Capital Investment and Labor Demand*

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Abstract

We study how tax policies that lower the cost of capital impact investment and labor demand. Difference-in-differences estimates using confidential US Census Data on manufacturing establishments show that tax policies increased both investment and employment, but did not lead to wage or productivity gains. Using a structural model, we show that the primary effect of the policy was to increase the use of all inputs by lowering overall costs of production. The policy further stimulated production employment due to the complementarity of production labor and capital. Supporting this conclusion, we find that investment is greater in plants with lower labor costs. Our results show that recent tax policies that incentivize capital investment do not lead manufacturing plants to replace workers with machines.

Keywords: capital-labor substitution, bonus depreciation, corporate taxation
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"Everybody must be sensible how much labour is facilitated
and abridged by the application of proper machinery.
It is unnecessary to give any example."
—Adam Smith (1776, book 1, chapter 1)

1 Introduction

How the adoption of capital for production impacts workers is one of the foundational questions of the economics discipline. This question is ever more relevant in the 21st century given the widespread concerns that a new generation of machines will replace human work and that tax incentives for investment may unnecessarily accelerate the adoption of capital equipment at the expense of workers.

Though this question is both seminal and timely, empirical attempts to study how capital investment impacts labor demand face a number of challenges. First, since modern firms combine many functions including R&D, production, and marketing, firm-level data often fail to identify the production workers who directly interact with machines. Second, because plants may adjust both capital and labor in response to productivity or demand shocks, answering this question requires a credible strategy to isolate the effects of capital investment on workers from other confounding forces. Finally, since the accumulation of capital is a dynamic process, measuring the effects of capital on workers requires tracking production units over an extended horizon in which all inputs are variable.

In this paper, we use confidential data from the US Census Bureau to study capital investment and labor demand in manufacturing plants. Differential exposure to a tax policy called bonus depreciation generates quasi-experimental variation in the cost of capital. Bonus depreciation lowers the cost of investment by allowing plants to deduct equipment expenses more quickly. By comparing plants that benefit the most from this incentive to those that benefit least, we isolate investment in capital equipment that is likely independent of other idiosyncratic shocks faced by a given plant. Since we follow plants between 1997 and 2011, our results measuring the impact of capital adoption on workers allow enough time for plants to fully adjust on multiple margins.

The combination of detailed plant-level data and cross-sectional variation in the generosity of tax incentives reveals a number of interesting facts. Difference-in-differences analyses show that plants respond to the tax policy by increasing their capital use and labor demand in similar magnitudes. By lowering the cost of production, the policy also stimulated plant output. Contrary to the expectations of policymakers (CEA, 2017), capital investment did not increase average worker earnings or plant productivity. Using these facts, we estimate a structural model that elucidates the economic forces that drive the reduced-form estimates. Instead of incentivizing plants to replace workers with machines, the policy's main effect was to lower the overall costs of production, which increased the use of all inputs. The fact that production employment increases more than other inputs implies that capital and production labor are complements in production. Together, our reduced form estimates and structural results show that tax incentives that stimulate capital investment do not induce plants to replace workers with machines.

Bonus depreciation is one of the largest incentives for capital investment in US history. The policy has been in nearly continual use since its inception in 2001. The US Treasury (2020) estimates that the version of bonus depreciation that was implemented as part of the Tax Cuts and Jobs Act of 2017 will cost the federal government $285 billion between 2019 and 2028. Bonus depreciation allows plants to deduct capital investments from their taxable income more quickly, lowering the cost of investment. The extent to which the policy affects the cost of capital depends on arbitrary tax rules that govern how quickly investments can be deducted in the absence of the policy. Assets that are typically deducted more slowly benefit more from the tax incentive because bonus accelerates deductions from further in the future. By comparing plants that benefit the most from this incentive—those that invest in long-lived assets that are depreciated more slowly—to plants that benefit less, we isolate investment in equipment that is likely independent of other drivers of capital accumulation.

The identifying assumption underlying our difference-in-differences estimation strategy is that, in the absence of the policy, outcomes for treated plants—the third of plants that benefit most from the policy—would track those of the remaining plants that benefit the least. We provide support for the validity of this identifying assumption in a number of different ways. First, we verify that outcomes at treated and control plants evolved in parallel prior to policy implementation in 2001. Second, we show that our estimates are stable in the presence of a number of control variables designed to mitigate concerns that correlations between plant characteristics and policy generosity do not drive our results. Third, we show that the capital response to the policy is much larger for eligible than for ineligible capital. Finally, we show that responses to the tax policy are not due to the major factors responsible for the decline in US manufacturing employment.

We estimate simultaneous capital and labor demand responses using confidential data from the Census of Manufactures and the Annual Survey of Manufactures. We find strong responses to the policy in both investment and capital stocks. Average investment for treated plants increased by 15.8% relative to non-treated plants after the policy was implemented, leading to a 7.8% increase in capital stocks by 2011.[1]

In contrast to the concern that plants will respond to bonus by replacing workers with machines, our labor demand findings show that the capital investment response is more than matched by concurrent increases in employment. By 2011, employment had increased by 9.5% in plants that benefited more from bonus relative to those that benefited less. These gains are concentrated among production workers, whose employment increased by 11.5%. Non-production employment also increased by 8.1%. That workers operating production machinery saw the largest gains suggests that capital and labor continue to be complementary inputs in modern manufacturing processes.[2]

A popular rationale for policies that stimulate investment is that the increased use of capital raises productivity and workers' wages. We test this claim by estimating the effects of the policy on average earnings and productivity. We estimate that average earnings decreased by 2.7% at treated plants, which contrasts the positive effect on employment. To understand this result, we study the effects of bonus depreciation on the composition of the workforce using state-industry aggregate data from the Quarterly Workforce Indicators. We find that bonus led to a relative increase in the shares of young, less educated, women, Black, and Hispanic workers. Accounting for these composition effects fully explains the observed decrease in average earnings; our estimates rule out average earnings increases greater than 1.7% at the 95% confidence level. Thus, while workers benefit from the availability of additional jobs, which are more likely to be filled by otherwise disadvantaged workers, the policy does not significantly increase average earnings. Finally, while we do not find that the policy increased plant-level total factor productivity, we do find that the policy allowed plants to expand their scale of production.

We illuminate the economic mechanisms underlying the effects of the policy by estimating a structural model of factor demands. We first implement the insight of Marshall (1890) and

[1]These results confirm the findings of House and Shapiro (2008) and Zwick and Mahon (2017) in our setting.

[2]While our plant-level data track the effects of the policy at individual production units, data aggregated at the state-industry level show that accounting for plant entry and exit does not alter our findings.

Hicks (1932) that policies that change the price of inputs impact both plants' choice of cost-minimizing inputs (substitution effect) and their profit-maximizing output level (scale effect). We show that the scale effect is identified by a linear combination of our reduced-form estimates. This calculation shows that, by lowering costs of production, the policy increased the use of both capital and labor by 10% ($p < 0.001$) and that this scale effect was responsible for 90% of the overall effect of the policy on labor demand. To a first-order approximation, the policy allowed plants to increase their scale; on average, plant managers did not replace workers with machines.[3]

We then use our model to estimate elasticities of substitution between capital, production labor, and non-production labor. These fundamental economic parameters are identified by our reduced-form estimates and we use a Classical Minimum Distance approach to recover these elasticities. We estimate that the Allen elasticity of substitution between capital and non-production labor is close to 0.6. This result follows from the fact that the scale effect is larger than the 8% increase in non-production employment. In contrast, the 11.5% increase in production employment yields an elasticity of substitution between capital and non-production labor of -0.4, implying that capital and production labor are complements in production. Our estimates reject values greater than 0.4 for this capital-labor elasticity of substitution at the 95% confidence level.[4]

To validate the model's finding that capital and labor are complements, we estimate heterogeneous effects of the policy on investment. Specifically, this complementarity should result in a larger elasticity of capital investment in plants with low costs of labor. We test this prediction across plants based on plant-level unionization, location in a right-to-work state, and by local labor market concentration. We find larger investment effects of the policy when labor costs are lower across all three instances. These results support the conclusion that capital and labor are complementary inputs and reveal that labor market institutions can impact capital investment.

