. We use two measures of robot-related patents: the number of patents in Panel A and the number of patent claims in Panel B. We normalize both measures so that the coefficients of Post$\times\Delta bonus_f\times$ Robot Patents can be interpreted as the additional effect of bonus depreciation change for firms having one standard deviation more patents than the average firms. In Panel A, firms with one standard deviation more robot-related patents raise capital expenditure 0.9% less and reduce employment 4.5% more than the average firms in response to the policy change. At the same time, those firms disproportionately downsize job postings by 17.4% and 13% more than the average firms for the positions in the first and second quartiles of software skill levels. These additional effects are larger than those for job positions with more software skill levels (10% for the third quartile and 14.6% for the fourth quartile). The estimation using the number of patent claims reports the consistent results in Panel B. Table F.4 reports that we cannot observe similar patterns with non-robot-related patents.

Figure 10 visualizes the overall effect of bonus depreciation change on the number of job postings across both automation technology and software skill levels. Note that the technol-

Figure 11: Firm-level Response of Job Postings Shares across Occupation Groups



Notes: The figure shows the response of the share of job postings across occupation groups via the difference-in-difference version of the model of equation (5). The occupation groups (non-routine manual, routine manual, routine cognitive, and non-routine cognitive jobs) are defined following Acemoglu and Autor (2011) and the share of each occupation group is calculated within a firm. Observations are at the firm-occupation group-year level. The covariates include firm-occupation group fixed-effects, occupation group-year fixed-effects, firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. The point estimates are the coefficients of $\Delta bonus_f \cdot 1[t > 2017Q3]$. Standard errors are clustered at firm level and the confidence intervals are at 95% level.

ogy level varies across firms, and the skill level varies across job positions. For visualization, we transform each measure from 0 (lowest) to 1 (highest). With the technology level fixed, the effect of bonus depreciation change monotonically increases by skill level. With the skill level fixed, the policy effect is larger for firms with lower technology levels. Note that the effect is not always negative because the policy change raises labor demand for high-skilled positions in firms with low technology levels. Higher technology level disproportionately lowers the policy effect for lower-skilled positions. This interaction effect is critical evidence that the policy change that reduces capital costs for machinery and equipment accelerates the automation process and labor displacement.

To link these results to the findings of the literature on automation, we investigate how the increase in bonus depreciation affects labor composition across occupation groups from

the literature. Following the classical way of Acemoglu and Autor (2011), we classify occupations into non-routine manual, routine manual, routine cognitive, and non-routine cognitive jobs.[13] According to a widely acknowledged narrative, the so-called routine-biased technological change (RBTC) hypothesis, automated capital lowers the employment share of routine workers who are in the middle of the wage distribution while raising the share of high-paying (non-routine cognitive) and low-paying (non-routine manual) jobs.

Figure 11 reports the difference-in-difference effects of bonus depreciation change on the shares of the occupation groups by automation technology. The low- and high-tech firms are at two standard deviations lower and higher than the average firms in terms of the number of robot-related patents. The composition of the occupation groups does not respond to the increase in bonus depreciation rate for the low-tech firms, which means that those firms do not experience the RBTC. On the contrary, the change in bonus depreciation lowers the share of routine cognitive jobs by 1.5 percentage points (2.5%) in the labor demand of the high-tech firms. At the same time, the share of non-routine cognitive jobs increases by 1.5 percentage points (6%), but the shares of manual jobs do not change. There are two takeaways from these results: First, a reduction of capital cost by bonus depreciation results in the reallocation of labor inputs towards non-routine tasks as the RBTC, supporting that automation is the mechanism of the policy effect. Second, the adoption of automated capital is more likely to displace labor inputs for cognitive tasks rather than manual ones.

6.4 IV Estimation

Though the baseline results indicate the causal effects of the policy-driven reduction in capital cost under the parallel trend assumption, our event-study design bears two concerns. First, the baseline estimates can be viewed as intent-to-treat effects (ITT). The constructed policy shock, $\Delta bonus_f$, captures a "potential" incentive for a firm to claim bonus depreciation based on spatial and industrial distributions of the firm's establishments before the tax reform rather than how much a firm indeed earns the benefit from the tax deduction. However, even if the realized tax deduction by bonus depreciation is observable, it cannot be used as an exogenous regressor because the amount of tax deduction is also affected by the amount of capital expenditure, which is endogenous. Second, the results do not indicate that the capital and labor inputs are adjusted in the same firms simultaneously. We may try an IV estimation of labor demand where the change in bonus depreciation is used as an instrument

[13] This classification is based on task contests of occupations from O*NET. Non-routine cognitive jobs include managerial, professional, and technical workers, such as physicians, analysts, and engineers. Routine cognitive jobs involve sales and administrative support, including retailers, travel agents, and bank tellers. Routine manual occupations are blue-collar jobs such as mechanics and assemblers. Non-routine manual jobs are service occupations, including gardeners, hairdressers, and baristas.

Table 3: IV Estimates of Main Outcomes

	(1)	(2)	(3)	(4)
	Log(Capx)	Log(Emp)	Log(Capx/Emp)	Log(Post)
Log(DTL)	-0.197***	0.330***	-0.909***	0.715**
	(0.063)	(0.087)	(0.235)	(0.298)
F-stat	19.98	19.98	19.98	19.98
Fitted Response	0.034	-0.057	0.158	-0.124
	(5)	(6)	(7)	(8)
	Log(Post_{Q1})	Log(Post_{Q2})	Log(Post_{Q3})	Log(Post_{Q4})
Log(DTL)	0.796**	0.422**	0.337	0.070
	(0.311)	(0.206)	(0.210)	(0.171)
F-stat	19.98	19.98	19.98	19.98
Fitted Response	-0.139	-0.073	-0.059	-0.012
Firm FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
Observations	20,957	20,957	20,957	20,957

Notes: Observations are at firm-year level. 2018 and 2019 are defined as the post-policy years. The covariates include firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

for capital expenditure. However, this specification obviously cannot satisfy the exclusion condition because labor demand is also directly affected by the relative factor price change by bonus depreciation, which is not through the change in capital expenditure.

The ideal way of identifying the average treatment effect (ATE) of the policy is to use our policy shock as an instrument of the realized tax deduction if it is observable. While we cannot observe the realized tax deduction, deferred tax liability (DTL) indirectly captures how much a firm claims the bonus depreciation. As shown in Section 6.1, the increase in the bonus depreciation rate mechanically lowers DTL by advancing the timing of taxable income reduction. At the same time, the increase in capital expenditure in response to the policy change also lowers DTL by raising the taxable income cut in the year of the capital purchase. [14] Using DTL as an instrumented variable also identifies simultaneous input adjustments without incurring a violation of the exclusion condition because it reflects both capital expenditure and factor price changes. Thus, we try an IV specification where the

[14] It is hard to extract the realized capital cost reduction from the response of DTL because we need more information on a set of purchased machinery and equipment before and after the tax reform and their tax deduction schedules.

change in bonus depreciation is used as an instrument for the log of DTL.

Column 1 of Table 3 shows that a 1% reduction in deferred tax liability by the increase in bonus depreciation raises capital expenditure by 0.197%. Considering that the change in bonus depreciation lowers deferred tax liability by 17.4% as shown in Table 4, this effect can be translated into a 3.4% increase in capital expenditure. Similarly, column 2 shows that a 1% reduction in deferred tax liability lowers employment by 0.33% which is equivalent to a 5.7% decrease in employment by the change in bonus depreciation. The capital expenditure and employment responses are combined into the 15.8% increase in their ratio (column 3). In column 4, the fitted response of the number of job postings is around -12.4%, which is consistent with the baseline estimate. Columns 5 to 8 present the IV estimates of the number of job vacancies by skill group and confirm the baseline results, showing disproportionate effects on the job vacancies with few software skills. The event-study graphs in Figure F.5 also confirm that there are no pre-trends in the IV estimation. Thus, these results validate the proposed mechanism of the bonus depreciation policy and indicate that the baseline results of the difference-in-difference estimation are not qualitatively different from the estimated ATE from the instrument approach.

6.5 Robustness Checks

The previous figures of the event study specifications provide visual placebo tests by inspecting the parallel trends assumption. Figure 7 also shows that the change in bonus depreciation does not affect ineligible investment as an alternative placebo test. The remaining identification threats in the empirical strategy using the change in effective bonus depreciation rate are the other shocks that concurrently happen for the firms more affected by the policy change. This section reports a wide range of robustness checks to alleviate this concern.

The first concern is that the change in bonus depreciation captures the differential shocks across industries that are correlated with the policy change right after the tax reform. To tackle this issue, we add sector-specific time fixed effects in the difference-in-difference regressions of the primary outcomes. [15] Table 4 shows that the point estimates with the fixed effects (columns 1, 3, 5, and 7) are smaller than the baseline estimates (columns 1, 3, 5, and 7), but the estimates stay strong and are statistically indistinguishable from the baseline estimates. Thus, the estimated effects of the increase in bonus depreciation are not driven by the other industry concurrent shocks.

Even if the sector-specific time trends do not contaminate the estimated policy effects, some firm-specific concurrent shocks may be correlated with the measure of policy shock

[15] One cannot directly control for the 4-digit industry-by-time fixed effects in this context because a firm is defined as a set of establishments having different 4-digit industry codes.

Table 4: Difference-in-Difference Estimates with Sector-Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(DTL)		Log(Capx)		Log(Emp)		Log(Capx/Emp)	
Post× $\Delta bonus_f$	-0.134**	-0.126**	0.035***	0.026**	-0.067***	-0.039**	0.189***	0.111**
	(0.058)	(0.062)	(0.009)	(0.010)	(0.016)	(0.019)	(0.036)	(0.045)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	N	Y	N	Y	N
Sector-Year FE	N	Y	N	Y	N	Y	N	Y
Observations	20,957	20,957	20,957	20,957	20,957	20,957	20,957	20,957

Notes: Observations are at firm-year level. 2018 and 2019 are defined as the post-policy years. The covariates include firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

and falsely drive the results. An essential feature of the bonus depreciation policy that helps alleviate this concern is that the increase in bonus depreciation rate has heterogeneous effects across states depending on the state-level conformity to the federal depreciation policy and state corporate tax rates. In other words, if a firm raises capital investment more in a state with bonus conformity and a high state corporate tax rate, the firm can reduce more corporate taxes from claiming the bonus depreciation. Thus, we should observe more significant responses from the establishments in the states with conformity and high state corporate tax rates than the other establishments within a firm.

To see if this hypothesis is confirmed, we construct the measure of bonus depreciation change at the establishment level following equation (4) and conduct the parallel establishment-level analysis using the event study design following equation (5). The primary outcome is the number of job postings because it is the only variable we can observe for each establishment. Column 1 of Table 5 reports the difference-in-difference effects of bonus depreciation change on the number of job postings after controlling for establishment and year fixed effects and shows that the reduction in capital cost has a negative effect on the number of job postings as at firm level. In column 2, we replace year fixed effects with firm-specific year fixed effects to absorb firm-level time-varying shocks. The point estimates decline to some extent, but the effect remains statistically significant, indicating that firm-specific concurrent shocks do not drive the estimated policy effects.

Still, the establishment-level estimate may falsely capture the effect of bonus depreciation change at the other establishments or any other correlated shocks at the other establishments through the firm's internal network. The firm-specific year fixed effects may not absorb these effects. To tackle this issue, we construct a leave-one-out bonus depreciation change using the locations and industry codes of the other establishments in the same firm and the bonus

Table 5: Difference-in-Difference Estimates at Establishment Level

	(1)	(2)	(3)	(4)	(5)
	Log(Number of Job Postings)				
Post× $\Delta bonus_{est}$	-0.053***	-0.022**	-0.061***	-0.051***	-0.059***
	(0.016)	(0.010)	(0.014)	(0.017)	(0.014)
Post× $\Delta bonus_{others}$			0.040		0.050
			(0.038)		(0.046)
Post× $\Delta bonus_{HQ}$				-0.015	-0.026
				(0.039)	(0.044)
Establishment FE	Y	Y	Y	Y	Y
Year FE	Y	N	Y	Y	Y
Firm-Year FE	N	Y	N	N	N
Observations	287,959	287,959	287,959	287,959	287,959

Notes: Observations are at firm-year level. 2018 and 2019 are defined as the post-policy years. The covariates include firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

depreciation change at the firm's headquarters. The results in columns 3 through 5 indicate that these spillover effects do not artificially generate the effect of the establishment-specific shock.

As another exercise to validate the policy effect, we divide our sample by several firm characteristics and see if the heterogeneity in the policy effects is consistent with the mechanism of bonus depreciation following the literature. First, firms with large deferred tax assets are less likely to claim bonus depreciation because they already can get a tax discount with their deferred tax asset (Edgerton, 2010). Second, firms with more significant financial constraints are expected to be more responsive to the change in bonus depreciation rate because the immediate cash flow from tax deductions could have a higher marginal value than the other firms. Accordingly, Zwick and Mahon (2017) find that large firms or firms who paid a non-zero dividend raised capital investment less than the other firms in response to the increase in bonus depreciation rate during the 2001 and 2008 recessions. For each of these firm characteristics, we split our sample into tertiles based on the values before the policy change and compare the difference-in-difference estimates of the bottom and top tertiles following Zwick and Mahon (2017).

Columns 1 and 2 in Panel A of Table 6 reports that the reduction in DTL is only observed for the firms in the bottom tertile based on deferred tax asset. These firms had almost no deferred tax assets before TCJA, while the firms in the top tertile accrued 926.5 million

Table 6: Difference-in-Difference Estimates by Firm Type

Panel A: By Deferred Tax Assets (DTA)						
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(DTL)		Log(Capx)		Log(Emp)	
Post× $\Delta bonus_f$	-0.220***	0.019	0.080***	0.022***	-0.116**	-0.043**
	(0.075)	(0.087)	(0.028)	(0.008)	(0.045)	(0.017)
DTA	Low	High	Low	High	Low	High
Avg. DTA	0.0M	926.5M	0.0M	926.5M	0.0M	926.5M
Observations	8,013	7,298	8,013	7,298	8,013	7,298
Panel B: By Firm Size						
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(DTL)		Log(Capx)		Log(Emp)	
Post× $\Delta bonus_f$	-0.278***	-0.014	0.085**	0.022***	-0.103*	-0.037**
	(0.106)	(0.088)	(0.035)	(0.008)	(0.055)	(0.016)
Firm Size	Small	Large	Small	Large	Small	Large
Avg. Asset	145.2M	34117.0M	145.2M	34117.0M	145.2M	34117.0M
Observations	6,535	7,222	6,535	7,222	6,535	7,222
Panel C: By Dividend Size						
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(DTL)		Log(Capx)		Log(Emp)	
Post× $\Delta bonus_f$	-0.226**	-0.013	0.070**	0.019**	-0.089*	-0.034**
	(0.111)	(0.085)	(0.031)	(0.008)	(0.053)	(0.016)
Dividend	Low	High	Low	High	Low	High
Avg. Dividend	0.0M	410.3M	0.0M	410.3M	0.0M	410.3M
Observations	8,867	7,362	8,867	7,362	8,867	7,362

Notes: Observations are at firm-year level. The average deferred tax asset, asset, and dividend are calculated in 2017. 2018 and 2019 are defined as the post-policy years. The covariates include firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

dollars on average. Accordingly, the firms in the bottom tertile raise capital expenditure and lower employment more than the top tertile in response to the increase in bonus rate. Panel B presents separate estimates for the firms in the bottom and top tertiles based on total assets. The results show that small firms are more responsive to policy change, which is consistent with Zwick and Mahon (2017). The third sample split is based on the amount of dividend before TCJA, a proxy of ex-ante financial constraints, and indicates that the low-paying firms are significantly more responsive to the policy change. Figures F.6, F.7, and F.8 also confirm that there is no pre-trend in these results. Thus, the heterogeneity analysis reveals that the estimated effects are consistent with the expected effects based on the mechanism of bonus depreciation.

Lastly, we validate the direct effect of capital investment on labor inputs. According

Table 7: Difference-in-Difference Estimates by Change in Firm Capital Investments

	(1) Log(Emp)	(2) Log(Post)	(3) Log(Post$_{Q1}$)	(4) Log(Post$_{Q2}$)	(5) Log(Post$_{Q3}$)	(6) Log(Post$_{Q4}$)
Post$\times\Delta bonus_f$	-0.066***	-0.141***	-0.173***	-0.090**	-0.087**	-0.022
	(0.017)	(0.053)	(0.056)	(0.037)	(0.039)	(0.044)
Post$\times\Delta bonus_f \times \Delta capx_f$	-0.018***	-0.005***	-0.020***	-0.013***	-0.007***	-0.011***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)
Observations	17,772	17,772	17,772	17,772	17,772	17,772

Notes: Observations are at the firm-year level. 2018 and 2019 are defined as the post-policy years. $\Delta capx_f$ is defined by the change in capital expenditure from 2016 to 2018. The covariates include firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. The covariates, firm and year fixed effects are controlled in all specifications. Standard errors are clustered at firm level.

to the hypothesis of automation, more capital adoption induced by factor price changes displace workers performing low-level tasks along with the direct substitution effect of factor price changes. Our baseline results of capital investment, employment, and their ratio only indirectly imply this may be the case. To check the effect of the bonus rate change on labor inputs through capital investment, we adjust the difference-in-difference specification to allow for additional interaction between the change in bonus depreciation and the change in capital investment after the reform ($Post \times \Delta bonus_f \times \Delta capx_f$). The coefficient of the interaction term captures the heterogeneous effect of bonus depreciation by the firm-level response of capital investment. To interpret the coefficient as the effect of one standard deviation increases, we also normalize $\Delta capx_f$.

Table 7 reports the estimated coefficients of $Post\times\Delta bonus_f$ and $Post\times\Delta bonus_f\times\Delta capx_f$. Column 1 shows that the employment reduction additionally drops by 1.8% when the change in a firm's capital investment is one standard deviation larger. It means that the response of a firm's employment to the increase in the bonus rate is amplified by the size of the change in capital investment, which supports the hypothesis of capital-labor substitution within a firm. Columns 3 to 6 report the estimates of the number of job postings across software skill quartiles. The effects of bonus depreciation change are monotonic, as in the baseline results.