A number of studies have estimated the effects of accelerated depreciation on business investment (Hall and Jorgenson, 1967; Cummins, Hassett and Hubbard, 1994; House and Shapiro, 2008; Edgerton, 2010; Zwick and Mahon, 2017; Ohrn, 2018, 2019; Maffini, Devereux and Xing, 2018; Fan and Liu, 2020; Guceri and Albinowski, 2021). A nascent literature explores the effect

[3]The model also shows that the scale effect is informative of the effects of the policy on plants' cost of capital. We leverage this insight to estimate cost-of-capital elasticities of capital and labor demand in Section 7.

[4]We relate these estimates to popular models of production by estimating the parameters of a translog cost function as well as a nested constant elasticity of substitution (CES) production function. As we discuss in Section 7, these results show that our reduced-form estimates are consistent with standard models of production estimated in Krusell, Ohanian, Ríos-Rull and Violante (2000), Acemoglu, Autor and Lyle (2004), Lewis (2011), and Ohanian, Orak and Shen (2021) and further inform the modeling of production functions.

of these incentives on employment (Garrett, Ohrn and Suárez Serrato, 2020; Ohrn, 2021).[5] Tuzel and Zhang (Forthcoming) study the short-run effects of state accelerated depreciation policies on computer purchases and the mix of occupational employment.[6] We add to these literatures by estimating the dynamic response of both capital and labor within plants. In doing so, we directly estimate the degree of complementarity between these different inputs to better understand how modern manufacturing technologies respond to tax incentives.

The elasticity of substitution between capital and labor is a fundamental economic parameter. High values of this elasticity raise concerns that workers are easily replaced with machines, potentially leading to increased income inequality (e.g., Zucman and Piketty, 2014). Given the centrality of this parameter, a large number of studies have attempted to provide precise and unbiased estimates.[7] In a meta-analysis of the literature, Gechert, Havranek, Irsova and Kolcunova (2021) find an average estimate of 0.9 (close to Cobb-Douglas), but show that correcting for publication bias yields a lower estimate of 0.3. Our study differs from previous work in that we use quasi-experimental variation in the cost of capital over a 10-year period, plant-level data on both capital and labor, and a multi-input structural model to separately identify this elasticity from scale effects. These innovations result in smaller estimates than in most studies and allay concerns that tax policies that promote capital investment lead to inefficiently low labor demand.

A particular type of capital investment that has garnered much attention is the increased use of industrial robots and other automative technologies. Studies based on investment patterns in several industrialized countries show that firm-level adoption of robots increases labor demand (Acemoglu, Lelarge and Restrepo, 2020; Dixon, Hong and Wu, 2021; Koch, Manuylov and Smolka, 2021). Assuming that a portion of the investment response we document is driven by robot adoption, our findings are consistent with these papers. In contrast, Acemoglu and Restrepo (2020) show robotization can decrease local labor demand by making highly automated firms more productive and shifting market share away from relatively more labor intensive firms.[8]

[5]Using IRS data, Zwick and Mahon (2017) find that firm payroll increases in response to bonus. Criscuolo, Martin, Overman and Van Reenen (2019) and Siegloch, Wehrhöfer and Etzel (2021) both explore joint capital and labor responses to place-based policies in the UK and Germany, respectively.

[6]Gaggl and Wright (2017) study a UK tax incentive for information, communication, and technology equipment, and find that such investment leads to increases in the share of skilled labor.

[7]Recent studies include Krusell, Ohanian, Ríos-Rull and Violante (2000), Karabarbounis and Neiman (2014), Doraszelski and Jaumandreu (2018), Raval (2019), Benzarti and Harju (2021), and Oberfield and Raval (2021).

[8]In a related paper, Graetz and Michaels (2018) show that industry-level adoption of robots does not lead to employment gains or losses.

As we show below, we also find that bonus depreciation had larger effects on employment growth in industries that Acemoglu and Restrepo (2020) identify as having a greater adoption of industrial robots. In earlier work, Garrett, Ohrn and Suárez Serrato (2020) used a similar approach to estimate the local labor market effects of bonus depreciation. They find bonus increased labor demand, but did not affect average earnings. The contrast between these findings is due to the fact that bonus depreciation decreases the cost of investments in all types of capital—not just robots. While robots may be substitutes for labor, our findings show that the average type of capital investment stimulated by bonus depreciation is not labor-replacing.

Acemoglu, Manera and Restrepo (2020) show that the US tax code has increasingly favored capital over labor due mainly to bonus depreciation. They theorize that when automative technologies and labor are highly substitutable, this tax favoritism can lead to too much automation. Adjusting their framework to incorporate all types of capital investments (robots and other) and our estimated complementarity between capital and labor, our results suggest that the increasingly favorable tax treatment of capital has not lead to inefficiently low levels of labor demand.

Our findings also connect directly to a number of broader trends in the US labor market. Consistent with the hollowing-out of the middle of the income distribution (see, e.g., Acemoglu and Autor, 2011; Autor, 2015; Jaimovich and Siu, 2019; Jaimovich, Saporta-Eksten, Siu and Yedid-Levi, 2021), we find that bonus shifted employment toward younger workers with fewer years of education who come from traditionally marginalized groups. It follows that bonus led to a shift towards tasks that can be performed by workers at the bottom of the income distribution. These results stand in contrast to the literature on skill-biased technological change (e.g., Berman, Bound and Machin, 1998; Autor, Levy and Murnane, 2003), but are consistent with aggregate changes in employment share by skill percentile presented in Acemoglu and Autor (2011).

Manufacturing has historically played an important role in the US labor market and continues to play an outsized role in political discourse (Charles, Hurst and Schwartz, 2019). Since the turn of the century, the US manufacturing sector has lost more than 5 million jobs. These job losses coincided with increased capital- and skill-intensity, increased import competition from China (Autor, Dorn and Hanson, 2013, 2016), and robotization (Acemoglu and Restrepo, 2020). In the face of these headwinds, bonus depreciation was able to stimulate both capital formation and labor demand, forcing us to reconsider the power of tax incentives in the modern economy.

Section 2 describes accelerated depreciation policies. Section 3 discusses our data sources.

Sections 4 and 5 present our research design and results. We place our results in the context of the transforming US manufacturing sector in Section 6. Section 7 estimates a model of factor demands to interpret our reduced-form estimates. Section 8 concludes.

2 Investment Tax Incentives in the 21st Century

Governments around the world have used accelerated depreciation policies for more than 100 years to stimulate business investment. These policies were initially used to spur defense spending during the First World War, were used again in the military buildup to the Second World War, and were used as a means to replenish industrial capital stocks in the aftermath of these wars.[9] While these policies gained popularity in the post-war years, base broadening tax reforms stymied additional applications of accelerated depreciation during the later years of the 20th century.

In 2001, the use of these policies came back into vogue when the US introduced "Bonus Depreciation." The policy allows firms to deduct a bonus percentage of the costs of equipment investments from their taxable income in the year the investment is made. Because costs are typically deducted slowly over time, bonus lowers the present value costs of new investments. For example, under 50% bonus, firms immediately deduct an additional 50% of investment costs. The remaining 50% of the costs are deducted according to normal depreciation schedules—usually the Modified Accelerated Cost Recovery System (MACRS). In addition to bonus, firms could also benefit from an accelerated deprecation policy referred to as §179 ("Section 179"), which allowed for full expensing of investment costs below a dollar limit.[10] Throughout the paper, we refer to these policies together as bonus depreciation, or more simply bonus.