Moreover, the number of job postings for the lowest-skilled (first quartile) positions additionally decreases by 2% in response to the change in bonus depreciation when the change in a firm's capital investment is one standard deviation larger. The negative effect of bonus depreciation on the number of job postings for higher-skilled positions gets mitigated as the change in a firm's capital investment is larger. Thus, a larger capital investment amplifies the negative effect of bonus depreciation on employment and accelerates the reallocation of labor inputs toward higher software skills.

We also conduct a parallel analysis of employment at the MSA(Metropolitan Statistical Area) level using the data from OEWS (Occupational Employment and Wage Statistics) and describe the specifications and results in Appendix C. The results at the local labor market could be different from the firm-level results for two reasons. First, publicly traded firms in our sample are more technologically advanced than smaller firms, and the policy effects on the smaller firms could be more negligible. Second, the aggregate-level result reflects the reallocation of workers. If a displaced worker from a firm can quickly get another job in the local labor market, then the decrease in employment could be mitigated, and the policy implication also should be different. The results in Appendix C confirm that our main findings with the publicly traded firms can be extended to the local labor market with smaller policy effects, indicating that the two reasons can alleviate the reduction in employment.

7 A Model of Automation

So far, we present the causal effects of the change in the effective bonus depreciation rate on a firm's allocation of factor inputs. In response to the reduction in capital cost, a firm raises investment in machinery and equipment and reduces labor demand, especially for positions with lower software skills. The heterogeneity of responses across skill groups is more pronounced for firms with higher automation technologies. These results imply that the effect of automation differs across different types of labor inputs in different firms. In this section, we present a task-based model that elucidates when a firm lowers labor demand in response to the reduction in capital cost and why the response in labor demand differs across technology and skill levels. We also show that the elasticity of substitution between capital and labor and the labor income share are the key components to understanding how the incidence of automation will be distributed across workers. Based on this model, we also conduct a quantitative analysis of the two components in the next section.

7.1 Environment

We develop a task-based model of automation that features multiple types of labor and heterogeneous firms. The economy is static. There are heterogeneous workers and a representative firm that produces the final good. Workers cannot insure against automation in the sense that their total income is completely determined by the labor income.[16]

[16] Alternatively, we can think of a case with complete markets where workers are ex-ante homogeneous and can trade contracts to transfer resources after their types are realized. We consider this complete-markets scenario a benchmark for welfare analysis but focus on the incomplete-markets case throughout the section.

Workers Workers are heterogeneous with respect to their labor types. Each type $g \in \mathcal{G} = \{1, \ldots, G\}$ consists of a unit mass of workers who are homogeneous within the type. Workers' problem is:

$$W_g = \max_{c_g, \ell_g} u(c_g, \ell_g) = \max_{c_g, \ell_g} \frac{1}{1-\gamma} \left(c_g - \kappa_g \frac{\ell_g^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}} \right)^{1-\gamma}$$

subject to their labor income $c_g = w_g \ell_g$. As is well known in the literature, there is no wealth effect on labor supply under this functional form (Greenwood, Hercowitz, and Huffman, 1988). Throughout the paper, we focus on the case where $\nu = \infty$ so that workers supply labor perfectly elastically. As a result, wages are determined at the constant κ_g for each labor type $g \in \mathcal{G}$, simplifying the analysis. As we will see in the following discussion, the quantity of labor adjusts in response to a shock instead of wages.

Firms There is a unit mass of firms differing in their automation technology $\eta \in [0, 1]$. Each firm produces output $y(\eta)$ by combining tasks $\{y(x, \eta)\}_{x \in \mathcal{T}}$ where $\mathcal{T} = [0, T]$ is the set of all tasks common across firms:

$$y(\eta) = \left(\int_0^T y(x, \eta)^{\frac{\lambda-1}{\lambda}} dx \right)^{\frac{\lambda}{\lambda-1}}.$$

The key feature of the production function is how to allocate the tasks across factor inputs. Each task can be produced by substitutable factors capital and different types of labor indexed by $g \in \mathcal{G}$ following:

$$y(x, \eta) = \begin{cases} \psi_k(x) k(x, \eta) + \sum_{g \in \mathcal{G}} \psi_g(x) \ell_g(x, \eta) & x \in \mathcal{A}(\eta) \\ \sum_{g \in \mathcal{G}} \psi_g(x) \ell_g(x, \eta) & x \notin \mathcal{A}(\eta) \end{cases}$$

where $k(x, \eta)$ is the amount of capital performing task x and $\ell_g(x, \eta)$ denotes the amount of labor group g allocated to x. Task production is characterized by task-level productivity of factors $[\psi_k(x), \{\psi_g(x)\}]_{x \in \mathcal{T}}$, where $\psi_k(x)$ is the productivity of capital at task x in a firm of type η and vice versa. We assume that factor productivity $\psi_k(x), \{\psi_g(x)\}$ and the comparative advantage of labor $\frac{\psi_g(x)}{\psi_k(x)}$ are increasing in x. $\mathcal{A}(\eta) \subseteq \mathcal{T}$ represents the set of tasks that can be technologically automated by capital with technology level η. So, tasks out of $\mathcal{A}(\eta)$ cannot be automated and can be produced just by labor. The set of automatable tasks is increasing in η in the sense that a larger η expands the set of automatable tasks ($\mathcal{A}(\eta_1) \subseteq \mathcal{A}(\eta_2)$ $\forall \eta_1 < \eta_2$). Note that tasks in $\mathcal{A}(\eta)$ are not always automated, and the automation decision also depends on the comparative advantage.

Consumption bundle Each firm produces differentiated varieties and there is a bundling firm that puts together the output of individuals firms $\{y(\eta)\}_{\eta\in[0,1]}$ using a CES aggregator:

$$y = \left(\int_0^1 y(\eta)^{\frac{\sigma-1}{\sigma}} d\eta\right)^{\frac{\sigma}{\sigma-1}}$$

where $\sigma > 1$ denotes the elasticity of substitution across varieties.

Capital market Capital producers supply capital elastically at the constant marginal cost R in the capital market. Only one type of capital can be employed at any task in any firm. Thus, we ignore any task-level heterogeneity in capital production. Later, we consider a fall in the marginal cost R to examine the welfare effects of the investment subsidies.

7.2 Equilibrium

Since the factors are perfectly substitutable at the task level, firms can distribute the tasks to the factors given factor costs and productivities for each task. Let $\mathcal{T}_g(\eta)$ be the set of tasks allocated to skill group g of firms of type η. Similarly, $\mathcal{T}_k(\eta)$ is the task set allocated to capital in the firms. Then, we can write the entire task set of the firms as a union of the subsets $\mathcal{T}(\eta) = \mathcal{T}_k(\eta) \cup (\cup_{g\in\mathcal{G}}\mathcal{T}_g(\eta))$. Notice that although the entire task set is the same across different types of firms, the allocation can vary based on the technology level. Cost minimization of firms of type η implies that the sets of tasks allocated as:

$$\mathcal{T}_k(\eta) = \left\{x \in \mathcal{A}(\eta) : \frac{R}{\psi_k(x)} \leq \frac{w_g}{\psi_g(x)} \text{ for } g \in \mathcal{G}\right\},$$
$$\mathcal{T}_g(\eta) = \left\{x : \frac{w_g}{\psi_g(x)} \leq \frac{w_{g'}}{\psi_{g'}(x)} \text{ for } g' \neq g \wedge \left(\frac{w_g}{\psi_g(x)} \leq \frac{R}{\psi_k(x)} \vee x \notin \mathcal{A}(\eta)\right)\right\}.$$

The tasks in $\mathcal{T}_k(\eta)$ are in the automatable set $\mathcal{A}(\eta)$ and are produced by capital with the lowest unit cost. In each subset $\mathcal{T}_g(\eta)$, a task x should not be in $\mathcal{A}(\eta)$ or should not be produced by labor g with a lower unit cost than capital. On top of that, labor g also has the comparative advantage in producing the task among labor groups.

Note that there are infinite ways to classify labor inputs into G groups. To partition them in a meaningful way in our context, we introduce a set of susceptible tasks for each group g and technology level η:

$$\Xi_g(\eta) = \left\{x \in \mathcal{A}(\eta) : \frac{w_g}{\psi_g(x)} < \frac{w_{g'}}{\psi_{g'}(x)} \text{ for } g' \neq g\right\}.$$

This set represents the tasks that are performed by labor group g if they are not automated

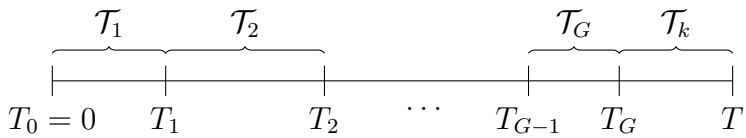


Figure 12: Task allocation

yet, but can be technologically automated. Now we classify labor inputs into G groups to satisfy:

$$\int_{\Xi_{g_2}(\eta)} 1dx \leq \int_{\Xi_{g_1}(\eta)} 1dx \quad \forall g_1 < g_2 \text{ and } \eta \in [0,1].$$

It means that a lower-level labor input has a larger set of susceptible tasks in mass and is at a higher risk of automation at any level of technology. Thus, we also call g as skill level in the sense that a higher-skilled group is less susceptible to automation.

Without loss of generality, we can reorder the tasks so that $\mathcal{T}_g(\eta) = [T_{g-1}(\eta), T_g(\eta)]$ for $g \in \mathcal{G}$ and $\mathcal{T}_k(\eta) = [T_G(\eta), T]$, where $0 = T_0(\eta) \leq T_1(\eta) \leq \cdots \leq T_G(\eta) \leq T$ as shown in Figure 12. This ordering allows us to capture the changes in task allocation in a parsimonious way. We focus on the case where all task subsets have positive measures and on equilibria where each task is uniquely assigned to one of the factors so that the strict inequalities hold.

Our model delivers the equilibrium firm-level production function and the unit cost function analogous in structure to those in the existing models (Acemoglu and Restrepo, 2021). Firms produce output according to the following production technology aggregated over the tasks:

$$y(\eta) = \left(\Psi_k(\eta)^{\frac{1}{\lambda}} k(\eta)^{\frac{\lambda-1}{\lambda}} + \sum_{g \in \mathcal{G}} \Psi_g(\eta)^{\frac{1}{\lambda}} \ell_g(\eta)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}},$$

where $k(\eta)$ and $\ell(\eta)$ are firm-level factor demands. $\Psi_k(\eta)$ and $\Psi_g(\eta)$ are the factor share parameters determined *endogenously* by the equilibrium task allocation:

$$\Psi_k(\eta) := \int_{T_G(\eta)}^{T} \psi_k(x)^{\lambda-1} dx,$$
$$\Psi_g(\eta) := \int_{T_{g-1}(\eta)}^{T_g(\eta)} \psi_g(x)^{\lambda-1} dx.$$

The production function takes the standard CES form except that the factor share parameters are also a part of the equilibrium outcome. By solving the cost minimization problem

of individual firms, we can characterize the unit cost function m of firm η and the firm-level cost shares:

$$m(R, \{w_g\}, \eta) = \left(\Psi_k(\eta) R^{1-\lambda} + \sum_{g \in \mathcal{G}} \Psi_g(\eta) w_g^{1-\lambda} \right)^{\frac{1}{1-\lambda}}.$$

The cost shares of capital and labor g at the firm level are given by:

$$\begin{aligned} s_k(\eta) =& \frac{\Psi_k(\eta) R^{1-\lambda}}{\Psi_k(\eta) R^{1-\lambda} + \sum_{h \in \mathcal{G}} \Psi_h(\eta) w_h^{1-\lambda}}, \\ s_g(\eta) =& \frac{\Psi_g(\eta) w_g^{1-\lambda}}{\Psi_k(\eta) R^{1-\lambda} + \sum_{h \in \mathcal{G}} \Psi_h(\eta) w_h^{1-\lambda}}. \end{aligned}$$

To gain intuition on how the factor shares are determined, suppose the cost of capital falls as will be the case in our comparative statics. If $\lambda < 1$, then, holding $\Psi_k(\eta)$ fixed, the cost share of capital will fall, as is clear from the above equation. However, a decline in R will raise the factor share parameter of capital as some tasks are reallocated from labor to capital. Thus, $\Psi_k(\eta)$ will rise and put an upward pressure on $s_k(\eta)$. The net effect can either raise or reduce the share of capital. Similarly, the reduction in capital cost directly raises the share of labor g. At the same time, it indirectly lowers the share by transferring some tasks in $\mathcal{T}_{ig}$ to $\mathcal{T}_{ik}$ and lowering Ψ_{ig}.

We can measure the degree of substitution as factor prices change by looking at the relative changes in factor shares. The following induced elasticities of substitution between capital and labor capture this.

Proposition 1 (Induced Elasticities of Substitution)**.** *The induced elasticity of substitution between capital and labor g can be expressed as:*

$$\lambda_{gk}(\eta) := 1 + \frac{\mathrm{d}\ln(s_g(\eta)/s_k(\eta))}{\mathrm{d}\ln(R/w_g)} = \underbrace{\lambda}_{\textit{capital deepening}} + \underbrace{\frac{\mathrm{d}\ln \Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\textit{task displacement}} - \underbrace{\frac{\mathrm{d}\ln \Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\textit{task absorption}}. \tag{6}$$

In principle, the induced elasticity of substitution between capital and labor g is composed of three different components, and each component corresponds to an aspect of the allocation of input factors.

Suppose that a reduction in capital cost relative to wages does not affect the task sets allocated to capital and labor g. Then, $\frac{\mathrm{d}\ln \Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)} = 0$ and $\frac{\mathrm{d}\ln \Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)} = 0$, so the induced elasticity of substitution between capital and labor g is given by λ. Note that this elasticity of substitution corresponds to that in the classical model with the CES production function.

We call λ reflects **capital deepening** in the sense that the relative volume of capital rises in response to relative cost reduction without the reallocation of tasks.

Suppose that a reduction in capital cost relative to wages makes unit productivity of capital higher than that of labor g for some tasks originally performed by labor g. i.e. $\frac{\psi_g(x)}{w_g} < \frac{\psi_k(x)}{R}$ for some $x \in T_g(\eta)$. Then, $\frac{\mathrm{d}\ln\Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)} > 0$ and $\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)} < 0$, so the induced elasticity of substitution between capital and labor g is given by equation (6). $\frac{\mathrm{d}\ln\Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)}$ is called **task displacement** because it reflects the reduction of task share of labor g by automation. $\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)}$ indicates **task absorption** in the sense that it represents the rise in task share of capital. We refer to those two effects as **task reallocation** as a whole.

Before moving on, we now define a competitive equilibrium of the economy.

Definition 1. *An equilibrium consists of an allocation* $\{k, [\ell_g, c_g]_g, [k(\eta), \ell_g(\eta), y(\eta)]_g, y\}$ *and factor prices* $\{[w_g]_g, R\}$ *such that:*

1. *the ideal price index condition holds*

$$1 = \int_0^1 p(\eta)^{1-\sigma} d\eta$$

   where $p(\eta) = \frac{\sigma}{\sigma-1} m(\eta)$*;*

2. *labor markets clear for all labor* $g \in \mathcal{G}$

$$\ell_g = \int_0^1 \ell_g(\eta) d\eta$$

   where ℓ_g *is the total supply of labor* g *and* $\ell_g(\eta)$ *is the demand from each firm;*

3. *capital market clears*

$$k = \int_0^1 k(\eta) d\eta$$

   where k *is the total supply of capital and* $k(\eta)$ *is the demand from each firm;*

4. *goods market clears*

$$y = \sum_{g \in \mathcal{G}} c_g$$

7.3 Comparative Statics

We are interested in how a decline in the cost of capital, which corresponds to the rise in the effective bonus depreciation rate in our empirical analysis, affects the demand for different types of labor. To see this, suppose the cost of capital falls by $d \ln R < 0$. In response, factor demands and the equilibrium allocation of tasks change. In our setup, wages are fixed, and labor demands change only through adjustments in quantities $\{\ell_g\}$. This setting is in line with our assumption in the empirical section that the effects of TCJA observed in the data are relatively short-term and do not give rise to wage adjustments. As a result, firms only substitute between capital and labor and not between labor types. In other words, we rule out the competition between different types of labor so that labor displacement occurs only through the re-assignment of tasks to capital.[17]

Examining factor demand changes boils down to characterizing the change in task allocation in response to factor price changes. To capture the task adjustments concretely, we introduce a measure of task change $\epsilon_g(\eta)$ for each labor type g within firm η. Then, a change in the variable $d\epsilon_g(\eta)$ measures the mass of tasks reallocated from labor g to capital in response to the shock. The following lemma summarizes how task allocation responds to factor price changes.

Lemma 1 (Changes in Factor Shares)**.** *Following a decrease in capital cost by $d \ln R < 0$, the factor share of labor group g in firm η declines by*

$$d \ln \Psi_g(\eta) = -\frac{\psi_g^{\lambda}(T_{g-1}(\eta))}{\Psi_g(\eta)} \frac{\mathrm{d}\epsilon_g(\eta)}{\mathrm{d} \ln R} d \ln R \leq 0. \tag{7}$$

The decrement is increasing in technology level η and decreasing in skill level g.

The lemma indicates that a reduction in capital cost lowers the labor factor share, but the decrement varies across skill and technology. Intuitively, the factor share parameter falls more if the displaced tasks are more critical to labor group g or more tasks are reassigned from labor g to capital. If a firm's technology level is higher, the set of automatable tasks is larger, and there is a less technological constraint for automation in response to factor price changes. On the other hand, the decrement is decreasing in g because the mass of susceptible tasks to automation is decreasing in g by definition.

[17] As Acemoglu and Restrepo (2021) point out, such "ripple effects" can be important in a long time horizon. However, we investigate direct responses to the shock in the short term and focus on the competition between capital and labor, which corresponds to our empirical setup.