Bonus and accelerated depreciation policies more generally have been politically popular because they only change the timing of tax deductions for businesses. Therefore, the cost of the policy appears very small over long time periods that do not account for the time value of money, such as in the case of the Congressional Budget Office's (CBO) 10-year forecasting window. Its popularity is, in large part, responsible for its near continuous use since 2001. Despite the CBO's generous measurement, bonus has real costs as a tax expenditure and real value as a subsidy because of the relative change in timing.

To understand the mechanics of bonus, consider a plant with a discount rate of 7% and a

[9] See Koowattanatianchai, Charles and Eddie (2019) for a historical account of accelerated depreciation policies.

[10] This dollar limit increased from \$24,000 to \$500,000 between 2001 and 2011. Between 2003 and 2011, the share of equipment investment that qualified for §179 was stable and averaged 12% (Kitchen and Knittel, 2016).

tax rate of 35% that purchases a computer for $1,000, which would normally depreciate over five years.[11] With straight-line depreciation, the firm deducts $200 each year from its taxable income, which lowers its tax liability by $\$200 \times 0.35 = \$70$. Under 50% bonus, the firm instead depreciates a bonus portion in the first year and receives an immediate deduction from taxable income of $600 ($\$500+(\$500 \times 0.2)$), but only deducts $100 in years two through five. In both cases, the firm deducts the full value of the asset over five years which, ignoring the time value of money, lowers its total tax liability by $350. Using a discount rate of 7%, the depreciation deductions without bonus are only worth $307.10 in present value (PV) terms, while the deductions purchased under 50% bonus have a PV of $328.55, 7% more than in the baseline. In this case, bonus decreases the after-tax cost of the investment by $21.45, or 3.1% relative to the original cost.

To see how bonus depreciation works in a more realistic setting, we start from the observation that the IRS sets tax depreciation schedules (IRS, 2002, see Table A.1 of Publication 946). Figure 1 shows examples of MACRS schedules for a tractor trailer (a 3-year asset) in Panel (A) and a barge (a 10-year asset) in Panel (B). The blue bars in this figure represent depreciation deductions over time in the absence of bonus depreciation. These schedules already partially front-load depreciation deductions. The orange bars show the schedule of deductions with 50% bonus depreciation. The benefit of bonus depreciation depends on the extent to which depreciation deductions are accelerated forward in time. Contrasting the two panels, it is clear that both assets benefit from bonus depreciation, but the longer lived asset—the barge which depreciates more slowly—benefits more. The fact that similar assets differentially benefit from bonus is at the heart of our identification strategy.

While this realistic example is instructive, it is useful to have a measure of the benefit of bonus depreciation that applies to all assets. Let z_0 be the original PV of depreciation deductions per dollar of investment and let b be the bonus depreciation percent. Under bonus, the PV of depreciation deductions per dollar of investment, z, is given by $z = b + z_0 \times (1 - b)$. The fact that $\frac{\partial z}{\partial b} = 1 - z_0$ shows that bonus provides a larger subsidy to longer-lasting capital. As in Figure 1, assets such as a barge—those with lower z_0—benefit more from an increase in b.

In the US, each asset class is assigned a depreciation schedule, which determines z_0. For equipment used in production, asset classes are defined by the activity for which a given piece of equipment is used. These classes align closely with NAICS industry definitions, instead of

[11] This example ignores practical aspects of tax accounting, such as the the half-year convention.

depending on the useful life of a specific asset.[12] For example, while equipment related to cutting timber is depreciated over a five year period, equipment used in the creation of wood pulp and paper is subject to a seven year schedule. Therefore, plants in different industries could use similar or identical equipment, but face different depreciation schedules. In Section 4, we discuss how we measure z_0 at the industry level.

It is important to consider that several real-world factors shape the application of accelerated depreciation policies. First, firms may not claim bonus if they have a tax loss or for other reasons (Kitchen and Knittel, 2016). Our estimates therefore capture the effect on all firms, including those that are eligible for bonus but are not able to immediately benefit from the policy.

Second, while the generosity of bonus varied over time, accelerated depreciation policies were in nearly continuous use between 2001 and 2011 and significantly lowered the cost of investment. Panel (C) of Figure 1 shows the effective bonus rate for two levels of investment, \$400,000 and \$1,000,000. The \$400,000 investment benefits from accelerated depreciation in all years after 2002 while the \$1,000,000 investment benefits in all years after 2002 with the exception of 2006 and 2007. The average bonus rate between 2002 and 2011 was 45%.[13] Using this bonus rate and estimates from Zwick and Mahon (2017) based on IRS data, we calculate that by increasing the PV of depreciation deductions, bonus lowered investment costs by 2.5%, on average.

Third, while the bonus amount varied over time, plants likely expected their investments to benefit from bonus in all years after 2001. These expectations were shaped by repeated extensions, increases in generosity, and several retroactive applications of the policy. In fact, Auerbach (2003) correctly predicted the 2003 increase in bonus depreciation generosity using an ordered probit model before it happened. Further supporting the view that firms expected to continually benefit from bonus, House and Shapiro (2008) estimate that in 2006, firms behaved as though the bonus depreciation rate was between 25% and 50% even when the statutory bonus depreciation rate was zero.

Finally, bonus impacts the cost of capital both by increasing the present value of depreciation deductions as well as by providing immediate cash flow. Bonus is economically equivalent to

[12]Since 1986, class lives are formally defined in Revenue Procedure 87-56, 1987-2 C.B. 674 (IRS, 2002). The procedure establishes two types of depreciable assets: (1) specific assets used in all business activities in Table B-1 and (2) assets used in specific business activities in Table B-2. For equipment used in manufacturing plants, most class lives are determined using Table B-2, which align closely with industry definitions.

[13]This rate combines 100% expensing for the 12% of §179 eligible investment with the average bonus rate between 2001 and 2011 of 38% for the remaining amount. Appendix B describes details of bonus depreciation and §179 expensing policies.

giving a firm that purchases a qualified asset an interest-free loan equal to the bonus portion multiplied by the tax rate and the value of the asset. The business *de facto* pays the loan back since it cannot take the tax deductions it would have taken under MACRS in later years. Recognizing the equivalence of bonus to an interest-free loan, Domar (1953) first theorized that accelerated depreciation policies could be especially valuable for financially constrained firms or those that would prefer to rely on retained earnings to finance capital investments. Edgerton (2010), Zwick and Mahon (2017), and Ohrn (2019) provide evidence that financing constraints help shape the response of investment to bonus depreciation.[14] The total impact of bonus on the cost of capital is therefore likely to significantly exceed the value of depreciation deductions.

From the perspective of policy analysis, our reduced form estimates capture the 10-year cumulative effects of bonus depreciation on investment and employment, inclusive of these real-world factors surrounding the policy. In Section 7, we recover the implied effect of bonus on the cost of capital using our reduced form estimates that incorporate these factors.

Since the US implemented bonus in 2001, a number of large economies have followed suit, using very similar instruments to decrease capital investment costs. These include the UK (Maffini, Xing and Devereux, 2019), China (Fan and Liu, 2020), Canada, and Poland (Guceri and Albinowski, 2021). Today, bonus and accelerated depreciation policies are being deployed to combat the world's largest economic crises, including global warming and the COVID-19 pandemic.[15] These trends highlight the importance of bonus depreciation and related policies in shaping investment and potentially labor demand in the 21st century.

3 Sources of US Manufacturing Data

This section describes the main datasets we use to measure the effects of bonus depreciation on various manufacturing outcomes; Appendix A precisely defines each of our variables.

We construct our primary dataset using the Census of Manufactures (CM), the Annual Survey of Manufactures (ASM), and the Longitudinal Business Database (LBD). The CM and the ASM are establishment-level manufacturing datasets containing detailed information on plants'

[14] Criscuolo, Martin, Overman and Van Reenen (2019) use similar logic to motivate the importance of credit constraints in shaping responses to industrial policies in the UK.

[15] The United Kingdom, Sweden, Russia, Germany, Ireland, Romania, and France have all relied on similar policies to speed the transition to environmentally sustainable production methods (Koowattanatianchai, Charles and Eddie, 2019). Australia, Austria, Germany, and New Zealand all included accelerated depreciation policies in their fiscal stimulus responses to the COVID-19 pandemic (Asen, 2020).

inputs and outputs and are considered the workhorse datasets of the US Census Bureau's Economic Census. The Census collects CM data quinquennially from the universe of manufacturing establishments in years ending in 2 and 7 (1997, 2002, 2007 in our data). The ASM collects annual data in all non-CM years for a sample of approximately 50,000 plants. Plants are selected to be part of the ASM in the year following the CM and are surveyed annually until the year after the following CM, when a new wave of ASM plants is selected. Larger plants are oversampled in the ASM and the largest plants are selected with certainty.

The ASM/CM data provide a unique opportunity to study how tax incentives for capital investment affect production. These data focus on plant-level production processes and include detailed measures of investment, materials cost, and total value of shipments (a proxy for plant-level revenue). CM data measure capital stocks directly and we integrate ASM data to construct capital stock measures using the perpetual inventory method in non-CM years (as in Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf, 2020). The full picture painted by our data allow us to study how plants adjust production in response to the policy and measures of outputs capture scale effects of the policy. Another advantage of these data is that they include several measures of labor inputs: the number of workers (i.e., employment), total payroll, average worker earnings, and number of hours worked. We also observe whether labor was employed in production or non-production related tasks. This division of employment by tasks allows us to test the popular concern that production-related tasks are at risk of being automated, particularly in response to policies that lower the cost of capital. Finally, we combine information on employment, capital stock, and material inputs to estimate plant-level measures of total factor productivity (TFP).[16] To avoid sensitivity to outliers, we winsorize all variables at the 1% level.

Our baseline regressions are performed on a balanced panel of establishments that are present in the ASM/CM between 1997 and 2011. A particular advantage of these data is that they allow us to track differences between treated and control plants for five years prior to policy implementation and to measure the effects of the policy over a 10 year horizon. To construct this sample we use establishment identifiers from the LBD that consistently track plants over time. Our final ASM/CM sample consists of approximately 160,000 plant-year observations.

[16] Following Criscuolo, Martin, Overman and Van Reenen (2019), we estimate residual TFP using industry-level cost shares. See Appendix A for details.

Our balanced sample sidesteps concerns that changes in the ASM sample construction across time could insert noise and discontinuous breaks in our results. Additionally, tracking capital accumulation and employment over a 15 year period eliminates concerns that plant responses may be constrained by adjustment frictions. By focusing on a balanced panel, our baseline results speak to how existing plants respond to the policy.

Due to the Census Bureau's ongoing concern with data privacy and disclosure risk (see, e.g., Abowd and Schmutte, 2019), we do not report summary statistics.[17] Chen (2019) and Giroud and Rauh (2019) rely on similar estimation samples using these data and disclosed summary statistics. The average plant in a similarly balanced panel has 165 employees, 77% of which are engaged in production-related tasks; capital investment averages $736,000 per year, of which 81% is in equipment (Chen, 2019).

We also rely on complementary data from the publicly-available Quarterly Workforce Indicators (QWI) (see, e.g., Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer and Woodcock, 2009; Curtis, 2018). The underlying microdata for QWI come from the Longitudinal Employer Household Dynamics program. These data are primarily derived from state unemployment insurance systems and also include worker and firm characteristics from a variety of surveys and administrative sources. We collapse these data at the industry-state level. These data complement the ASM/CM data in three ways. First, they allow us to explore whether bonus had different employment effects on workers with different characteristics, including education, gender, age, race, and ethnicity. Accounting for the effects of bonus on the demographic composition of the workforce refines our understanding of the wage effects of the policy. Second, our state-industry analyses account for any potential effects of the policy on entry and exit. Finally, we use these data to estimate the effects of bonus on plants that are not included or that are underrepresented in our ASM/CM sample, such as small and young firms.

4 Identifying Responses to Bonus Depreciation

Our research strategy compares how bonus depreciation impacted manufacturing outcomes across industries that differentially benefited from the policy. We first describe how we classify which industries had the most to gain from bonus depreciation. We then describe our event-study,

[17]It is common practice for papers relying on confidential Census Bureau data to not report variable means or other summary statistics for analysis samples (see, e.g., Foster, Haltiwanger and Syverson, 2008).

difference-in-differences framework that uses this classification to identify how US manufacturing plants responded to the policy.

4.1 Treatment Variation in Bonus Depreciation

Recall from Section 2 that the plants that benefit the most from bonus are those that would depreciate assets over a longer time horizon in the absence of the incentive, i.e. those with lower values of z_0. We rely on industry-level (4-digit NAICS codes) measures of z_0 based on administrative tax return data from Zwick and Mahon (2017) and classify plants into the treatment group if they are in an industry j that benefits the most from bonus depreciation. Let Bonus_j be an indicator equal to one if the plant's z_0 is in the bottom tercile of the z_0 distribution.[18] Relying on the z_0 distribution also captures variation in the cost of capital due to §179 expensing. Like bonus depreciation, §179 most benefits plants that invest in longer-lived assets, with lower z_0.

We rely on this binary treatment for two reasons. First, to calculate z_0, some assumption of discount rates must be made. By relying on this simple dichotomy, our treatment indicator is agnostic with regard to discount rates. Second, there is a clear break in the z_0 distribution at the 33rd percentile, making this a natural comparison of most- to least-treated units.[19]

Our indicator of bonus treatment is designed to mitigate endogeneity concerns. One specific concern in this context is that bonus depreciation may affect the mix of investments across asset classes. As a result, an industry's z_0 may be endogenous with regard to the policy. This concern is allayed by the fact that our measure of z_0 is calculated using only eligible investments made in the non-bonus periods of our sample. As these investments are less likely to be affected by bonus, the z_0 distribution and our bonus indicator should not be endogenous with respect to the policy.[20] Additionally, recall that IRS asset classes are defined by asset *use* and not *type*. A plant's z_0 is unlikely to change even when plants change the types of assets they purchase,

[18] For each asset class, Zwick and Mahon (2017) calculate z_0 using a discount rate of 7%. Using data from IRS form 4562, they compute industry-level z_0s by aggregating the asset-class measures according to their importance in an industry's overall investment.

[19] We show this natural break in Panel (A) of Figure A1, which presents a histogram of the z_0 distribution across industries. Zwick and Mahon (2017, §III.B, p.228) also classify plants in the bottom tercile of the z_0 distribution as treated in their dichotomous treatment definition. Garrett, Ohrn and Suárez Serrato (2020) obtain similar estimates of bonus on local labor markets when defining dichotomous treatments at the 25th, 33rd, and 40th percentiles. As we show below, we also obtain similar results when we define treatment status using these different thresholds.

[20] We also address this endogeneity concern empirically by investigating the stability of z_0 over time in Appendix B. There, we use sector-level IRS SOI data on investment shares in each asset class to show that sector-level z_0s are stable over the years 2000–2011.

because their use is unaffected by the policy.

4.2 Empirical Specifications

We estimate the effects of bonus on manufacturing outcomes using event study difference-in-differences regressions of the form

$$Y_{it} = \alpha_i + \sum_{y=1997,\ y\neq 2001}^{2011} \beta_y \big[\text{Bonus}_j \times \mathbb{I}[y=t]\big] + \gamma \mathbf{X}_{i,t} + \varepsilon_{it}, \quad (1)$$

where Y_{it} is an outcome of interest for plant i in year t and industry j. α_i is a plant-level fixed effect that captures all time-invariant components of manufacturing activity. $\mathbf{X}_{i,t}$ is a vector of fixed effects that varies across specifications. Our coefficients of interest are β_{1997} through β_{2011}, which describe the relative increase in the outcome for plants that benefit most from bonus relative to 2001.