Proposition 2 (Changes in Labor Demands)**.** *Following a decrease in capital cost by* $d\ln R < 0$*, the change in labor demand by firm* η *can be characterized by:*

$$d\ln \ell_g(\eta) = d\ln\left(\frac{y}{m(\eta)^\sigma}\right) + \lambda d\ln m(\eta) + d\ln \Psi_g(\eta).$$

The change in labor demand is increasing in skill group g*.*

The change in the demand for skill group g consists of the productivity effect ($d\ln(y/m(\eta)^\sigma)$), the direct substitution effect ($\lambda d\ln m(\eta)$), and the task displacement effect ($d\ln \Psi_g(\eta)$). First, the productivity effect captures the increased demand for goods, and thus a firm's demand for labor rises due to the increase in aggregate output regardless of skill and technology levels. Moreover, labor demand of firm η disproportionately increases according to the decrease in the unit production cost of the firm. Second, the decline of capital cost affects firm η's labor demand by the direct substitution effect. This effect is driven by capital deepening and the sign of the effect depends on the substitution elasticity across tasks. Lastly, the labor demand is affected by the reallocation of tasks. The task displacement effect is weakly negative because some tasks can be reassigned from labor to capital by automation, leading to a decline in the factor share parameter $\Psi_g(\eta)$.

As shown in Lemma 1, the task displacement effect is larger for lower-skilled labor, so the change in labor demand is increasing in skill level g. How the change in labor demand varies across automation technology level is indecisive. Note that the unit cost declines more for firms having higher technologies because their automatable task set is larger. At the same time, the task displacement effect is larger for higher η. So, the productivity and task displacement effects move in the opposite directions by technology level. At the same time, how the direct substitution effect differs across technology level also relies on the sign of λ. If $\lambda > \sigma$, then the change in labor demand is necessarily decreasing in automation technology level.

The literature sometimes focuses more on the change in labor income shares as a consequence of automation. The change in labor income shares are equivalent to that in labor cost shares in our setting since the markup is constant. The response in labor cost shares directly follows to Proposition 2.

Proposition 3 (Changes in Labor Cost Shares)**.** *Following a decrease in capital cost by* $d\ln R < 0$*, the response of the cost share of labor type* g *is determined by the deviation of*

the elasticity of labor g from the average elasticity:

$$d\ln s_g(\eta) = \left[s_k(\eta)(\lambda_{gk}(\eta) - 1) + \sum_{h \in \mathcal{G}, h \neq g} s_h(\eta)(\lambda_{gk}(\eta) - \lambda_{hk}(\eta)) \right] d\ln R. \tag{8}$$

The change in labor share is increasing in skill level g.

The interpretation of the result is intuitive. The first term on the right-hand side $(s_k(\eta)(\lambda_{gk}(\eta) - 1))$ corresponds to the finding of the literature saying that the labor income share moves to the same direction as capital cost only when the elasticity between capital and labor exceeds 1.[18] In that case, a decline of capital cost lowers the labor income share. Our model gives an additional term $(\sum_{h \in \mathcal{G}, h \neq g} s_h(\eta)(\lambda_{gk}(\eta) - \lambda_{hk}(\eta)))$, which captures the reallocation of tasks to labor group g relative to the other groups. If a skill group has a larger elasticity of substitution than the other skill groups, then a reduction in capital cost additionally lowers the income share of that skill group.

The previous results show that the degree of substitution between capital and labor varies across skill groups and that the heterogeneity in the substitution elasticity makes labor demand and labor income share respond to a reduction in capital cost in different ways. Similarly, the following proposition shows that the welfare incidence of a reduction in capital cost differs across skill groups by the task displacement effect and that the difference in the incidence solely depends on the relative responses of income shares.

Proposition 4 (Welfare Change by Labor Type)**.** *Following a decrease in capital cost by $d\ln R < 0$, the welfare change is determined by group-specific capital-labor substitution effect as well as the productivity effect:*

$$d\ln W_g = \left(\frac{\mathrm{d}\ln u_g}{\mathrm{d}\ln c_g} + \frac{\mathrm{d}\ln u_g}{\mathrm{d}\ln \ell_g} \right) \left[d\ln y + (1 + \sigma_{kk} s_k) d\ln R + d\ln \left(\frac{s_g}{s_k} \right) \right] \tag{9}$$

where $\sigma_{kk} := \frac{m m_{RR}}{m_R^2} < 0$ is the Allen elasticity of capital substitution and s_g and s_k are the income shares aggregated over firms.

The proposition shows how a reduction in capital cost affects the welfare of different types of workers. The first part is the productivity effect captured by $d\ln y$, which raises overall labor demand. The second channel is the substitution between capital and labor. $(1 + \sigma_{kk} s_k) d\ln R$ captures the substitution effect between capital and the "overall" labor

[18] Notice that the proposition generalizes the result in Hubmer and Restrepo (2021) to the setting with multiple types of labor. To see this more clearly, suppose there is a single type of labor g. Then, we can re-express equation (8) as $d\ln s_g(\eta) = (1 - s_g(\eta))(\lambda_{gk}(\eta) - 1) d\ln R$, which is essentially the same as what Hubmer and Restrepo (2021) derive.

input and depends on the curvature of unit cost function with respect to capital (σ_{kk}) and the capital income share (s_k). If the Allen elasticity of capital substitution and the capital income share are small enough, a fall in the capital cost tends to reduce the employment of skill group g.

Lastly, the relative substitution effect is determined by the change in labor income share of each skill group relative to the capital income share. Note that the welfare gap among skill groups solely depends on the responses of income shares of skill groups except for the utility functions. Thus, in the subsequent quantitative analysis, we investigate how the evolution of labor income share varies by skill group in the automation process. Then, these effects on employment are adjusted by the relative size of the curvatures of consumption utility and labor disutility.

8 Sufficient Statistics Approach

The model clarifies the mechanisms by which a reduction in capital cost induces the input adjustment between capital and labor and provides the form of uneven welfare incidence of automation. In this section, we estimate capital-labor substitution elasticity by skill and technology levels and decompose the elasticity into the mechanisms presented in the model by linking the model and the reduced-form estimates following the sufficient statistics approach (Chetty, 2009; Kleven, 2020). We also check how the heterogeneity in the elasticity affects the welfare gap among skill groups in the automation process by focusing on the decline of the labor income share.

8.1 Elasticity of Substitution between Capital and Labor

The elasticity of substitution between capital and labor has been considered the key parameter to understand the incidence of some phenomena in the labor market, such as movements in income shares, the effectiveness of employment-creation policies, and the displacement of new technologies. However, researchers have struggled to estimate the parameter. Diamond, McFadden, and Rodriguez (1978) found that the elasticity cannot be obtained from time series analysis because factor price movements are not separable from rising investment-augmenting technology. Thus, applied researchers tried to find a plausibly exogenous cross-sectional variation in factor prices. For instance, Karabarbounis and Neiman (2014) uses cross-national variation in investment price changes relative to consumption price changes and Raval (2019) utilizes exogenous location-specific wages across local labor markets. However, the studies do not allow or explicitly explain that the elasticity of substitution can vary

across observations, which our model captures. Karabarbounis and Neiman (2014) suggest that non-unitary elasticities of substitution could be important to understand the secular decline of the labor share better.

Here, we estimate the heterogeneous capital-labor elasticity of substitution across skill and technology levels and investigate how much task reallocation can account for the elasticity. To be consistent with our empirical results, we focus on the worker classes based on software skill level. Following the sufficient statistics approach, we do not need to estimate the entire model to estimate the elasticity of substitution, and we can re-express the elasticity as the function of sufficient statistics, the reduced-form estimates. Note that the decrease in the effective bonus depreciation rate directly lowers the cost of capital ($\frac{\partial \log R}{\partial \theta} < 0$).

Proposition 5. *We can express the induced elasticity of substitution at technology level η and skill level g as:*

$$\lambda_{gk}(\eta) := \frac{\mathrm{d}\ln(\ell_g(\eta)/k(\eta))}{\mathrm{d}\ln(R/w_g)} = \frac{\beta_g(\eta) - \beta_k(\eta)}{\rho} \tag{10}$$

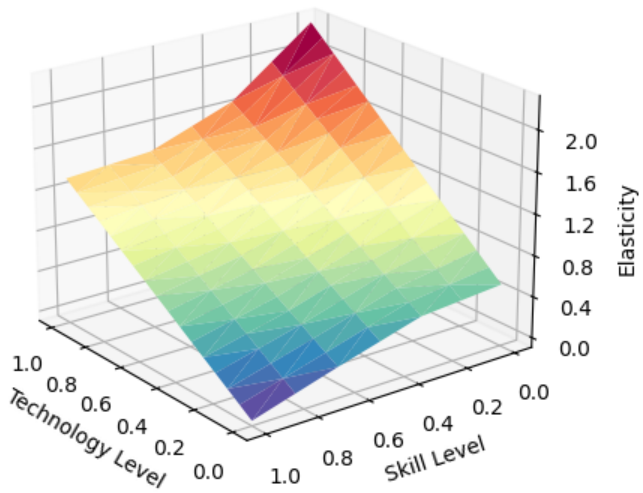
where ρ is the effect of bonus depreciation rate on the cost of capital ($\frac{\partial \log R}{\partial bonus}$).

This equation shows that the elasticity of substitution is a function of the effects of bonus depreciation on employment, capital, and cost of capital. β's are the estimated difference-in-difference estimates of capital and employment across software skill levels from Section 6. We set ρ as the average change in the effective bonus depreciation rate (15%) under the assumption that the other components of capital cost are not affected by TCJA.

Figure 13 reports the distribution of the capital-labor substitution elasticity across technology and skill levels. The distribution is partially determined by the difference-in-difference estimates of employment in Figure 10 but is also affected by the heterogeneous response of capital investment across the technology level. The substitution elasticity is larger for firms with higher automation technology because the higher technology level allows the firms to replace more labor tasks with capital. A higher skill level, on the contrary, lowers the elasticity because machinery and equipment can complement workers having skills to handle them or because capital cannot substitute labor for tasks that are hard to automate. The interaction effect of technology and skill levels is striking. The substitution elasticity is nearly zero for the highest-skilled positions in firms with the lowest technology, while exceeding 2 for the lowest-skilled positions in firms with the highest technology.

We can compare these values with that from the literature. Karabarbounis and Neiman (2014) estimate macro-level elasticity of substitution to be from 1.17 to 1.49 across different data sets, which is larger than 1, the value from the Cobb-Douglas production function. It

Figure 13: Elasticity of Substitution by Technology and Skill Levels



Notes: The figure shows the capital-labor substitution elasticity across the number of software skills (skill level) and the number of robot-related patents (technology level) based on equation (10). We transform each measure from 0 (lowest) to 1 (highest) and display them in reverse order for a clear visualization. The difference-in-difference estimates are from Section 5 and the change in capital cost is set as the average change in the effective bonus depreciation rate.

means that capital and labor are highly substitutable, and their estimate is considered the upper bound of this parameter in the literature. Curtis et al. (2021) also utilize a bonus depreciation policy during the Great Recession and report that the estimated elasticity of substitution is around -0.4, which means that capital and labor are complementary in general.[19] The average of our elasticities of substitution is the closest to [0.48, 0.58] from Raval (2019), which utilizes firm-level data and exogenous variation in labor cost across local labor markets in the U.S.

We then decompose the skill-level elasticity of substitution into the different effects shown in equation (6). Simply put, we can express the elasticity of substitution between capital and labor group g in a firm with technology level i as:

$$\lambda_{gk}(\eta) = \underbrace{\lambda}_{\text{capital deepening}} + \underbrace{\frac{\mathrm{d}\ln\Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\text{task displacement}} - \underbrace{\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\text{task absorption}}.$$

For doing this, we need a couple of additional assumptions: First, there is no task displacement effect for the highest skill group ($\frac{\mathrm{d}\ln\Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)} = 0$ for $g = \bar{g}$). In our model, capital

[19] Curtis et al. (2021) reports the Allen elasticity of substitution, but they also directly compare their estimate with the estimated Morishima elasticity of substitution from the literature.

Table 8: Decomposition of Substitution Elasticity

Skill Level	Skill_{Q1}	Skill_{Q2}	Skill_{Q3}	Skill_{Q4}	Average
λ_{gk}	1.436	0.902	0.785	0.366	0.872
Capital Deepening	0.070	0.070	0.070	0.070	0.070
Task Absorption	0.296	0.296	0.296	0.296	0.296
Task Displacement	1.069	0.536	0.418	0.000	0.506

Notes: The elasticity of substitution between capital and each skill group is averaged over all technology levels. Capital deepening effect is $E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}_{Q1}, g \in \mathcal{G}]$, task absorption effect is $E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_{Q4}] - E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}_{Q1}, g \in \mathcal{G}]$, and task displacement effect for labor g is $E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_h] - E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_{Q4}]$.

substitutes for labor from lower-level tasks, so the highest-skilled job positions are not displaced by capital adoption. The absence of task displacement for high-skilled workers is also commonly assumed in the literature. Second, firms with the lowest technology level cannot adopt automated capital ($\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)} = 0$ and $\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)} = 0$ for $\eta = \underline{\eta}$). This assumption is consistent with our model and empirical results and is also reasonable because automation needs some level of technology.

By the first assumption, the capital deepening effect is captured by the estimated λ_{gk} for all skill groups in the firms with the lowest automation technology. We use the firms in the first quartile of the technology level to estimate this effect ($E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}_{Q1}, g \in \mathcal{G}]$). The task absorption effect is captured by the gap between the estimated λ_{gk} for the highest skill group and estimated λ_{gk} for the firms with the lowest automation technology under the first assumption ($E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_{Q4}] - E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}_{Q1}, g \in \mathcal{G}]$). Similarly, task displacement effect for labor g is given by the gap between the estimated λ_{gk} for that skill group and the estimated λ_{gk} for the highest skill group ($E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_h] - E[\hat{\lambda}_{gk}(\eta)|\eta \in \mathcal{H}, g \in \mathcal{G}_{Q4}]$).

Table 8 reports the decomposition of capital-labor substitution elasticity across software skill levels. The first row presents the elasticity across the skill groups, corresponding to Figure 13. Note that capital and labor are complementary if λ_{gk} is smaller than 0, and they are substitutable if the elasticity is larger than 0. The capital deepening effect in the second row is constant and positive, meaning that labor is still substitutable for capital without task reallocation. The task absorption effect in the third row reflects how many tasks are newly allocated to capital by the change in the relative factor price. By our assumption, the task displacement effect accounts for the difference in the elasticity across skill groups. For the lowest skill group, the task displacement effect mostly accounts for the elasticity and diminishes as the software skill level increases. Though the elasticity for each skill group

is constant, the average elasticity could vary over time if the composition of skill groups changes.

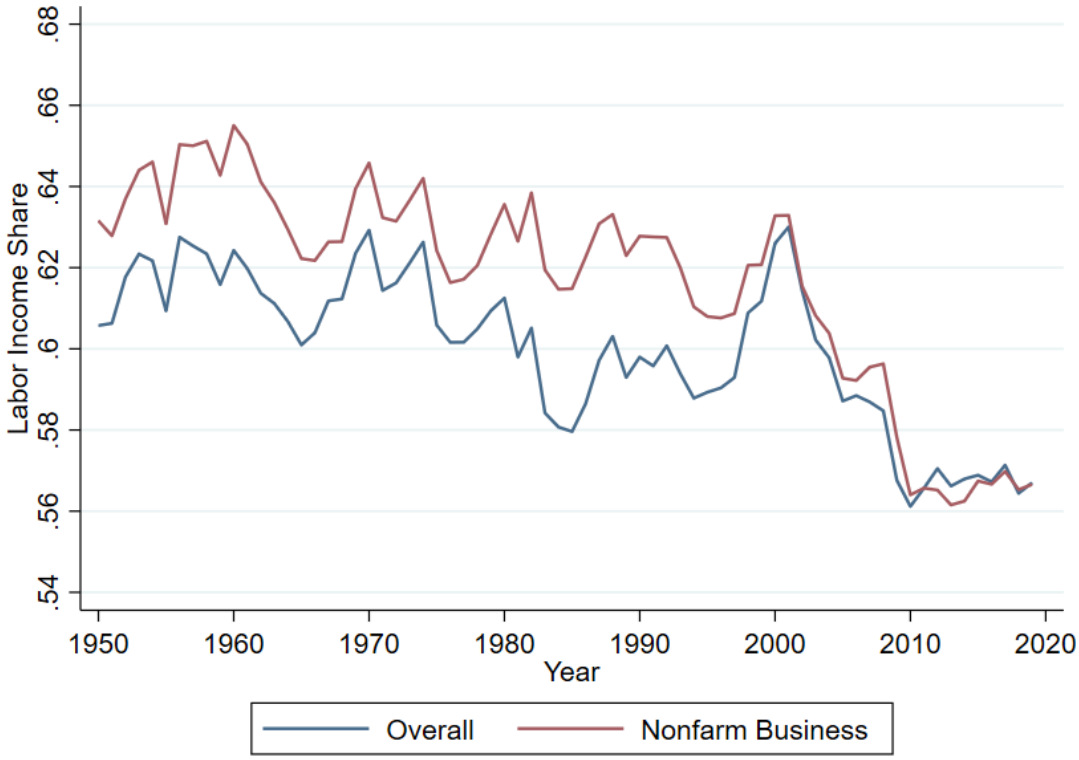
8.2 Labor Income Share

Now we move on to another component of the welfare consequence of automation: labor income share. The recent decline of labor income share has widely been discussed in the literature, and automation is suggested as a primary driver of the phenomenon (Acemoglu and Restrepo, 2018; Autor and Salmons, 2018; Hubmer and Restrepo, 2021; Bergholt, Furlanetto, and Maffei-Faccioli, 2022). The novelty of our setting is that the evolution of labor income share could vary across different types of workers. Plus, both the change in factor prices and non-neutral technological progress induce automation and lower labor income share. In this section, we investigate the heterogeneous patterns in the recent decline of labor income share in the U.S. across different workers. The heterogeneous elasticity of substitution between capital and labor estimated from the last section is a crucial ingredient in this exercise. We also decompose the decline into the contribution of factor price changes and technological progress in the automation process.

Figure 14 reports the labor income share for the overall and nonfarm business sectors in the U.S. from 1950 to 2019. Though the measurement of labor income share is subject to debate, there is a consensus that it has declined since the early 1980s and that the steepest decline occurs in the 2000s. Many other advanced countries show a similar trend (Karabarbounis and Neiman, 2014), which means that the driving factor is not country-specific. A pattern not discussed much in the literature is that the labor share has been relatively flat since 2010. In this exercise, we focus on the changes in labor income share from 2000 to 2019.

In our model, two channels induce automation, subsequently lowering labor income share. First, as shown in our empirical analysis, a reduction in capital cost relative to wage encourages firms to lower task demand for workers and raise task demand for capital per an effective unit. The incidence of this change differs across skill groups because the elasticity of substitution varies. Second, technological progress removes technology barriers in automating tasks that workers initially performed. The two channels accelerate automation in the sense that they facilitate reallocating tasks from labor to capital. The first channel relaxes the financial constraints of automation, and the second mitigates the technological constraints of automation. Formally, the change in the income share of skill group g can be decomposed

Figure 14: Labor Income Share over Time in the U.S.



Source: U.S. Bureau of Labor Statistics (BLS) and authors' calculations.

as:

$$d\ln s_g = \underbrace{\frac{\partial \ln s_g}{\partial \ln(R/w_g)} d\ln(R/w_g)}_{\text{contribution of factor price changes}} + \underbrace{\frac{\partial \ln s_g}{\partial \ln\left(\tilde{\Psi}_g/\tilde{\Psi}_k\right)} d\ln\left(\tilde{\Psi}_g/\tilde{\Psi}_k\right)}_{\text{contribution of direct technological progress}} \tag{11}$$

The first term on the right-hand side reflects the contribution of the change in factor prices corresponding to equation (8). The second term measures the contribution of automation orthogonal to the changes in factor prices. As in Acemoglu and Restrepo (2021), we can think of it as any direct non-neutral technological change that induces a change in the relative task shares. The change in overall labor share is the weighted sum of these changes over skill groups. We report the derivation of the empirical version of equation (11) from our model of automation in Appendix E.

To conduct the decomposition, we need the measures of factor prices, factors, and automation. To capture the overall changes in the rental rate of capital, we transform equation (1)

to a gross version:

$$R_{t+1} = \frac{1-\alpha_t\tau_t}{1-\tau_t}\left[p_t(1+r_{t+1}) - p_{t+1}(1-\delta)\right]$$

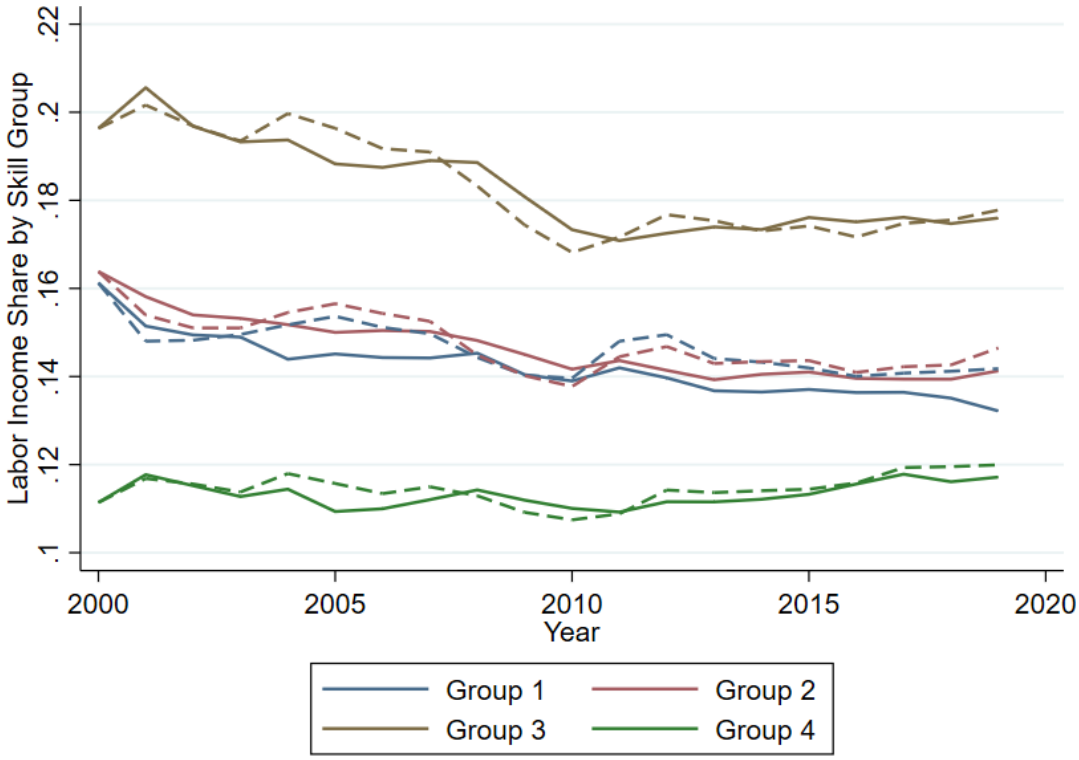
where $1+r_{t+1}$ denotes the gross real interest rate and p_t is the price index for capital goods.[20] We use Moody's BAA bond rate as the gross real interest rate, and the price index is from the National Income and Product Accounts (NIPA) data on equipment capital. Capital stock at constant national price is from Penn World Table (PWT). To be consistent with our empirical results, we classify all occupations into four skill groups based on software skill levels from Lightcast. We calculate the employment and average wage for each skill group from the American Community Survey (ACS). We use the ratio between the employment of occupations in each skill group and capital stock as a proxy for the level of automation. Then, the change in the ratio orthogonal to factor price changes reflects the effect of technological progress. This way is similar to a conventional approach that considers the change in occupational composition as a key consequence of automation in the labor market (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Hershbein and Kahn, 2018; Webb, 2019; Acemoglu et al., 2022).

In Figure 15, the solid lines indicate the evolution of income shares for the skill groups from data, and the dashed lines are the evolution of simulated income shares from our model. Each type of lines sum up the overall labor income share. Note that the labor income share of the highest skill group increases while those of the other workers sharply decline. The simulated income shares from our model follow these patterns well for two reasons. First, the heterogeneity in the elasticity of substitution between capital and labor makes factor price changes reduce the income share of lower-skill groups more. Second, the task share of lower-skill groups relative to the task share of capital declines faster than the highest-skill group. Thus, the displacement effect of automation is more pronounced for low-skilled workers, while it could raise the income share of high-skilled workers.

Figure 16 reports the evolution of overall labor income share. Note that the actual overall labor share (solid line) sharply declined from 2000 to 2010 and slightly rose after the Great Recession. The simulated labor share (dashed line) follows this trend, which means that our automation model with factor price changes and technological progress explains the secular trend in the U.S. labor market well. Moreover, factor price changes only account for 27% of the variation in overall labor share even though the cost of capital declines 45% during this period. It means that the reduction in the capital cost displaces some labor inputs but

[20] This equation is equivalent to the household's first-order condition with respect to capital in a dynamic version of our model. We incorporate capital taxation and bonus depreciation to capture the change in effective capital cost.

Figure 15: Labor Income Share by Skill Group

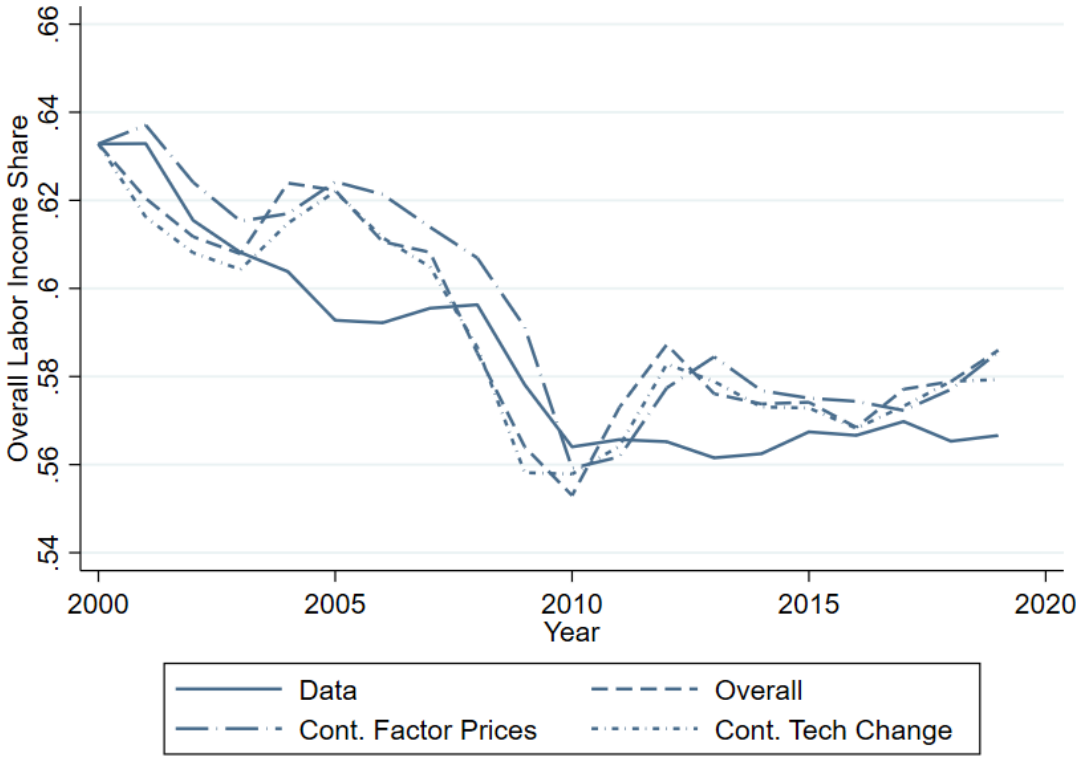


Notes: The solid lines are income shares across the software skill levels and they sum to the overall labor share. We classify occupations into quartiles based on software skill requirements from Lightcast and calculate the income share of the skill groups from ACS. The dashed lines are the simulated income shares based on our model. The details of the simulation is reported in Appendix E.

raises total factor productivity and labor demand to some extent in the long run.

In this section, we link the estimated effects of bonus depreciation changes and the automation model and show that the elasticity of substitution between capital and labor highly varies across skill groups due to the task displacement effect. The parameter heterogeneity also results in labor income share decreasing more for workers with fewer software skills in response to factor price changes and technological progress that accelerate automation. Thus, our results indicate that assuming the homogeneous elasticity of substitution between capital and labor may mislead the results of economic analysis on the labor market and obscure essential welfare implications.

Figure 16: Overall Labor Income Share



Notes: The solid line is the labor share for the non-farm business sector based on data from the BLS. The dashed line is the simulated labor share based on our model. The long-dashed dot and shot-dashed dot lines indicate the contributions of factor price changes and technological progress, respectively. The contributions are as defined in the text and Appendix E.

9 Conclusion

The growing adoption of automated capital such as robots and AIs has raised concerns from policy makers and economists about labor displacement. However, there has been relatively little work on firm-level causal effects of automation because of endogeneity issues and data limitations. This paper investigates how firms adjust labor inputs in response to a reduction in capital cost in the automation process. We utilize an increase in bonus depreciation rate for the purchase of machinery and equipment as an exogenous variation in the cost of capital. Our empirical strategy is based on two facts: 1) the increase in bonus depreciation is more advantageous for the firms relying more on long-lived capital; 2) the increase in bonus depreciation is more advantageous for the firms more exposed to the states conforming to the federal depreciation policy. Using these facts, we construct a firm-level effective bonus depreciation rate that captures how much a firm can reduce capital costs for machinery and

equipment.

We find that the investment stimulus raises investment in machinery and equipment while reducing overall employment at the same time. Our results also highlight that the change in labor demand in response to investment stimulus highly varies across skill groups. Firms disproportionately reduce labor demand for job positions that require fewer computer software skills, while labor demand for jobs with more computer software skills does not change much at the same time. We also find that these responses are more significant for firms with higher automation technologies. These patterns indicate that the investment stimulus on machinery and equipment accelerates a firm's adoption of automated machines in a way that labor demand for jobs with fewer software skills is disproportionately displaced.

Our unique setting in which capital cost for adopting automation exogenously declines makes it possible to estimate the elasticity of substitution between capital and labor and how much task displacement accounts for it. To do so, we develop a task-based model of automation following Acemoglu and Restrepo (2021) and Hubmer and Restrepo (2021) and connect the model to the reduced-form estimates following the sufficient statistics approach of Chetty (2009). Our estimation suggests that the elasticity of substitution between capital and labor highly varies across skill groups and increases as the software skill level increases. We also argue that task displacement by automation accounts for the major portion of higher elasticity of substitution for lower-skilled labor. This heterogeneity governs the welfare incidence of automation across workers as we show with the decline of the labor income share.

Our results should be cautiously interpreted because we only cover publicly traded firms much bigger than the average U.S. firms. Considering that the technology level of a firm should affect the allocation of input factors, our estimates should change if we include smaller firms in the sample. Our estimated elasticity of substitution between capital and labor is also micro-level. It does not consider the reallocation of inputs across firms, so our estimate could be different from the macro-level elasticity depending on how much the reallocation effect is. Our future work will extend this framework to the national level and examine how micro-level and macro-level implications could differ.

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Appendices

A Firm Matching

This section describes how a firm is linked across multiple firm-level data sets. The difficulty is rooted in the fact that the data sets do not have a common firm identifier. We first link establishments from Lightcast to firms in Compustat. The direct matching with firm names does not work because many firm names in the Lightcast job posting data self-reported by the employers so that they contain abbreviations or misspellings. Rather we conduct a fuzzy matching algorithm utilizing firm names and industry codes. Basically, we try to be conservative in picking the right matches rather than maximizing matching rates.

First, we standardize firm names in each data set following Wasi and Flaaen (2015). Wasi and Flaaen (2015) parses a string variable containing company names into several pieces and standardizes each piece based on rule-based patterns and common knowledge to improve the match quality when linking. For instance, "Incorporate", "Inc.", or ",Inc" are standardized to "inc" and "Corporation", "Co.", or "Corp" are standardized to "co". A part of firm name that represents industry is also abbreviated. For example, "Manufacturing" or "Manufacturer" change to "mfg" and "Industry" or "Industries" are replaced with "ind". The abbreviation of the common factors is important because a fuzzy matching method put more weights on longer words and the common factors have less information than the unique parts of the names. Using the Stata package called **reclink2** that performs probabilistic record linkage, we collected the perfectly or almost perfectly matched firm names between the two data sets. At this stage, we restrict that the unique parts of the names are the same, while allowing the common factors can be slightly different.

Second, we construct a measure of industry-to-industry connectedness based on the input-output account data from BEA.[21] The industry linkage is important because a matched establishment from Lightcast would be a part of the matched firm in Compustat. Their industry codes are not necessarily the same, but they should be relevant industries to some extent. For each 4-digit industry, we define the shares of input and output from the other industries as upstream and downstream linkages. With the unmatched names from the first trial, we conduct the fuzzy matching again with the names and industry linkages at the same time. Here, we collect the matches which have the same unique parts, but different common factors if the industry linkage is in top 5%.

Third, we employ another proprietary database called Computer Intelligence Technology

[21] https://www.bea.gov/industry/input-output-accounts-data

Database (CiTDB). CiTDB does not include all establishments in the U.S., but covers a large portion of all establishments (3.2 million) since 2010 and provides firm structure and detailed address of the establishments. For a firm, there is a unique firm identifier and one can identify the headquarter and branches of the firm. So, we first link the firm names from CiTDB to those from Compustat following the same way of the first stage. For a firm matched here, we can identify addresses and industry codes of its branches. Then we try the fuzzy matching between the establishments from Lightcast that are not matched in the second trial and the matched branches from CiTDB based on their names, industry codes, and county codes. Here, we only collect the matches with the same industry and county codes, but slightly different names with possible minor typos. Table A.1 reports the examples of the matched names between Compustat and Lightcast.

Linking Compustat and PatentView is relatively simple and has already been done in many other papers. We use the matched firm list provided by Autor et al. (2020).

Table A.1: Examples of Matched Firm Names

Names from Compustat	Names from Lightcast
CECO ENVIRONMENTAL CORP	Ceco Environmental Company
CECO ENVIRONMENTAL CORP	Ceco Environmental Corporation
CECO ENVIRONMENTAL CORP	CECO Environmental
ANDERSONS INC	Anderson
ANDERSONS INC	Anderson Companies
ANDERSONS INC	The Andersons, Inc
ANDERSONS INC	Andersons
BRADY CORP	Brady Companies
BRADY CORP	The Brady Companies
BRADY CORP	Brady Companies, Inc
BRADY CORP	Brady Companies Llc
BRADY CORP	Brady Corporation
BRADY CORP	Brady Companies, Llc
CONSTELLATION BRANDS	Constellation Brands Incorporated
CONSTELLATION BRANDS	Constellation Brands, Inc
CONSTELLATION BRANDS	Constellation Brands Beer Division
CROSSFIRST BANKSHARES INC	Crossfirst Bank
CROSSFIRST BANKSHARES INC	Crossfirst Bank Headquarters
ENVISTA HOLDINGS CORP	Envista Holdings
ENVISTA HOLDINGS CORP	Envista
ENVISTA HOLDINGS CORP	Envista Holdings Corporation
ARCONIC CORP	Arconic, Inc
ARCONIC CORP	Arconic
ARCONIC CORP	Arconic , Pa
ARCONIC CORP	Arconic Inc
ARCONIC CORP	Arconic Aerospace
PROVIDENT FINANCIAL HOLDINGS	Provident Financial Management
PROVIDENT FINANCIAL HOLDINGS	Provident Financial
PROVIDENT FINANCIAL HOLDINGS	Provident Financial Holdings
PROVIDENT FINANCIAL HOLDINGS	Provident Financial Services
TTEC HOLDINGS INC	Ttec Holdings, Inc
TTEC HOLDINGS INC	Ttec Corporate
TTEC HOLDINGS INC	Ttec
PACIFIC GAS & ELECTRIC CO	Pacific Gas and Electric Company
PACIFIC GAS & ELECTRIC CO	Pacific Gas Technology
PACIFIC GAS & ELECTRIC CO	Pacific Gas & Electric/Hr

B Patent Classification

This section describes the procedure of identifying robot-related patents among all patents issued by US Patent Trademark Office (USPTO) from 1975 to 2019. First, we extract features of a patent from its patent description using a natural language processing (NLP) method and calculate patent-to-patent semantic distance following the literature (Whalen et al., 2020; Kelly et al., 2021). Second, we identify the inventors of all patents having the lemmas "robot" and "manipulator" (a traditional word for robot) in title or description. Third, we collect all patents of these inventors. Fourth, we collect the patents close to each patent of these inventors in terms of semantic distance. The key idea of this approach is that the inventors collected by the searching embed the other important keywords related to the original search word in all of their patents. We, laymen to a specific field, do not know what the other keywords should be, but the inventors in that field know them and embed them in their patents. Thus, their patents are the best training set reflecting the features of the keyword.