The identifying assumption behind this strategy is that outcomes at treated and control plants would evolve in parallel in the absence of bonus. This assumption is likely to hold because differences in z_0 are generated by the largely arbitrary assignment of IRS depreciation schedules to different types of assets defined not by their nature, but by their use. The primary threat to this assumption is that other trends during the time period correlate with bonus treatment. Because Bonus_j varies at the industry level, we cannot include industry-year fixed effects to directly address this threat. Instead, we rely on four empirical tests to support our identification assumption. First, we use the event study estimates to compare pre-period trends in outcomes between the treated and control units. In this context, the absence of differential trends suggests that the identifying assumption is likely to hold in the post-period. Second, we use the fact that, while equipment capital was eligible for bonus depreciation, investment in structures was generally not eligible. We separately estimate effects of bonus depreciation on eligible equipment capital and ineligible structures capital. Larger effects on treated equipment capital suggest we are precisely measuring the effect of bonus depreciation and not of other shocks that would violate our identifying assumption. Third, we show that our results are robust to inclusion of state-by-year fixed effects as well as to flexible controls for trends related to plant characteristics. Specifically, we include plant size bins interacted with year fixed effects, firm size bins interacted with year fixed effects, and TFP bins interacted with year fixed effects.[21] These controls ensure

[21] Plant size is determined by the book value of assets in 2001 and firm size is defined as the count of employees in all establishments across a firm in 2001. We define four bins for each variable.

that the effects of bonus are not confounded by trends that affect plants or firms of different sizes or productivity. Finally, in Section 6, we additionally show that our results are unrelated to major drivers of manufacturing transformation in the 21st century, including changes in capital and skill intensities, import competition exposure, and robotization.

We quantify the effects of bonus depreciation in two ways. First, we estimate the average effect of bonus over the full treatment period using pooled regressions of the form

$$Y_{it} = \alpha_i + \beta[\text{Bonus}_j \times \text{Post}_t] + \gamma \mathbf{X}_{i,t} + \varepsilon_{it}. \quad (2)$$

The difference-in-differences (DD) estimate, β, measures the average increase in an outcome for the treatment group relative to the control group. Second, because many of our outcome variables (such as capital and employment) are stocks that evolve slowly over time, we also report long-difference (LD) estimates, which correspond to β_{2011} in Equation (1). LD estimates measure the cumulative effect of accelerated depreciation policies on plant outcomes over the 10-year period 2002–2011.[22] One major benefit of measuring 10-year effects is that adjustment costs are unlikely to dramatically affect these long-run results. Because federal bonus depreciation interacts with the design of state tax systems, we cluster standard errors at the 4-digit NAICS-by-state level following guidance in Bertrand, Duflo and Mullainathan (2004) and Cameron and Miller (2015).[23]

5 Effects of Bonus Depreciation on US Manufacturing

This section presents our estimates of the effects of bonus depreciation on manufacturing outcomes. We first measure the effects of the policy on investment and capital stocks. Next, we estimate the effects of bonus on labor demand, as measured by employment and wage outcomes. Finally, we characterize how the incentive affects plant output and productivity.

5.1 Capital Investment Response

We begin by exploring the effects of bonus depreciation on investment in physical capital. Panel (A) of Figure 2 shows the results of estimating Equation (1) when the outcome is log investment. Three results are immediately apparent. First, differences in investment between the treatment and control groups are small and stable in the pre-period, supporting our empirical strategy.

[22] To minimize the number of disclosed coefficients, we only report LD estimates for select specifications.

[23] Appendix C describes these interactions and shows that our results are generally robust to clustering at a more conservative industry level.

Second, log investment for the treated group jumps by nearly 10 log points immediately upon policy impact in 2002 and remains elevated throughout the post period. These differences are statistically significant in all years after 2002. Third, while our baseline estimates include plant and state-by-year fixed effects, we obtain similar estimates when we flexibly control for time trends based on plant size, firm size, and productivity. The sustained relative increase in investment captured by each series suggests accelerated depreciation policies increase investment levels rather than only shifting capital expenditures across years. On the whole, these results show that bonus depreciation has a large and statistically significant effect on investment behavior in the manufacturing sector, confirming that the findings of House and Shapiro (2008) and Zwick and Mahon (2017) hold in our setting.[24]

Panel (A) of Table 1 presents estimates of the effects of bonus on log investment. Column (1) reports difference-in-differences (DD) estimates with only plant and year fixed effects and shows a relative investment increase of 17% ($p < 0.001$). Estimations that progressively include state-by-year fixed effects, plant size bins-by-year fixed effects, TFP bins-by-year fixed effects, and firm size bins-by-year fixed effects yield a narrow range of estimates between 15.1 and 15.8%.[25]

Since investment data can include spells of non-investment, we consider alternative outcome variables that capture extensive margin responses. Panel (B) of Table 1 estimates the effect of bonus depreciation on the inverse hyperbolic sine (IHS, i.e., $\ln(x + \sqrt{x^2 + 1})$) of investment. The IHS of investment captures both intensive and extensive margins of response and takes similar values as the simple log outcome for large values of investment. Indeed, the results in Panel (B) are nearly identical to those in Panel (A), suggesting that extensive margin responses to the policy are relatively unimportant in our sample of large plants. Panel (C) of this table reports the effects of bonus on investment scaled by the pre-period capital stock. This outcome also captures extensive margin responses and shows that bonus led to significant increases in investment.[26] In sum, across all three investment outcomes we find large, positive, and statistically significant

[24] As we discussed above, Zwick and Mahon (2017) use the same threshold for bonus treatment in their event study analyses, which show that investment in treated firms increased by 11.8% relative to firms in the control group between 2002-04. Over that same period, our event study coefficients indicate that investment for the treatment plants increased by 10.1%. See Appendix D for more details.

[25] Column (2) includes the same controls as the "Baseline" estimates presented in Panel (A) of Figure 2 and column (5) corresponds to the specifications with "Additional Controls."

[26] These estimates can be translated into percent increases by dividing the coefficient by investment as a share of pre-period capital. Assuming this fraction is 0.2, the estimate from column (5) in Panel (C) implies that bonus increased investment by 13.9%. Corresponding event study coefficients are presented in Appendix Figure A3.

effects of bonus depreciation on capital expenditure.

One strength of the ASM/CM data is that we observe measures of capital stock used in production. Given the large investment response, we also expect the policy to increase the capital stock of treated plants. We show that this is indeed the case in Panel (B) of Figure 2. Differences in the capital stock between treated and untreated plants are not statistically significant in the pre-period. The graph then shows that, relative to plants that benefited less from bonus, treated plants saw a persistent increase in their capital stock. This increase is robust to the inclusion of additional controls. Given this gradual increase, we focus on the long-differences (LD) estimates of bonus. Columns (1) and (2) of Table 2 show that by 2011 bonus depreciation led to a relative increase in the capital stock of between 7.78 and 8.04%.

ASM/CM data also allow us to separately estimate the effects on equipment and structures. Columns (3)–(6) of Table 2 show that the ten-year effect of bonus depreciation on equipment capital stock is three times larger than the effect on the stock of structures. Because during our period bonus depreciation mostly applied to equipment investment, finding a larger equipment response gives credence to our argument that estimated responses are due to the tax policy itself and not to other coincident unobservable shocks. In addition to serving as a useful validating exercise, these estimates are informative of how plants combine different types of capital in production. As we discuss in Section 7, bonus may influence investment in structures through both a scale effect and a substitution effect.