There are three advantages of this approach. First, this is unsupervised algorithm to collect the patents having some specific features. The common way to do this in the literature is that the authors or some trained assistants classify a set of sample patents into the patent groups of interest and that the authors use the classified patents as the training set and apply some neural-network-based algorithm (Webb, 2019; Mann and Püttmann, 2021; Kogan et al., 2021). Their approach is a supervised machine learning in the sense that human judgement determines the criteria of the classification. In other words, it is hard to know what are the exact criteria of their judgement or it is hard to assess their judgement was right. On the contrary, our algorithm does not need any human judgement and just depends on the set of relevant inventors as nodes.

Second, this algorithm is easy to generalize and one needs a single keyword for the classification. For instance, if you want to collect all the patents related to "video game", you can collect the inventors of the patents including the lemma "video game" in the abstract. And then you can collect semantically close patents to each patent invented by the collected inventors. The patents just including the lemma "video game" may not include the patents related to physical engine, a core tool for game producing, but the patents collected by this algorithm are more likely to include these kinds of patents because this approach utilizes much more keywords potentially related to the original keyword "video game".

Third, this algorithm utilizes the semantic relationship between patents. The common text-based approach in the literature to classify patents depends on the frequency of words in a document. Term frequency-inverse document frequency (TF–IDF) method is one of this

kind (Kelly et al., 2021; Kogan et al., 2021). The main drawback of this approach is that it loses information from semantics of the words. For instance, this approach cannot detect that "strong" and "powerful" have the same meaning in certain contexts. our procedure adopts the recent neural-network-based model to analyze semantic features of documents, so-called **Doc2Vec**. Doc2Vec is an extension of Word2Vec, a popular model analyzing word-to-word semantic relationship. Here, we briefly explain Doc2Vec algorithm based on Le and Mikolov (2014).

Let's start from the Word2Vec algorithm. The purpose of this algorithm is to represent a word as a vector so that we can measure a semantic distance between two words or can apply arithmetic operations to a set of words. For instance, we want to make a vector operation "king - man + woman = queen" be valid. Given a sequence of words (vectors) $w_1, w_2, \cdots, w_n$, we can construct a prediction model to maximize the log likelihood of the word vector given k previous words and k next words:

$$\frac{1}{N}\sum_{i=k+1}^{N-k} \log p(w_i|w_{i-k}, \cdots, w_{i+k}).$$

Note that the order of neighboring words around w_i matters to predict w_i. The likelihood function is usually given by the multi-dimensional logistic function, in other words softmax function:

$$p(w_i|w_{i-k}, \cdots, w_{i+k}) = \frac{e^{b+Ug(w_{i-k},\cdots,w_{i+k};W)}}{\sum_j e^{b+Ug(w_{j-k},\cdots,w_{j+k};W)}} \tag{B.1}$$

where b, U, and W are the bias terms, weight matrix, and word embedding matrix (i.e. $W = [w_1 \cdots w_n]$). g is typically given by the average of $\{w_{i-k}, \cdots, w_{i+k}\}$. The set of word vectors can be trained in a recursive way and converges. The distance between two different word vectors measures how the words are semantically close to each other.

Doc2Vec extends this algorithm to reflect the information from the previous paragraph along with the nearby words when predicting a word. This means that not only a word is represented by a vector, but also a paragraph is a vector in the same space of word vectors. The paragraph vector adds more information that may be missing in the current context, $\{w_{i-k}, \cdots, w_{i+k}\}$. The only difference from Word2Vec is to add the previous paragraph vector to g in equation (B.1):

$$p(w_i|w_{i-k}, \cdots, w_{i+k}) = \frac{e^{b+Ug(d,w_{i-k},\cdots,w_{i+k};W,D)}}{\sum_j e^{b+Ug(d,w_{j-k},\cdots,w_{j+k};W,D)}} \tag{B.2}$$

where d is the previous paragraph vector that is represented by a column in the paragraph embedding matrix D.

Applying Doc2Vec to all patent descriptions, we can represent each patent as a vector reflecting the semantic relationship in the vector space. To identify robot-related patents, we calculate the distance between the vector representing each patent of the inventors collected in the previous step and those of all the other patents and pick out the patents in the 10th percentile in terms of the semantic distance. The features of the robot-related patents are robust to the cut-off points.

C Aggregate Employment Results using OEWS

This section provides the aggregate employment results with OEWS (Occupational Employment and Wage Statistics) extended from the main results in Section 6. Note that our firm-level analysis only covers the publicly traded U.S. firms that account for a small portion of total labor force in the U.S. Thus, the additional analysis in this section checks whether the same trends show up in the other firms and at aggregate level.

The OEWS program provides employment and wage estimates annually across metropolitan statistical areas (MSA) for more than 800 occupations following Standard Occupational Classification (SOC). The OEWS data set is the most suitable aggregate-level data for us in the sense that our analysis focuses on the heterogeneous employment responses to the change in bonus depreciation rate across skill groups.

For the MSA-level analysis, we construct the effective bonus depreciation rate for each MSA using the parallel way of equation (4):

$$bonus_{mt} = \left[\sum_{i \in I_m} \frac{L_{mi}}{L_m} (1 - z_i) \right] (\tau_{fed,t} + 1_{mt} \tau_{mt}) \theta_t$$

where I_m represents the set of industries of MSA m and $\frac{L_{mi}}{L_m}$ is the employment weight of industry $i \in I_m$ within m in 2014-2016 before TCJA. We use Quarterly Workforce Indicators (QWI) to construct the employment weight of industry because OEWS does not provide industry information. The difference in $bonus_{mt}$ before and after TCJA captures how much the tax reform affects the effective bonus depreciation rate at m.

To see how the tax reform affects the aggregate employment across skill groups, we also classify SOC occupations based on the skill requirements from the Lightcast job postings. We calculate the average requirements of a skill measure for each occupation in 2016 before the tax reform and classify occupations into quartiles following Section 6.2. For comparison, we also use the occupation-level measures from Acemoglu and Autor (2011) and Webb (2019) to classify occupations.

We show the event study estimates at MSA level parallel to the firm-level results following equation (5). As in the main analysis, we divide $\Delta bonus_m$ by the average across MSAs, so that we can interpret the coefficients as the average effects. The OEWS estimates are constructed from a sample of about 1.1 million establishments collected over a 3-year period. So, we report the results of four 3-year periods (2008-2010, 2011-2013, 2014-2016, and 2017-2019) and the last period is the treated period.

Figure C.1 reports the effects of the change in bonus depreciation on MSA-level employ-

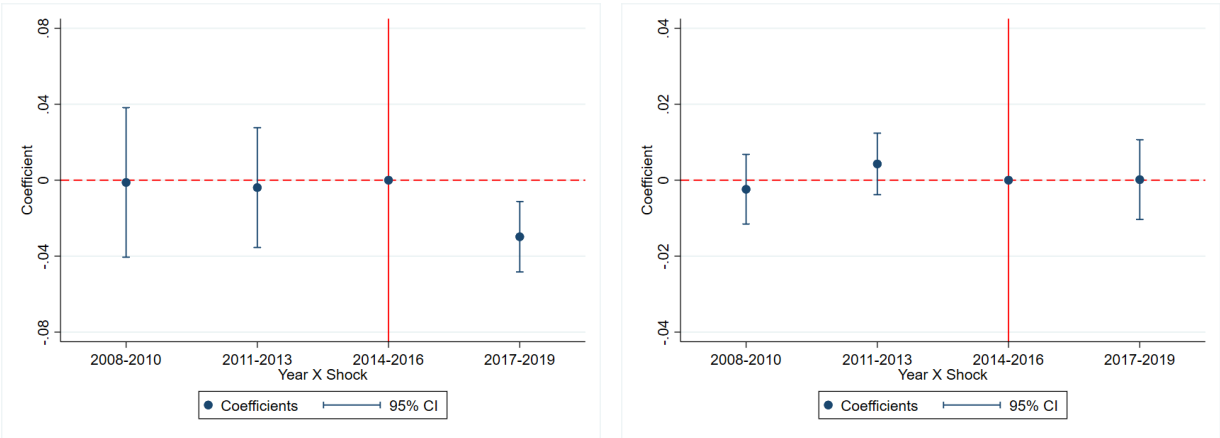
ment and annual wage. Panel (a) shows that employment declines about 2.9% on average in response to the change in bonus depreciation, suggesting a similar conclusion as the main firm-level results though the scale of the effects are larger in the firm-level results. Panel (b) indicates that the change in bonus depreciation does not affect annual wages, supporting that it is valid to focus on employment rather than wages in our firm-level analysis.

The difference in the scale of employment changes is reasonable by three reasons. First, publicly traded firms are more technologically advanced and more responsive to the reduction in capital cost than smaller firms. According to Acemoglu and Restrepo (2018), firms are restricted both by financial and technological constraints when they adopt automation technologies. Even if new machinery and equipment get affordable for small firms by the change in bonus depreciation, they may not adopt new capital because they do not have technological capacity to implement them. Second, small firms already got similar benefits by another policy called Section 179. The policy already provided small firms with a full tax deduction for the purchase of new capital, which is equivalent to 100% bonus depreciation rate (Tuzel and Zhang, 2021). Third, the aggregate-level result reflects reallocation of workers in the local labor market. If a worker is displaced by automation technology in a firm, she could get another job and employment does not change in this case. This reallocation of displaced workers cannot be captured in the firm-level analysis.

Figure C.2 reports he difference-in-difference effect of bonus depreciation change on employment by skill level. To generate the parallel results to the firm-level analysis, we calculate the average skill levels of an occupation based on skill requirements from the Lightcast job posting data. Then, the occupations are classified into quartiles for each skill measure. The figures confirm our firm-level results with the most clear monotonic increase in software skill levels. As in the firm-level results, we cannot find similar patterns with the other skills. Thus, our main findings with firms can be expanded to the local labor market.

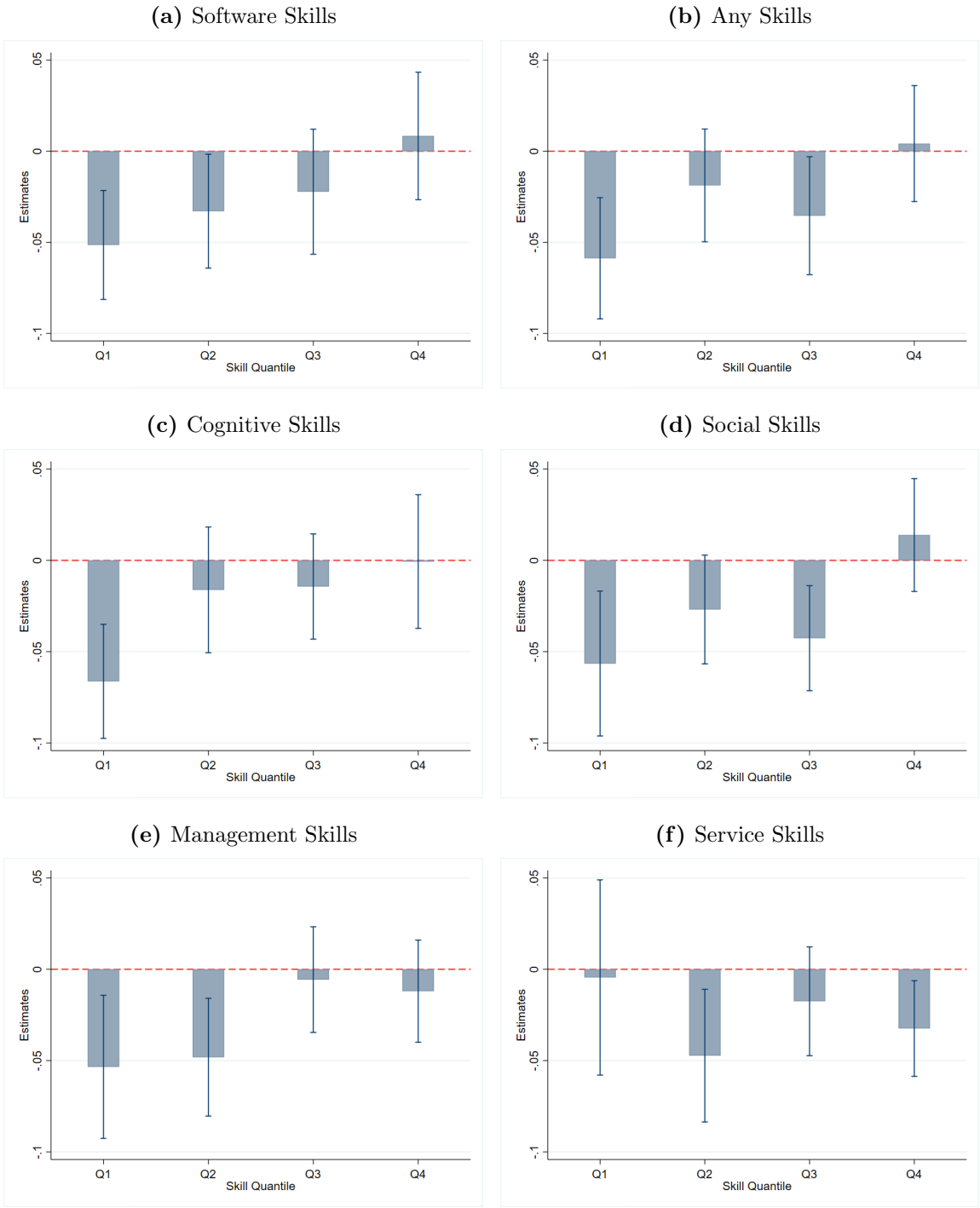
Figure C.1: Dynamic MSA-level Responses of Employment and Wage

(a) Employment **(b)** Annual Wage



Notes: The observations are at MSA-SOC-year level. The panels (a) and (b) show the dynamic response of employment and annual wage via the annualized version of the model of equation (5). The base period (2014-2016) is before the announcement of the Tax Cuts and Jobs Act and we use MSA-SOC-level employment in 2014-2016 as a weight. The MSA-by-SOC, SOC-by-year fixed effects, and MSA population are controlled. Standard errors are clustered at MSA level and the confidence intervals are at 95% level.

Figure C.2: MSA-level Responses of Employment by Skill Level



Notes: Each figure shows the difference-in-difference estimates of the number of job postings across skill groups based on a skill measure. For each skill measure, we calculate the average skill level of an occupation before the tax reform and classify the occupations into quartiles based on the skill levels. We use MSA-SOC-level employment in 2014-2016 as a weight. The MSA-by-SOC, SOC-by-year fixed effects, and MSA population are controlled. The point estimates are the coefficients of $\Delta bonus_m \cdot 1[t = \text{2017-2019}]$. Standard errors are clustered at MSA level and the confidence intervals are at 95% level.

D Derivation of Model

D.1 Consumption Aggregator

The Lagrangian of the cost minimization problem is

$$\mathcal{L} = -\int_0^1 p(\eta)y(\eta)d\eta + m\left[\left(\int_0^1 y(\eta)^{\frac{\sigma-1}{\sigma}}d\eta\right)^{\frac{\sigma}{\sigma-1}} - y\right]$$

where m is the Lagrange multiplier. The FOCs to the problem delivers the demand for good η.

$$p(\eta) = my^{\frac{1}{\sigma}}y(\eta)^{-\frac{1}{\sigma}}$$

Substitute the above equation into the constraint to obtain the price index m.

$$m = \left(\int_0^1 p(\eta)^{1-\sigma}d\eta\right)^{\frac{1}{1-\sigma}}$$

Normalizing by the price index gives the ideal price index condition that the factor prices must satisfy.

$$1 = \int_0^1 p(\eta)^{1-\sigma}d\eta$$

Individual firms' problem gives the relationship between the price of good η and the unit cost of production.

$$\max_{y(\eta)} p(\eta)y(\eta) - m(\eta)y(\eta) = my^{\frac{1}{\sigma}}y(\eta)^{\frac{\sigma-1}{\sigma}} - m(\eta)y(\eta)$$

$$\frac{\sigma-1}{\sigma}my^{\frac{1}{\sigma}}y(\eta)^{-\frac{1}{\sigma}} = m(\eta)$$

$$p(\eta) = \frac{\sigma}{\sigma-1}m(\eta)$$

D.2 Unit Cost Function and Aggregated Production Function

Note that we can order the tasks to divide the task set into subsets.

$$
\begin{aligned}
y(\eta) &= \left(\int_0^T y(x,\eta)^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}} \\
&= \left(\sum_{g=1}^{G} \int_{T_{g-1}(\eta)}^{T_g(\eta)} y(x,\eta)^{\frac{\lambda-1}{\lambda}} dx + \int_{T_G(\eta)}^{T} y(x,\eta)^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}} \\
&= \left(\sum_{g=1}^{G} \int_{T_{g-1}(\eta)}^{T_g(\eta)} (\psi_g(x)\ell_g(x,\eta))^{\frac{\lambda-1}{\lambda}} dx + \int_{T_G(\eta)}^{T} (\psi_k(x)k(x,\eta))^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}}
\end{aligned}
$$

$$
\mathcal{L}(\eta) = -Rk(\eta) - \sum_g w_g \ell_g(\eta) + m(\eta)\left(\left(\int_0^T y(x,\eta)^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}} - y(\eta)\right)
$$

where $m(\eta)$ is the Lagrange multiplier. Then, the FOCs to the cost minimization problem are given below.

$$
\begin{aligned}
w_g &= m(\eta)y(\eta)^{\frac{1}{\lambda}}[\psi_g(x)\ell_g(x,\eta)]^{-\frac{1}{\lambda}}\psi_g(x) \\
\ell_g(x,\eta) &= m(\eta)^{\lambda} w_g^{-\lambda} y(\eta)\psi_g(x)^{\lambda-1} \\
k(x,\eta) &= m(\eta)^{\lambda} R^{-\lambda} y(\eta)\psi_k(x)^{\lambda-1}
\end{aligned}
$$

Substitute these into the production function to obtain the unit cost function of firm η.

$$
\begin{aligned}
y(\eta) &= \left(\sum_{g=1}^{G} \int_{T_{g-1}(\eta)}^{T_g(\eta)} (w_g^{-\lambda} y(\eta)\psi_g(x)^{\lambda})^{\frac{\lambda-1}{\lambda}} dx + \int_{T_G(\eta)}^{T} (R^{-\lambda} y(\eta)\psi_k(x)^{\lambda})^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}} \\
m(\eta) &= \left(\sum_{g=1}^{G} \Psi_g(\eta) w_g^{1-\lambda} + \Psi_k(\eta) R^{1-\lambda}\right)^{\frac{1}{1-\lambda}}
\end{aligned}
$$

It is straightforward to derive the cost shares from the unit cost function. The definition of the cost share of capital is that $s_k(\eta) = \frac{R(k(\eta)/y(\eta))}{m(\eta)}$. Then it immediately follows that $s_k(\eta) = \frac{\Psi_k(\eta)R^{1-\lambda}}{m(\eta)^{1-\lambda}}$. To derive the aggregated production function, total factor demands of

firm η are given below.

$$\begin{aligned}
k(\eta) =& \int_{T_G(\eta)}^{T} k(x,\eta)dx \\
=& \int_{T_G(\eta)}^{T} m(\eta)^{\lambda} R^{-\lambda} y(\eta)\psi_k(x)^{\lambda-1}dx \\
=& m(\eta)^{\lambda} R^{-\lambda} y(\eta)\Psi_k(\eta) \\
\ell_g(\eta) =& m(\eta)^{\lambda} w_g^{-\lambda} y(\eta)\Psi_g(\eta)
\end{aligned}$$

Substitute these into the production function to derive the production function aggregated across the tasks.

$$\begin{aligned}
\psi_k(x)k(x,\eta) = m(\eta)^{\lambda}R^{-\lambda}y(\eta)\psi_k(x)^{\lambda} = k(\eta)\Psi_k(\eta)^{-1}\psi_k(x)^{\lambda} \\
\int_{T_G(\eta)}^{T} [\psi_k(x)k(x,\eta)]^{\frac{\lambda-1}{\lambda}}dx = \Psi_k(\eta)^{\frac{1}{\lambda}}k(\eta)^{\frac{\lambda-1}{\lambda}} \\
\int_{T_{g-1}(\eta)}^{T_g(\eta)} (\psi_g(x)\ell_g(x,\eta))^{\frac{\lambda-1}{\lambda}}dx = \Psi_g(\eta)^{\frac{1}{\lambda}}\ell_g(\eta)^{\frac{\lambda-1}{\lambda}} \\
y(\eta) = \left(\Psi_k(\eta)^{\frac{1}{\lambda}}k(\eta)^{\frac{\lambda-1}{\lambda}} + \sum_{g\in\mathcal{G}} \Psi_g(\eta)^{\frac{1}{\lambda}}\ell_g(\eta)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}
\end{aligned}$$

D.3 Proofs

D.3.1 Proof of Proposition 1

Proposition 6 (Induced Elasticity of Substitution)**.** *The induced elasticity of substitution between capital and labor g can be expressed as:*

$$\lambda_{gk}(\eta) := 1 + \frac{\mathrm{d}\ln(s_g(\eta)/s_k(\eta))}{\mathrm{d}\ln(R/w_g)} = \underbrace{\lambda}_{\textit{capital deepening}} + \underbrace{\frac{\mathrm{d}\ln\Psi_g(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\textit{task displacement}} - \underbrace{\frac{\mathrm{d}\ln\Psi_k(\eta)}{\mathrm{d}\ln(R/w_g)}}_{\textit{task absorption}}.$$

Proof. The ratio of factor shares is:

$$\frac{s_g(\eta)}{s_k(\eta)} = \frac{\Psi_g(\eta)}{\Psi_k(\eta)}\left(\frac{w_g}{R}\right)^{1-\lambda}.$$

The log derivative of the ratio with respect to relative prices is:

$$\frac{\mathrm{d}\ln(s_g(\eta)/s_k(\eta))}{\mathrm{d}\ln(R/w_g)} = \frac{\mathrm{d}\ln(\Psi_g(\eta)/\Psi_k(\eta))}{\mathrm{d}\ln(R/w_g)} + \lambda - 1,$$

which gives the expression in the proposition. □

D.3.2 Proof of Lemma 1

Lemma 1 (Changes in Factor Share Parameters)**.** *Following a decrease in capital cost by $d\ln R < 0$, the factor share of labor group g in firm η declines by*

$$d\ln\Psi_g(\eta) = -\frac{\psi_g^{\lambda}(T_{g-1}(\eta))}{\Psi_g(\eta)}\frac{\mathrm{d}\epsilon_g(\eta)}{\mathrm{d}\ln R}d\ln R \leq 0. \tag{D.1}$$

The decrement is increasing in technology level η and decreasing in skill level g.

Proof. Recall that $\Psi_g(\eta) = \int_{T_{g-1}(\eta)+\epsilon_g(\eta)}^{T_g(\eta)} \psi_g(x)^{\lambda}dx$ where $\epsilon_g(\eta)$ captures the reallocation of tasks from skill g to capital. Then, Leibniz's rule implies:

$$\begin{aligned} d\ln\Psi_g(\eta) =& \frac{1}{\Psi_g(\eta)}\frac{\mathrm{d}}{\mathrm{d}\ln R}\int_{T_{g-1}(\eta)+\epsilon_g(\eta)}^{T_g(\eta)} \psi_g(x)^{\lambda}dx \\ =& \frac{1}{\Psi_g(\eta)}\left(-\psi_g(T_{g-1}(\eta))^{\lambda}\frac{\mathrm{d}\epsilon_g(\eta)}{\mathrm{d}\ln R}\right)d\ln R, \end{aligned}$$

which is the expression in the lemma. Here, $\frac{\mathrm{d}\epsilon_g(\eta)}{\mathrm{d}\ln R}$ captures the task reallocation from labor group g to capital in response to capital cost changes.

Now we would like to show that $\frac{\mathrm{d}\epsilon_g(\eta)}{\mathrm{d}\ln R}$ is decreasing in η and increasing in g. Suppose that $\eta_1 < \eta_2$. By the definition, $\mathcal{A}(\eta_1) \subseteq \mathcal{A}(\eta_2)$ and $\Delta\mathcal{T}_g(\eta_1) \subseteq \Delta\mathcal{T}_g(\eta_2)$ where $\Delta\mathcal{T}_g$ is the set of tasks reallocated from labor group g to capital. Considering our ordering of tasks within each labor group, it means that $\frac{\mathrm{d}\epsilon_g(\eta_2)}{\mathrm{d}\ln R} \leq \frac{\mathrm{d}\epsilon_g(\eta_2)}{\mathrm{d}\ln R}$. Now suppose that $g_1 < g_2$. By our partition rule of labor inputs, the set of susceptible tasks is larger for g_1:

$$\int_{\Xi_{g_2}(\eta)} 1dx \leq \int_{\Xi_{g_1}(\eta)} 1dx \quad \forall\eta \in [0,1].$$

In other words, whatever $\Delta R < 0$, $\Delta\mathcal{T}_{g_1}(\eta) = \left\{x \in \Xi_{g_1}(\eta) : \frac{R+\Delta R}{\psi_k(x)} < \frac{w_{g_1}}{\psi_{g_1}(x)} < \frac{R}{\psi_k(x)}\right\}$ is larger than $\Delta\mathcal{T}_{g_2}(\eta)$ for all η, which is equivalent to $\frac{\mathrm{d}\epsilon_{g_2}(\eta)}{\mathrm{d}\ln R} \leq \frac{\mathrm{d}\epsilon_{g_1}(\eta)}{\mathrm{d}\ln R}$.

□

D.3.3 Proof of Proposition 2

Proposition 7 (Labor Demand Changes)**.** *Following a decrease in capital cost by $d\ln R < 0$, the change in labor demand by firm η can be characterized by:*

$$d\ln \ell_g(\eta) = d\ln \frac{y}{m(\eta)^\sigma} + \lambda d\ln m(\eta) + d\ln \Psi_g(\eta).$$

The change is decreasing in technology level η and increasing in skill level g.

Proof. The total demand for labor g by firm η is determined by wage, demand for firm η's output, and the factor share parameter: $\ell_g(\eta) = m(\eta)^\lambda w_g^{-\lambda} y(\eta)\Psi_g(\eta)$. Since wages are fixed in our setting, we have $d\ln \ell_g(\eta) = d\ln y(\eta) + \lambda d\ln m(\eta) + d\ln \Psi_g(\eta)$. The first term is the productivity effect at the firm level and the second term is the task reallocation effect for labor g within firm η. The firm-level productivity effect is, in turn, determined by the demand for individual firm. The profit maximization problem of the bundling firm gives the demand for each individual firm. Consider the Lagrangian of the bundling firm:

$$\mathcal{L} = -\int_0^1 p(\eta)y(\eta)d\eta + m\left[\left(\int_0^1 y(\eta)^{\frac{\sigma-1}{\sigma}} d\eta\right)^{\frac{\sigma}{\sigma-1}} - y\right],$$

where $p(\eta)$ is the price charged by firm η and m is the Lagrange multiplier. Then the corresponding first-order condition is:

$$\begin{aligned} p(\eta) =& m y^{\frac{1}{\sigma}} y(\eta)^{-\frac{1}{\sigma}} \\ \implies y(\eta) =& m^\sigma y p(\eta)^{-\sigma} \end{aligned}$$

Note that m is the aggregate price index, $m = \left(\int_0^1 p(\eta)^{1-\sigma} d\eta\right)^{\frac{1}{1-\sigma}}$. We normalize the prices with the aggregate price index m and set $m = 1$.

Now to derive the relationship between an individual firm's price and its unit cost function, consider the profit maximization problem of firm i.

$$\max_{y(\eta)} p(\eta)y(\eta) - m(\eta)y(\eta) = m y^{\frac{1}{\sigma}} y(\eta)^{\frac{\sigma-1}{\sigma}} - m(\eta)y(\eta)$$

The first-order condition gives $p(\eta) = \frac{\sigma}{\sigma-1} m(\eta)$, where $\frac{\sigma}{\sigma-1}$ is the markup. By substituting $p(\eta)$ into the firm's demand, we can write the change in demand for good η as $d\ln y(\eta) = d\ln y - \sigma d\ln m(\eta)$, which delivers the expression in the proposition. The first term on the right hand side is the aggregate productivity effect and the second term is the cost reduction effect at the firm level as a result of falling capital costs. □

D.3.4 Proof of Proposition 3

Proposition 8 (Changes in Factor Shares at the Firm Level)**.** *Following a decrease in capital cost by $d\ln R < 0$, the response of the cost share of labor type g is determined by the deviation of the elasticity of labor g from the average elasticity:*

$$d\ln s_g(\eta) = \left[s_k(\eta)(\lambda_{gk}(\eta) - 1) + \sum_{h\in\mathcal{G}, h\neq g} s_h(\eta)(\lambda_{gk}(\eta) - \lambda_{hk}(\eta)) \right] d\ln R.$$

Proof. Starting from the expression $s_g(\eta) = \frac{\Psi_g(\eta)w_g^{1-\lambda}}{\Psi_k(\eta)R^{1-\lambda}+\sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda}}$, we take its derivative with respect to $\ln R$ holding w_g fixed as before. Then, using the expressions for the cost shares, we obtain the following expression:

$$\begin{aligned}
&d\ln s_g(\eta) \\
&= d\ln \frac{\Psi_g(\eta)w_g^{1-\lambda}}{\Psi_k(\eta)R^{1-\lambda} + \sum_{g\in\mathcal{G}}\Psi_g(\eta)w_g^{1-\lambda}} \\
&= d\ln \Psi_g(\eta)w_g^{1-\lambda} - d\ln\left(\Psi_k(\eta)R^{1-\lambda} + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda}\right) \\
&= d\ln \Psi_g(\eta)w_g^{1-\lambda} - \frac{1}{\Psi_k(\eta)R^{1-\lambda} + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda}}\left[d(\Psi_k(\eta)R^{1-\lambda}) + \sum_{h\in\mathcal{G}} d(\Psi_h(\eta)w_h^{1-\lambda})\right] \\
&= d\ln \Psi_g(\eta) - \frac{1}{\Psi_k(\eta)R^{1-\lambda} + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda}} \\
&\times \left[\Psi_k(\eta)R^{1-\lambda} d\ln \Psi_k(\eta)R^{1-\lambda} + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda} d\ln \Psi_h(\eta)w_h^{1-\lambda}\right] \\
&= d\ln \Psi_g(\eta) - \frac{1}{\Psi_k(\eta)R^{1-\lambda} + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda}} \\
&\times \left[\Psi_k(\eta)R^{1-\lambda}\left(d\ln \Psi_k(\eta) + (1-\lambda)d\ln R\right) + \sum_{h\in\mathcal{G}}\Psi_h(\eta)w_h^{1-\lambda} d\ln \Psi_h(\eta)\right] \\
&= d\ln \Psi_g(\eta) - s_k(\eta)d\ln \Psi_k(\eta) - s_k(\eta)(1-\lambda)d\ln R - \sum_{h\in\mathcal{G}} s_h(\eta)d\ln \Psi_h(\eta).
\end{aligned}$$

We can further simplify the expression by substituting the induced elasticities derived in

Proposition 1.

$$
\begin{aligned}
d\ln s_g(\eta) =& d\ln\Psi_g(\eta) - d\ln\Psi_k(\eta) + d\ln\Psi_k(\eta) - s_k(\eta)\left(d\ln\Psi_k(\eta) + (1-\lambda)d\ln R\right) \\
&- \sum_{h\in\mathcal{G}} s_h(\eta)\left(d\ln\Psi_h(\eta) - d\ln\Psi_k(\eta) + d\ln\Psi_k(\eta)\right) \\
=& \left[\lambda_{gk}(\eta) - \lambda - s_k(\eta)(1-\lambda) - \sum_{h\in\mathcal{G}} s_h(\eta)[\lambda_{hk}(\eta) - \lambda]\right] d\ln R
\end{aligned}
$$

By rearranging the terms we obtain the expression in the proposition. □

D.3.5 Proof of Proposition 4

Proposition 9 (Welfare Change by Labor Type)**.** *Following a decrease in capital cost by $d\ln R < 0$, the welfare change is determined by group-specific capital-labor substitution effect as well as the productivity effect:*

$$
d\ln W_g = \left(\frac{\mathrm{d}\ln u}{\mathrm{d}\ln c_g} + \frac{\mathrm{d}\ln u}{\mathrm{d}\ln \ell_g}\right)\left[d\ln y + (1+\sigma_{kk}s_k)d\ln R + d\ln\left(\frac{s_g}{s_k}\right)\right] \tag{D.2}
$$

where $\sigma_{kk} < 0$ is the Allen elasticity of capital substitution and s_g and s_k are the income shares aggregated over firms.