5.2 Labor Demand Response

Our results thus far verify that in our setting, bonus depreciation had large, positive impacts on investment and capital stocks in the US manufacturing sector. We now turn our attention to the important but under-explored question of whether plants used this increase in capital to replace workers, or if plants hired additional workers to interact with the new machinery.

Figure 3 shows event study coefficients depicting the effect of bonus on log employment. Both our baseline and additional controls specifications show that treated and control plants had similar employment trends before 2001. In 2002, we immediately observe that, relative to control plants, treated plants saw a large and statistically significant increase in the number of workers. This effect continues throughout the sample period and increases further in later years.

Panel A of Table 3 reports estimates of the effects of bonus on employment. Column (5) shows that employment at treated plants increased by 7.9% ($p < 0.001$), on average, between 2001 and 2011. Across our different sets of controls, this difference-in-differences estimate ranges between 7.85 and 8.5%. The long difference estimate in column (7) shows that, by 2011, the plants that benefited most from bonus had a relative employment increase of 9.5% ($p < 0.001$). Not only are the effects of bonus on the employment stock large and statistically significant at the 0.001 level, they are also larger than the effects of the policy on the capital stock. This finding is surprising given the popular concern that modern equipment investment is labor replacing and that the tax policy we study directly stimulates such investment.

An immediate question raised by this surprising finding is whether the increase in employment is driven by production workers who directly interact with machines or by workers specializing in non-production tasks, such as management or sales. Relative to other administrative datasets that do not capture production tasks (e.g., the LEHD or IRS tax data), the ASM/CM data provide a unique opportunity to answer this question.[27] Panels (A) and (B) of Figure 4 present event study graphs of the effects of bonus on production and non-production employment. Both graphs show large and positive effects of bonus on both types of employment. Panels (B) and (C) of Table 3 report estimates of the effect of bonus on these types of employment. Comparing the long differences estimates in column (7), we find that the effect on production employment is more than 40% larger than the effect on the employment workers specializing in non-production tasks.[28] Our results are therefore not consistent with the hypothesis that bonus induced a shift from production employment to automated technologies or to technologies that are more likely to be complementary to non-production employment.

As we discuss in Section 3, the results above focus on a balanced panel of plants. One possibility that is not captured by our baseline results is that, facing a lower cost of capital, new plants may choose to engage in more capital-intensive forms of production. If this were the case, and if entry comprised an important share of overall capital investment, the large effect on employment could disappear when including the effect of bonus on new firms. To explore this possibility, we now estimate the effects of bonus on employment using QWI data at the state-industry level. Importantly, these aggregated data capture extensive margins of response,

[27] We follow Berman, Bound and Griliches (1994) in using the production/non-production task dichotomy in the ASM data when estimating labor demand.

[28] As we show in Table A3, the result that the effect of bonus on production employment is larger than for non-production employment is robust to measuring employment in terms of hours worked. This table also shows that plants increase their use of materials in response to bonus.

such as plant exit or entry, that our balanced panel omits by construction. Figure 5 shows event study estimates of bonus depreciation on employment using quarterly data at the state-industry (4-digit-NAICS) level from QWI. We include state-by-industry and state-by-quarter fixed effects in this regression. We observe no differential pre-trends between treated and control industries and employment in treated industries increases shortly after the policy is implemented. The effect of bonus on employment grows through the end of the panel. Finally, the dynamics of the event study estimates are a near perfect match with the ASM/CM estimates presented in Figure 3.[29] These results suggest that entry and exit margins do not substantially alter our estimates of the effects of bonus depreciation on employment.

Due to the balanced panel nature of our ASM/CM data, our baseline results are not representative of smaller or younger firms. In Appendix Figure A4, we present event study employment estimates that focus on these types of firms using QWI data. Panel (A) focuses on smaller firms—those with 50 or fewer employees—and shows that bonus had similar effects on the employment of small firms. Panel (B) studies the effects of bonus on firms 0–5 years old and shows that bonus also elevated the employment of young firms. Importantly, the similar results for small and young plants show that the effect of bonus on employment is not confined to the sample of large plants in our balanced panel and is generalizable to the full US manufacturing sector.[30]

5.2.1 Additional Robustness Checks

Before discussing the effects of bonus on labor earnings and productivity, we demonstrate the robustness of the effects on employment.[31] We first estimate the effects of bonus on employment using alternative definitions of treatment. Panel (A) of Appendix Figure A5 shows that we find similar employment effects when we define treatment using the 25th and 40th percentiles of the z_0 distribution. In Panel (A) of Appendix Figure A6, we also show that we obtain similar results using the continuous variation in the variable z_0.[32]

We now show that our results are robust to controlling for a number of potential confounding

[29] Column (1) of Appendix Table A5 reports corresponding regression coefficients.

[30] The slightly larger effect for young firms is consistent with Isphording, Lichter, Löffler, Nguyen, Pöge and Siegloch (2021), who suggest that young firms are more likely to be financially constrained than small firms.

[31] Due to disclosure limits related to the use of Census Data, we rely primarily on QWI data at the industry-state level to perform these robustness checks.

[32] Additionally, Panel (B) of Appendix Figure A6 relates the treatment intensity z_0 to employment growth and shows that industries with lower values of z_0 experienced relatively larger increases in employment. The strong linear relationship between z_0 and employment growth explains why our results are not sensitive to how we define exposure to bonus in our analyses.

factors. First, one potential concern is that producers of capital goods benefit from the policy both by a reduction in the cost of production and an increase in the demand for their products. If this were the case, our estimates would overstate the effects of a reduction in the cost of investment on labor demand. In Panel (B) of Appendix Figure A5, we show that this is not the case, as we find similar effects of bonus on employment when we additionally control for indicators for NAICS industries that produce capital goods interacted with year fixed effects. Second, an additional concern is that plants in long-duration industries face differential changes in the costs of capital, which could potentially bias our results. Panel (C) of Appendix Figure A5 shows that our results are robust to controlling for industry-level quintiles of effective interest rates from COMPUSTAT interacted with year fixed effects. Finally, we show that our results are also robust to controlling for growth in the use of information and communication technologies (ICT). We use BEA data on the share of ICT capital to construct quintiles of exposure to growth in ICT. In Panel (D) of Appendix Figure A5, we show that we obtain similar results when we additionally control for interactions of this measure of ICT exposure with year fixed effects.

Since bonus depreciation was enacted as a countercyclical fiscal measure, one concern is that the industries that benefit most from bonus also experience differential exposure to the business cycle. To show that our results are not driven by differential exposure to the business cycle, we use NBER-CES industry-level data to estimate the effects of bonus on investment and employment going back to the 1991 recession. As we show in Appendix Figure A7, long duration industries did not have differential trends during the 1991 recession. Moreover, these industry-level results confirm that bonus depreciation increased both investment and employment after 2001.

Finally, as shown in Garrett, Ohrn and Suárez Serrato (2020), bonus depreciation can have spillover effects on local labor markets. One potential concern is that our results may capture these spillover effects in addition to the reduction in the cost of capital. In Appendix Table A4, we show that we obtain similar plant-level effects of bonus on employment and investment when we additionally control for local exposure to bonus depreciation.[33] Overall, these robustness checks support the interpretation that our estimates capture the plant-level effects of a policy-driven reduction in the cost of capital on employment.

[33] As in Garrett, Ohrn and Suárez Serrato (2020), we measure local exposure to bonus using the share of workers in long duration industries in a given county. The finding that bonus has positive spillover effects on employment assuages the concern that the policy may hurt workers through negative market-level spillover effects (e.g., as in Acemoglu, Lelarge and Restrepo, 2020). In addition to showing that we obtain similar average plant-level effects, we do not find evidence that plant-level effects vary according to local exposure.