Proof. We use Shephard's lemma to obtain $\ell_g = m_g y$ where $m_g := \frac{\partial m}{\partial w_g}$. Then, we can derive an expression for the elasticity of labor demand that depends on the cost function and the elasticity of output as follows:

$$
\begin{aligned}
d\ln \ell_g =& d\ln m_g + d\ln y \\
=& \frac{1}{m_g}\frac{\partial m_g}{\partial \ln R} d\ln R + d\ln y \\
=& \frac{1}{m_g}\frac{\partial m_g}{\partial R}\frac{\mathrm{d}R}{\mathrm{d}\ln R} d\ln R + d\ln y \\
=& \frac{m_{gR}}{m_g} R d\ln R + d\ln y.
\end{aligned}
$$

The first term turns out to be a product of the Allen elasticity of substitution (σ_{gk}) and the

cost share of capital:

$$
\begin{aligned}
\frac{m_{gR}}{m_g}R =& \frac{m_{gR}}{m_g}\frac{Rk}{k} \\
=& \frac{m_{gR}}{m_g}\frac{Rk}{m_R y} \quad (\because \text{Shaphard's lemma}) \\
=& \frac{m m_{gR}}{m_g m_R}\frac{Rk}{my} \\
=& \sigma_{gk} s_k.
\end{aligned}
$$

Note that σ_{gk} can be expressed as a function of the induced elasticity (λ_{gk}). Starting from the induced elasticity, we can express:

$$
\begin{aligned}
\lambda_{gk} &= \frac{\mathrm{d}\ln(m_g/m_R)}{\mathrm{d}\ln(R/w_g)} \\
&= \frac{\mathrm{d}\ln m_g}{\mathrm{d}\ln(R/w_g)} - \frac{\mathrm{d}\ln m_R}{\mathrm{d}\ln(R/w_g)} \\
&= \frac{\mathrm{d}m_g}{\mathrm{d}(R/w_g)}\frac{(R/w_g)}{m_g} - \frac{\mathrm{d}m_R}{\mathrm{d}(R/w_g)}\frac{(R/w_g)}{m_R} \\
&= \frac{\mathrm{d}m_g}{\mathrm{d}R}\frac{\mathrm{d}R}{\mathrm{d}(R/w_g)}\frac{(R/w_g)}{m_g} - \frac{\mathrm{d}m_R}{\mathrm{d}R}\frac{\mathrm{d}R}{\mathrm{d}(R/w_g)}\frac{(R/w_g)}{m_R} \\
&= \frac{\mathrm{d}m_g}{\mathrm{d}R}w_g\frac{(R/w_g)}{m_g} - \frac{\mathrm{d}m_R}{\mathrm{d}R}w_g\frac{(R/w_g)}{m_R} \\
&= \frac{\mathrm{d}m_g}{\mathrm{d}R}\frac{R}{m_g} - \frac{\mathrm{d}m_R}{\mathrm{d}R}\frac{R}{m_R} \\
&= m_{Rg}\frac{R}{m_g} - m_{RR}\frac{R}{m_R} \\
&= \frac{m_{Rg}}{m_g}R - \frac{m_{RR}}{m_R}R \\
&= \frac{m_{Rg}}{m_g}\frac{Rk}{k} - \frac{m_{RR}}{m_R}\frac{Rk}{k} \\
&= \frac{m_{Rg}}{m_g}\frac{Rk}{m_R y} - \frac{m_{RR}}{m_R}\frac{Rk}{m_R y} \\
&= \frac{m m_{Rg}}{m_g m_R}\frac{Rk}{my} - \frac{m m_{RR}}{m_R m_R}\frac{Rk}{my} \\
&= \sigma_{gk} s_k - \sigma_{kk} s_k \\
&= (\sigma_{gk} - \sigma_{kk}) s_k
\end{aligned}
$$

Then, the response of labor demand for skill group g can be expressed as:

$$\begin{aligned}
d\ln \ell_g =& \frac{m_{gR}}{m_g} R d\ln R + d\ln y \\
=& \left[\frac{\lambda_{gk}}{s_k} + \sigma_{kk}\right] s_k d\ln R + d\ln y \\
=& \left[1 + \frac{d\ln(s_g/s_k)}{d\ln(R/w_g)} + \sigma_{kk} s_k\right] d\ln R + d\ln y \\
=& (1 + \sigma_{kk} s_k) d\ln R + d\ln\left(\frac{s_g}{s_k}\right) + d\ln y.
\end{aligned}$$

□

E Labor Share Decomposition

This section explains how we calculate the evolution of labor income share for each skill group. Note that we do not distinguish the change in labor cost share and that in labor income share because markups are fixed in our model with CES demand. As we see from proposition 2, the change in labor cost share of each skill group can be expressed as:

$$\begin{aligned} d\ln s_g =& d\ln\left(\frac{\Psi_g w_g^{1-\lambda}}{\Psi_k R^{1-\lambda} + \sum_{g\in\mathcal{G}} \Psi_g w_g^{1-\lambda}}\right) \\ =& d\ln(\Psi_g/\Psi_k) - s_k(1-\lambda)d\ln(R/w_g) - \sum_{h\in\mathcal{G}} s_h d\ln(\Psi_h/\Psi_k). \end{aligned} \tag{E.1}$$

We can rewrite the change in relative factor shares as a component driven by the change in factor prices and the other component driven by technological change:

$$\begin{aligned} d\ln(\Psi_g/\Psi_k) =& \frac{\partial\ln(\Psi_g/\Psi_k)}{\partial\ln(R/w_g)} d\ln(R/w_g) + \left[d\ln(\Psi_g/\Psi_k) - \frac{\partial\ln(\Psi_g/\Psi_k)}{\partial\ln(R/w_g)} d\ln(R/w_g)\right] \\ =& (\lambda_{gk}-\lambda)d\ln(R/w_g) + [d\ln(\Psi_g/\Psi_k) - (\lambda_{gk}-\lambda)d\ln(R/w_g)] \\ \equiv& (\lambda_{gk}-\lambda)d\ln(R/w_g) + d\ln\left(\widetilde{\Psi}_g/\widetilde{\Psi}_k\right) \end{aligned} \tag{E.2}$$

where $d\ln\left(\widetilde{\Psi}_g/\widetilde{\Psi}_k\right)$ denotes the change in relative task shares orthogonal to the factor price changes. As in Acemoglu and Restrepo (2021), we can think of it as any direct technological change that induces a change in the relative task shares.

Combining equations (E.1) and (E.2) gives:

$$\begin{aligned} d\ln s_g = & \underbrace{\left[s_k(\lambda_{gk}-1) + \sum_{h\neq g} s_h(\lambda_{gk}-\lambda_{hk})\right] d\ln(R/w_g)}_{\text{contribution of factor price changes}} \\ & + \underbrace{d\ln\left(\widetilde{\Psi}_g/\widetilde{\Psi}_k\right) - \sum_{h\in\mathcal{G}} s_h d\ln\left(\widetilde{\Psi}_h/\widetilde{\Psi}_k\right)}_{\text{contribution of technological progress}}. \end{aligned} \tag{E.3}$$

The first line on the right-hand side indicates the contribution of changes in capital cost relative to wage for skill group g. If the elasticity of substitution between capital and labor are same across labor types ($\lambda_{hk} = \lambda_{gk}\ \forall h$), then the elasticity larger than 1 guarantees that the labor share declines as the cost of capital decreases. The skill group that has the elasticity larger than the other groups ($\lambda_{gk} > \lambda_{hk}\ \forall h$) experiences the largest reduction in labor income

share when the cost of capital decreases. The second and third lines reflect the contribution of technological progress that is embedded in the changes in task shares orthogonal to the changes in factor prices. To be specific, the two lines imply that technological progress facilitating task replacement from skill group g to capital disproportionately reduces labor share of that group.

To enable the decomposition of the evolution of labor income share, we use a discrete approximation of equations (E.3):

$$\begin{aligned}\frac{s_{gt+1} - s_{gt}}{s_{gt}} = &\left[s_{kt}(\lambda_{gk} - 1) + \sum_{h \neq g} s_{ht}(\lambda_{gk} - \lambda_{hk}) \right] \Delta \ln(R_t / w_{gt}) \\ &+ \Delta \ln\left(\widetilde{L}_{gt}/\widetilde{K}_t\right) - \sum_{h \in \mathcal{G}} s_{ht} \Delta \ln\left(\widetilde{L}_{ht}/\widetilde{K}_t\right).\end{aligned}$$

We use the ratio between employment of skill group g and capital as the proxy for the ratio between task shares. We take the residuals from the regressions of the log change in the employment-capital ratios on the log change in the relative factor prices to extract the contribution of technological change orthogonal to the factor price changes. The change in overall labor income share is simply calculated as the weighted average of the changes labor income share of all skill groups.

F Tables and Figures

Table F.1: Examples of Depreciation Schedule by MACRS

Description of Assets	Class Life (Year)
Automobiles, Taxis	3
Information Systems	6
Computers	5
Data Handling Equipment, Except Computers	6
Airplanes (airframes & engines)	6
Any Semi-conductor Mfg. Equip.	5
Telephone Station Equip.	10
Mfg. of Motor Vehicles Equip.	12
Ship & Boat Building Machinery and Equip.	12
Railroad Cars & Locomotives	15
Vessels, Barges, Tugs, & Similar Water Transportation Equip	18
Industrial Steam and Electric Generation Systems	22

Source: Section 168(a) of the Internal Revenue Code (IRC).

Table F.2: Examples of Deferred Tax Liability (DTL)

Year	PP&E	Accounting Depreciation	Tax Depreciation 1	DTL 1	Tax Depreciation 2	DTL 2
1	1000	100	200	-30	1000	-270
2	900	100	200	-60	0	-240
3	800	100	200	-90	0	-210
4	700	100	200	-120	0	-180
5	600	100	200	-150	0	-150
6	500	100	0	-120	0	-120
7	400	100	0	-90	0	-90
8	300	100	0	-60	0	-60
9	200	100	0	-30	0	-30
10	100	100	0	0	0	0

Notes: PP&E (property, plant, and equipment) represents buildings, machinery, land, office equipment, furniture, and vehicles. We assume that accounting depreciation is 10% over 10 years and that the corporate tax rate is 30%. Tax depreciation 1 is a straight-line depreciation method which allows tax deductions for 20% of the purchase price for 5 years. Tax depreciation 2 represents an accelerated depreciation method with 100% bonus depreciation rate. Deferred tax liability is calculated by the gap between accounting depreciation and tax depreciation times the corporate tax rate. Deferred tax liability by 100% bonus depreciation rate is smaller than that by the straight-line depreciation method for the first 5 years.

Table F.3: Difference-in-Difference Estimates of Average Skill Levels

	(1) Log(Schooling Years)	(2) Log(Experience Years)	(3) Log(Number of Skills)	(4) Log(Software Skills)	(5) Log(Social Skills)	(6) Log(Cognitive Skills)
Post× $\Delta bonus_f$	0.038	-0.028	0.175	0.098***	-0.054***	0.014
	(0.030)	(0.049)	(0.149)	(0.032)	(0.017)	(0.017)
Firm FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Average Level	14.99	4.08	13.31	1.24	1.08	0.84
Observations	20,710	20,710	20,710	20,710	20,710	20,710

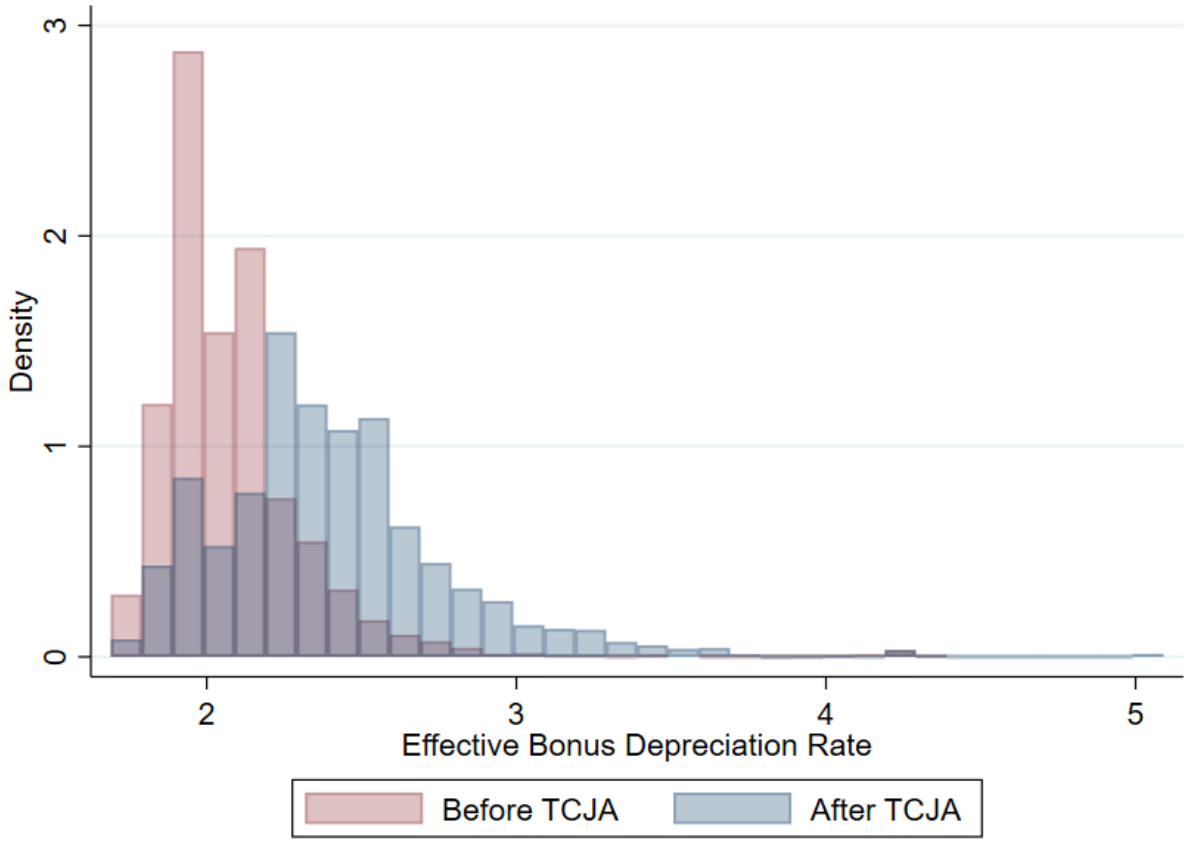
Notes: Observations are at firm-by-year and the outcomes are the average skill levels at firm-by-year. 2018 and 2019 are defined as the post-policy years and the means of skill levels are calculated in 2017. Columns (4)-(7) reports the response of the number of job postings by software skill level. The covariates include firm fixed-effects, year fixed-effects, firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at the firm level.

Table F.4: Difference-in-Difference Estimates of Main Outcomes by Non-Robot Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(Capx)	Log(Emp)	Log(Post)	Log(Post$_{Q1}$)	Log(Post$_{Q2}$)	Log(Post$_{Q3}$)	Log(Post$_{Q4}$)
Post$\times\Delta bonus_f$	0.035***	-0.072***	-0.126**	-0.159***	-0.070*	-0.067	-0.023
	(0.009)	(0.017)	(0.050)	(0.058)	(0.042)	(0.044)	(0.046)
Post$\times\Delta bonus_f\times$ Non-Robot Patents	-0.004	-0.032	-0.101**	-0.124**	-0.073	-0.061*	-0.086**
	(0.004)	(0.026)	(0.041)	(0.054)	(0.047)	(0.037)	(0.042)
Firm FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y
Observations	20,957	20,038	20,957	20,957	20,957	20,957	20,957

Notes: Observations are at firm-year level. 2018 and 2019 are defined as the post-policy years. The covariates include firm fixed-effects, year fixed-effects, firm-level tax reports (non-recurring taxes, foreign income taxes, investment tax credits, and other unrecognized tax benefits), and weighted averages of state corporate tax rates. Standard errors are clustered at firm level.

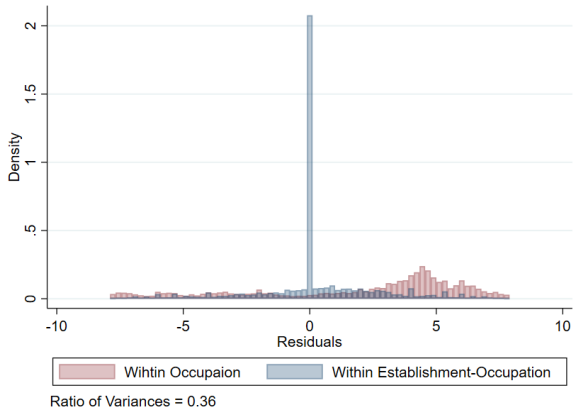
Figure F.1: Distribution of Bonus Depreciation before and after TCJA



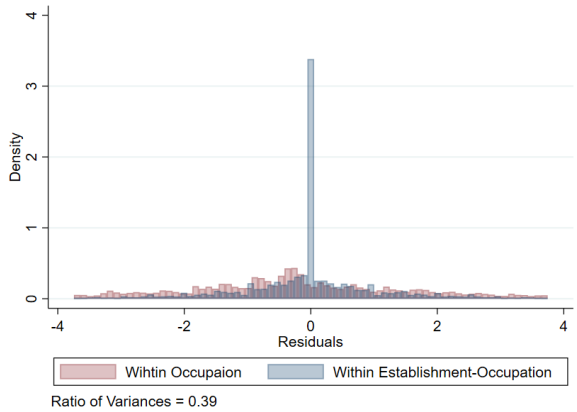
Notes: The effective bonus depreciation for a firm is calculated following equation (4). The average rate is 2.12 before TCJA and is 2.44 after TCJA, so it increases by 15% by the tax reform.

Figure F.2: Variance of Skill Measures

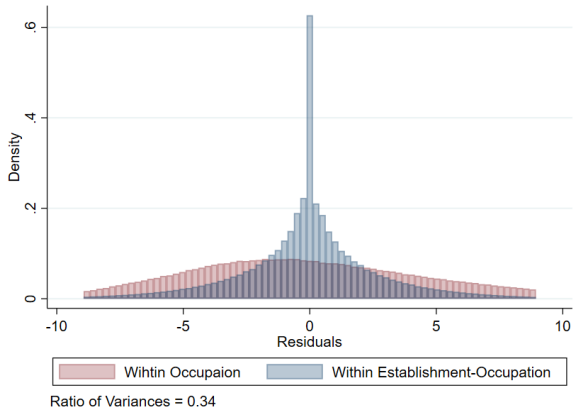
(a) Schooling Year



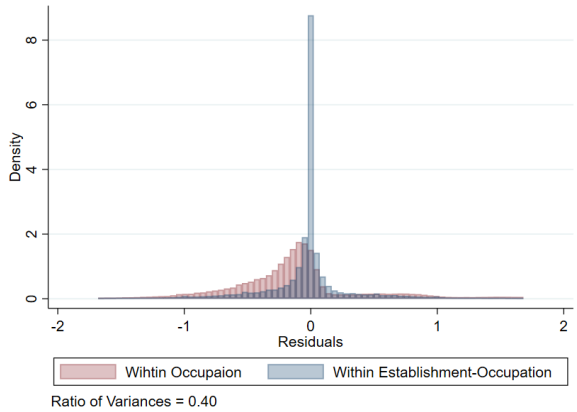
(b) Experience Year



(c) Number of Skills



(d) Number of Software Skills



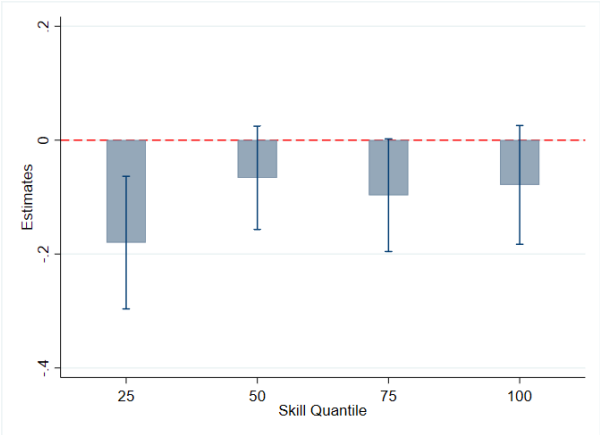
(e) Number of Cognitive Skills

(f) Number of Social Skills

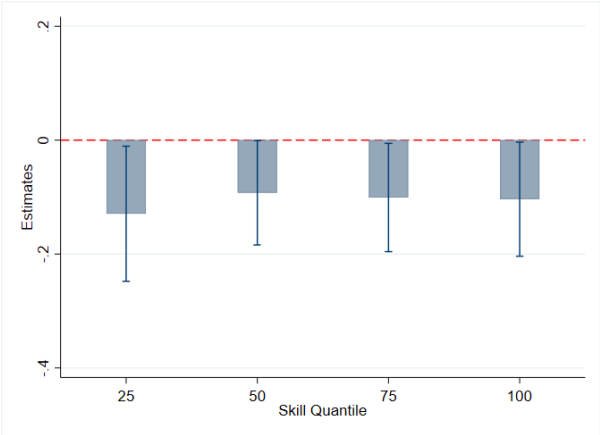
Notes: The red densities are the skill distributions within occupation and the green ones are the skill distributions within firm-by-occupation during 2013-2019. The values are demeaned and zero means the average skill level within occupation or within firm-by-occupation for each distribution. The ratio of variances is the variance of the skill measure within firm-by-occupation divided by that within occupation.