5.3 Labor Earnings

Policymakers often motivate tax incentives for investment by arguing that worker pay will rise as plants increase investment (e.g., CEA, 2017). To investigate this claim, we measure the effect of bonus depreciation on the log of total plant payroll divided by total plant employment. Figure 6 presents event study plots of the effects of bonus on average worker earnings. Relative to control plants, workers in treated plants saw a decrease in average earnings per worker. Columns (1)–(5) of Panel (A) of Table 4 show that relative earnings dropped by close to 2% in the post-period.[34] These results are especially surprising given the increase in labor demand we documented in the previous section.

A natural explanation for the negative effect of bonus on average earnings is that bonus changes the composition of the workforce. QWI data allow us to explore whether this is the case. Figure 7 presents event study plots on the fraction of employees at a plant with high school or less education and the fraction of employees that are 35 years of age or younger. As in previous analyses using QWI data, we include state-by-industry and state-by-quarter fixed effects.[35] Both plots indicate that the employment increase due to bonus depreciation was accompanied by a shift toward a less educated and younger workforce. Multiplying the difference-in-differences estimate by the base fraction of young employees at treated plants (29.9%), we estimate that the share of young workers (19–34) increased by 3.8%. Based on the fraction with high school education or less (25.3%), the difference-in-differences estimate suggests that the share of lower education workers increased by 1.0%. Given that less educated and younger workers are, on average, paid relatively less, these results provide the first piece of evidence that the estimated decrease in average earnings per worker may be due to compositional changes in worker characteristics induced by the tax policy.

As a second piece of evidence that bonus may shift the composition of the workforce, Figure 8 presents event study analyses describing the effects of bonus depreciation on the fractions of workers that are female, non-white, Hispanic or Latino, and Black. In addition to state-by-industry and state-by-quarter fixed effects, these analyses also include bins of 1997–2001 changes in gender and racial shares at the state-industry-level interacted with year fixed effects. These

[34] We find a similar negative effect when we estimate the impact of bonus on average earnings using QWI data; see column (2) of Appendix Table A5.

[35] We report point estimates in columns (3) and (4) of Appendix Table A5.

flexible controls ensure that our estimates are not contaminated by ongoing changes in the gender and racial composition of the manufacturing workforce during this time.

The plots in Figure 8 show that industries that were more exposed to bonus experienced relative shifts toward a more female, more Hispanic or Latino, and more Black workforce. Differences-in-differences estimates imply that bonus increased the share of female workers by 3.2%, the share Hispanic or Latino by 8.5%, and the share of Black workers by 1.6%. As workers in each of these groups have lower average earnings, these results are also consistent with the hypothesis that changing worker characteristics in response to the policy had a dampening effect on average earnings per worker.

While these results are suggestive, we precisely attribute the decrease in average wages to compositional changes in the workforce using two methodologies. First, we control for the endogenous change in worker composition when we regress log average earnings on bonus. The negative and statistically significant effect of bonus on average earnings disappears when we control for the shares of young workers and of those with at most a high school education. Further controlling for the shares of non-white workers and female workers yields a precise null effect with a 95% confidence interval between -0.28% and 1.7% (see Table A7 for details). Second, we perform an analysis based on Kitagawa (1955), Oaxaca (1973), and Blinder (1973) to decompose the overall change in average earnings per worker into changes in worker demographics and changes in other factors, including wages. Between 2001 and 2011, this method finds that changes in the composition of the workforce account for 91% of the total decrease in average earnings. The combined empirical evidence indicates that most of the observed decrease in earnings can be attributed to the fact that bonus depreciation led plants to hire workers with fewer years of formal education as well as more young, racially diverse, and female workers. Appendix H provides a more detailed description of these analyses.

Overall, our results shows that bonus depreciation did not increase average earnings per worker.[36] However, our employment results shows that bonus depreciation disproportionately helped disadvantaged workers at a time when their employment prospects in the manufacturing sector were dwindling (Gould, 2018).

[36] This result is consistent with Fuest, Peichl and Siegloch (2018), who find that local tax cuts across German municipalities did not increase average earnings.

5.4 Productivity and Production Responses

In addition to touting the employment and earnings effects of capital investment, policymakers often appeal to a theory of "capital deepening," whereby increases in capital investment can lead to productivity growth (see, e.g., CEA, 2017). Panel (A) of Figure 9 presents results from an event-study of the effects of bonus on our measure of plant-level TFP. Contrary to the capital deepening hypothesis, we do not find evidence that capital investment led to increases in plant productivity. Indeed, Panel (B) of Table 4 reports statistically insignificant estimates for both difference-in-differences and long differences analyses. Column (5) of this panel implies a 95% confidence interval of the effect of bonus on productivity between -1.4% and 0.8%.[37]

While bonus did not increase plant productivity, the mere fact that bonus decreased overall costs of production may have allowed plants to expand their operations. The event study in Panel (B) of Figure 9 shows that this was indeed the case. Column (5) of Panel (C) of Table 4 shows that the sales of treated plants (measured by the total value of shipments) saw a relative increase of 5.4%, on average, between 2001 and 2011. Since Panel (B) of Figure 9 shows that the effect of bonus on production grew over time, we also report long differences estimates in Panel (C) of Table 4. By 2011, the plants that benefited the most from bonus increased their sales by between 7.5 and 8.1%, relative to control plants.

In light of our earlier results, these findings suggest that bonus helped treated plants increase their overall scale. Since productivity and earnings remain unchanged, it is likely that affected plants achieved this new scale by relying on the same fundamental technologies they were using prior to the policy. In Section 7, we explore the degree to which the scale effect explains the documented capital and labor responses.

6 Tax Policy in a Transforming Manufacturing Sector

In analyzing the effects of bonus depreciation, it is crucial to place our findings in the context of the ongoing transformation of the US manufacturing sector. Doing so helps ensure that our

[37] As we show in the previous section, bonus impacts the composition of the workforce. One concern is that our TFP estimates are biased downwards since plants shift their employment to workers with fewer years of education and experience. However, this effect is likely to be quantitatively small. Assuming that these workers are paid their marginal product and using the average labor cost share of 25% and the unconditional decrease in average earnings of -2.73% (column (7) of Panel (A) of Table 4) would imply a correction to our TFP estimates of +0.68% ($= -2.73\% \times 25\%$). This correction would revise our -1.53% (column (7) of Panel (B) of Table 4) estimate to -0.85%, which still does not provide evidence in favor of the capital deepening hypothesis.

results are driven by the effects of tax policy and not by sector-level trends. Additionally, it is valuable to explore whether bonus depreciation stunted or accelerated the ongoing transformation of the sector.

Charles, Hurst and Schwartz (2019) document that from 2000–2017, the US manufacturing sector lost 5.5 million jobs.[38] The authors go on to show that these losses were not accompanied by declines in overall output and were concentrated among males with relatively little education. This increase in "skill intensity" was paired with an increase in "capital intensity," i.e., an increase in the share of productivity attributable to capital. Two leading factors contributing to the overall decline of manufacturing employment are the dramatic increase in import competition from China documented in Autor, Dorn and Hanson (2013), Acemoglu, Autor, Dorn, Hanson and Price (2016), Autor, Dorn and Hanson (2016), and Pierce and Schott (2016) and the increased adoption of automated production processes investigated by Acemoglu and Restrepo (2020).[39]

We first show that increases in skill and capital intensities, import competition from China, and automation are not correlated with bonus depreciation in ways that may impact our empirical results. To do so, we use the ASM/CM plant-level data to re-estimate our main difference-in-differences estimates in the presence of controls for each of these four forces. As in Charles, Hurst and Schwartz (2019), we measure skill intensity at the plant-level as the share employment in non-production roles in 2001. To operationalize this control, we create bins based on quartiles of the distribution of this variable and we interact them with year fixed effects. Our capital intensity control is constructed in a similar manner, but is based on the 2001 plant-level ratio of total capital assets to total employment. We control for the "China Shock" using industry-level changes in import competition from China between 2000–2007 from Acemoglu, Autor, Dorn, Hanson and Price (2016) interacted with year fixed effects. Finally, we use data from Acemoglu and Restrepo (2020) on industry-level changes in the number of industrial robots per 1,000 workers between 1993–2007, which we also interact with year fixed effects.