Figure F.3: Effects of Bonus Depreciation by Additional Skill Measures

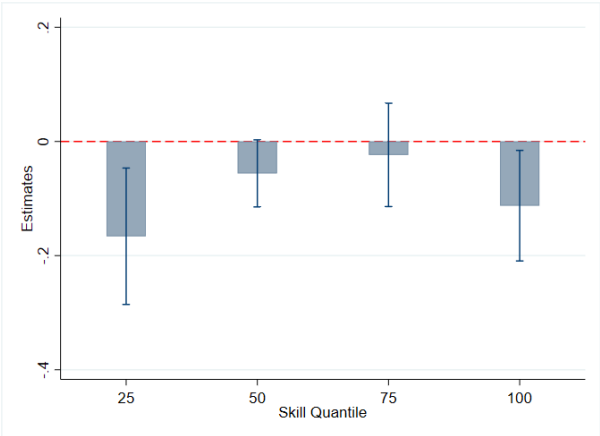
(a) Cognitive Skills



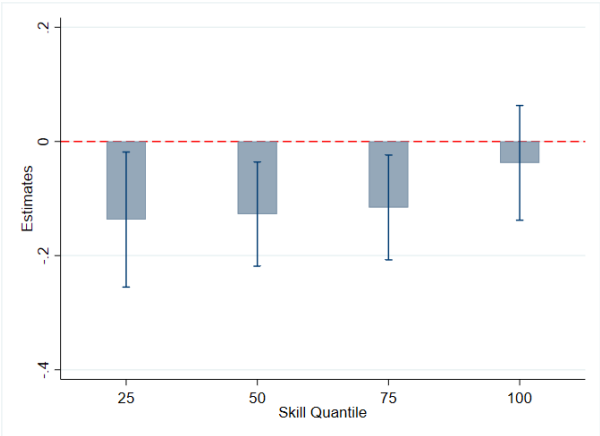
(b) Social Skills



(c) Management Skills



(d) Service Skills



Notes: Each figure shows the difference-in-difference estimates of the number of job postings across skill groups based on a skill measure. For each skill measure, we calculate the average skill level of a job (firm-by-occupation pair) before the tax reform and classify the jobs into quartiles based on the relative skill level within the firm and aggregate them at firm-skill group-quarter level. The point estimates are the coefficients of $\Delta bonus_f \cdot 1[t > 2017Q3]$ in the difference-in-difference version of equation (5). Standard errors are clustered at firm level and the confidence intervals are at 95% level.

Figure F.4: Robot Patents of Top 20 Firms

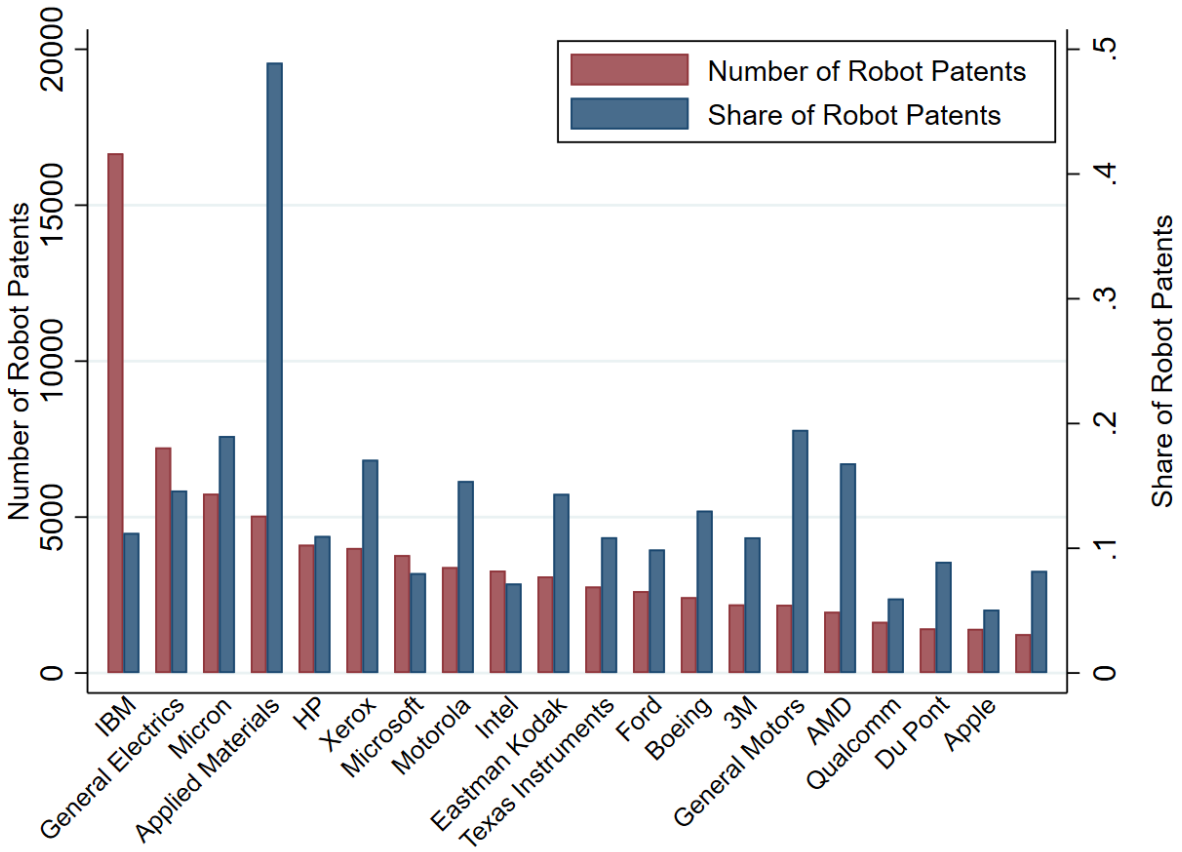
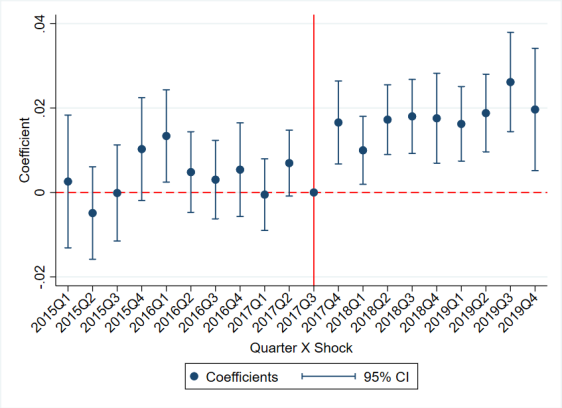
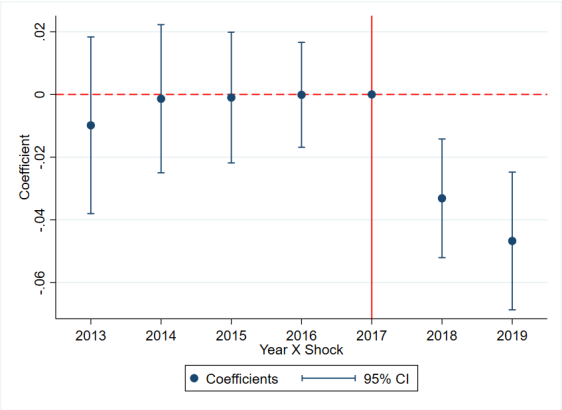


Figure F.5: Dynamic Firm-level Responses with IV Estimation

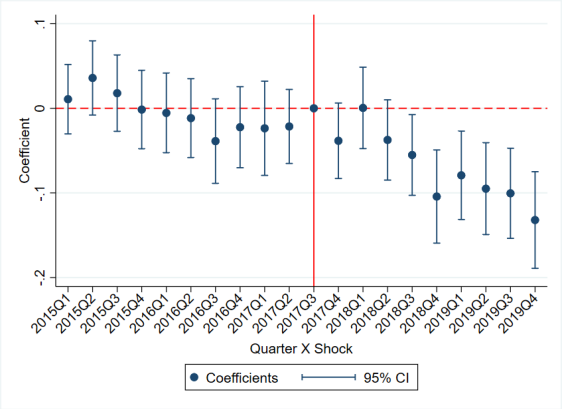
(a) Capital Expenditure



(b) Employment



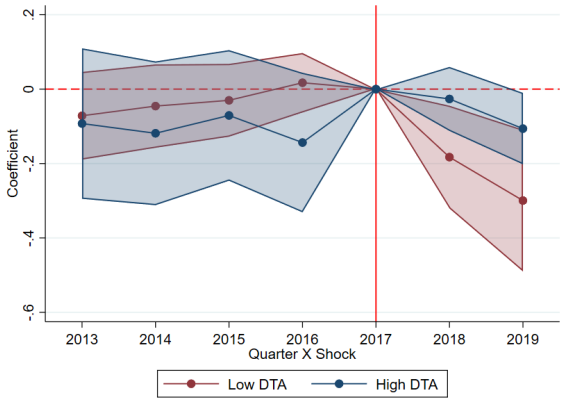
(c) Job Postings



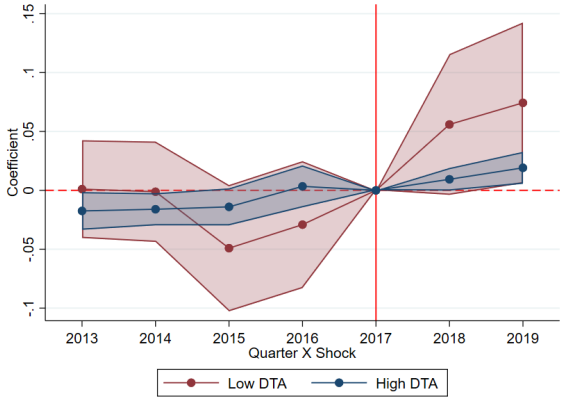
Notes: The figures show the dynamic responses of capital expenditure, employment, and the number of job postings via the IV version of equation (5). For easier comparison with the baseline results, the graphs plot the fitted responses from the IV regressions rather than the coefficients of Log(DTL). The base period (2017Q3 for capital expenditure and the number of job postings, and 2017 for employment) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013Q1 to 2019Q4 for capital expenditure and the number of job postings, and from 2013 to 2019 for employment. Standard errors are clustered at firm level and the confidence intervals are at 95% level.

Figure F.6: Dynamic Firm-level Responses by Deferred Tax Assets

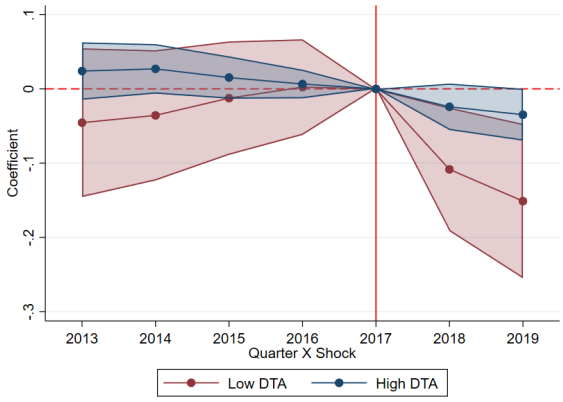
(a) Deferred Tax Liability



(b) Capital Expenditure



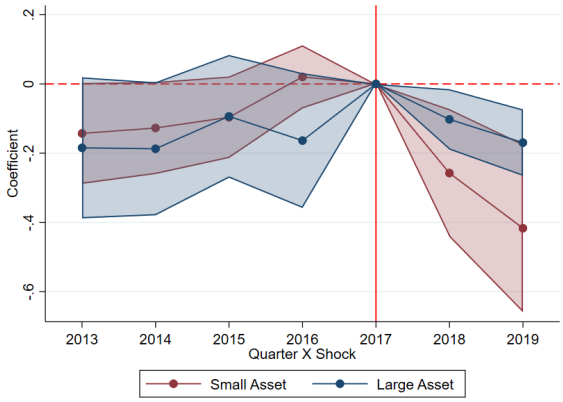
(c) Employment



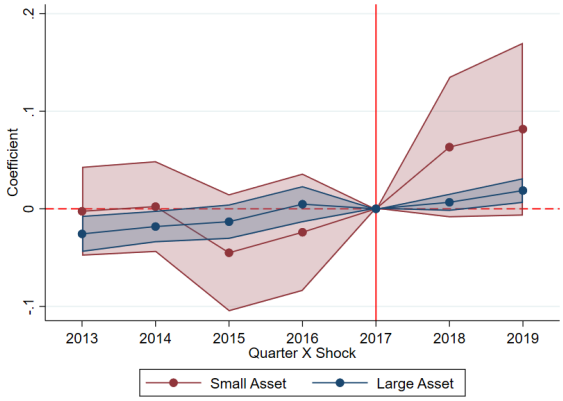
Notes: The figures show the dynamic responses of net deferred tax liabilities, capital expenditure, and employment by the level of deferred tax assets (DTA) via the model of equation (5). The base period (2017) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013 to 2019. Standard errors are clustered at firm level and the confidence intervals are at 95% level. The red lines indicate the effects for the firms in the bottom tertile of DTA, while the blue lines report those for the firms in the top tertile of DTA.

Figure F.7: Dynamic Firm-level Responses by Firm Size

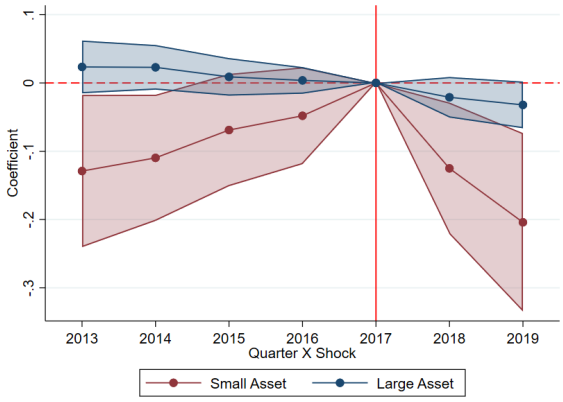
(a) Deferred Tax Liability



(b) Capital Expenditure



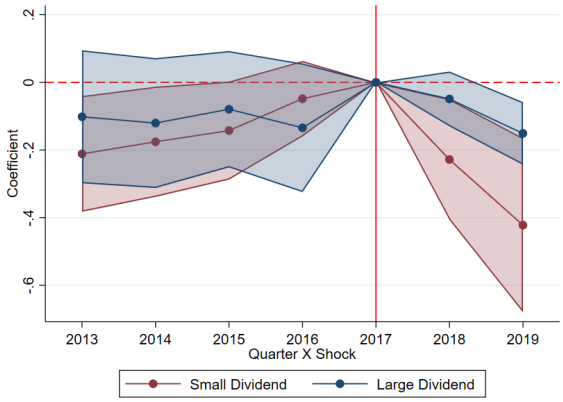
(c) Employment



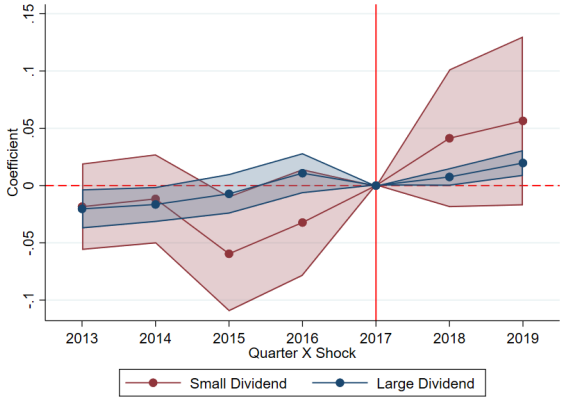
Notes: The figures show the dynamic responses of net deferred tax liabilities, capital expenditure, and employment by the level of total assets via the model of equation (5). The base period (2017) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013 to 2019. Standard errors are clustered at firm level and the confidence intervals are at 95% level. The red lines indicate the effects for the firms in the bottom tertile of assets, while the blue lines report those for the firms in the top tertile of assets.

Figure F.8: Dynamic Firm-level Responses by Dividend

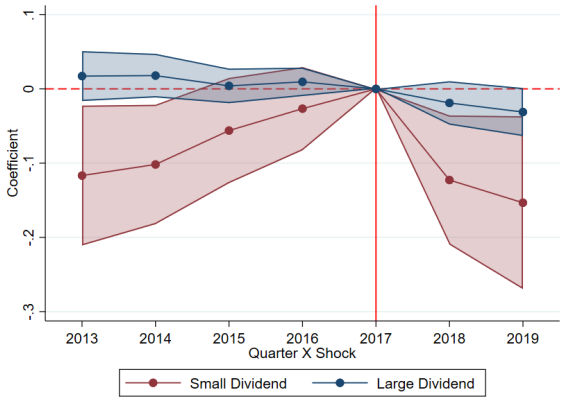
(a) Deferred Tax Liability



(b) Capital Expenditure



(c) Employment



Notes: The figures show the dynamic responses of net deferred tax liabilities, capital expenditure, and employment by the level of dividend via the model of equation (5). The base period (2017) corresponds to the announcement of the Tax Cuts and Jobs Act. Our estimation sample is from 2013 to 2019. Standard errors are clustered at firm level and the confidence intervals are at 95% level. The red lines indicate the effects for the firms in the bottom tertile of dividend, while the blue lines report those for the firms in the top tertile of dividend.