Table 5 re-estimates our differences-in-differences parameters describing the effects of bonus on investment, employment, and mean earnings. For reference, columns (1), (3), and (5) display estimates we previously presented in columns (5) of Tables 1, 3, and 4. For comparison, columns (2), (4), and (6) include plant and state-by-year fixed effects as well as the four controls for skill

[38] Appendix G compares the scale of our estimates of the effects of bonus depreciation relative to these aggregate employment losses.

[39] Both of these forces could also cause or mediate changes in skill and capital intensity.

intensity, capital intensity, Chinese import exposure, and robotization. As this table shows, the effect of bonus on investment is essentially unchanged when including these controls. Employment responses to bonus depreciation are slightly attenuated, decreasing from 7.9 to 6.9%. We also continue to find that bonus depreciation does not lead to significant gains in average earnings for the workers of more affected plants.[40] Overall, this table shows that our estimated effects of bonus are essentially unchanged in the presence of controls for salient drivers of the transformation of the US manufacturing sector.[41]

We now investigate whether bonus depreciation exacerbated or mitigated the effects of these key drivers of sectoral change. To do so, we include interactions between the difference-in-differences term and the cross-sectional continuous components of each control described above (e.g., 2001 capital stock per total employment). For comparability in interpretation, we normalize each interactor to have mean zero and divide it by its interquartile range. As such, the interaction terms are interpreted as differences in the effect of bonus depreciation between units in the 25th and 75th percentiles of each factor. Table 6 presents results from these analyses for our two main outcomes, log investment and log total employment.[42] Column (1) shows that investment responses to bonus depreciation are larger in plants with higher skill intensity. The interaction term in the employment regression is positive, but statistically insignificant at conventional levels. In column (2), we find that both investment and employment responses are larger in plants with high levels of capital intensity. These results imply that bonus depreciation did not encourage plants to swim against the current by investing in technologies characterized by low levels of capital and skill intensity. Two additional points related to this finding are worth mentioning. First, even if bonus contributed to the transition to capital intensive forms of production, the employment effects of bonus were larger in plants that were initially more capital intensive. Second, this result further validates the research design as capital intensive plants are those that experience the largest cash flows benefits from accelerated depreciation policies.

Column (3) of Table 6 estimates interaction effects of bonus and import competition. In-

[40]Intuitively, controlling for skill intensity works in the same way as controlling for plant-level employment demographics. For this reason, we find similar null effects on average earnings as we do in Section 5.3.

[41]One possibility is that these controls may change the underlying variation from the tax policy. This could happen, for instance, by limiting the effect of the policy on skill or capital intensity. If this were the case, these specifications could risk over-controlling for some of the effects of bonus depreciation. For this reason, we do not view these results as our preferred estimates.

[42]Appendix Table A9 presents estimates from models in which all interaction terms are included together. Signs and magnitudes of all coefficients are the same.

creased import competition depresses the effects of bonus depreciation on both investment and employment. These results are intuitive; investment incentives have the least effect in the US industries that are most exposed to import competition from China. Finally, column (4) explores interaction effects between bonus and exposure to robotization. We find positive point estimates on the interactions with robotization, but only the employment interaction is statistically significant. Surprisingly, these results contradict concerns that capital investments stimulated by tax policy are labor replacing via the adoption of robots. The industries that automated most during the period also increased employment the most in response to bonus depreciation.[43]

The results of Table 6 directly address a salient policy concern that investment incentives like bonus depreciation simply prop-up non-competitive industries, prolonging their slow and painful demise. These analyses show that this is not so in the case of bonus depreciation. We find that the policy has the largest impact on the most skill-intensive, most capital-intensive, most automated, and least exposed to Chinese import competition; bonus depreciation is most effective for the industries that are most likely to thrive in the transforming landscape of US manufacturing.

7 Estimating Factor Demands Using Tax Policy Variation

We now use the reduced-form estimates from Section 5 to estimate a model of demand for factors of production. The model yields three insights. First, by incorporating the result of Marshall (1890) and Hicks (1932) that plants respond to changes in input prices by adjusting both their scale and input mix, the model quantifies the importance of the mechanisms through which bonus depreciation stimulates labor demand. Second, the model recovers the implied effects of the policy on the cost of capital, which allows us to compute cost of capital elasticities of capital and labor demand inclusive of financing constraints and other real-world factors that shape the effects of tax policy. Finally, the model leverages tax policy variation to estimate elasticities of substitution between capital and different types of labor, which are fundamental economic parameters.

[43] This finding, which suggest workers and robots are not direct substitutes is not without precedent. Graetz and Michaels (2018) find robot adoption does not decrease employment. Klenert, Fernandez-Macias and Antón Pérez (2020) show the adoption of robots in Europe led to increases in employment without any change in the share of low-skill workers.

7.1 Model Setup

The model considers the production and pricing decisions of plants in the manufacturing sector. Plants have a production function with constant returns to scale, which uses the three inputs: capital K, production labor L, and non-production labor J. Plants first optimally choose inputs to minimize costs. Plants then maximize profits by choosing their output level. The output market is characterized by monopolistic competition where demand has a constant price elasticity (see, e.g., Hamermesh, 1996; Harasztosi and Lindner, 2019; Criscuolo, Martin, Overman and Van Reenen, 2019).[44] Bonus depreciation lowers the cost of capital, which we denote by $\phi \equiv \frac{\partial \ln(\text{Cost of Capital})}{\partial \text{Bonus}} < 0$. ϕ includes both the increased present value of depreciation deductions and reductions in financing frictions.[45] Appendix I provides a detailed derivation of the model.[46]

These simple assumptions allow us to characterize the effect of bonus on plants' demands for inputs of production. The reduction in the cost of capital ϕ impacts both the choice of cost-minimizing inputs (substitution effect) and the profit-maximizing output level (scale effect). To see this, note that the effect of bonus on the demand for capital is

$$\beta^K = \frac{\partial \ln K}{\partial \text{Bonus}} = (\underbrace{-s_J\sigma_{KJ} - s_L\sigma_{KL}}_{\substack{\text{Substitution}\\ \text{Effect}}} - \underbrace{s_K\eta}_{\substack{\text{Scale}\\ \text{Effect}}}) \times \underbrace{\phi.}_{\substack{\text{Bonus Lowers}\\ \text{Cost of Capital}}} \tag{3}$$

In their price-theoretic treatment of factor demands, Jaffe, Minton, Mulligan and Murphy (2019) interpret this equation as the production analogue of the Slutsky equation, since it separates substitution effects conditional on output from changes in the plant's scale. Plants increase their capital to the extent that lower production costs help each plant increase its sales. The strength of this scale effect depends on the cost share of capital s_K and the elasticity of product demand η.

[44] The model assumes that plants take input prices as constant. As we show above, we do not find that bonus impacts the wages of workers conditional on composition. In related work, Garrett, Ohrn and Suárez Serrato (2020) also estimate a null effect of bonus on average wages accounting for spillover effects within local labor markets. One possibility is that bonus impacts the pre-tax prices of capital goods. While classic papers show that tax incentives for investment can impact the prices of capital goods (e.g., Goolsbee, 1998), House, Mocanu and Shapiro (2017) show tax incentives have not impacted capital goods prices in recent years, partly because of the growth of imported capital goods as a share of investment. Indeed, House and Shapiro (2008) show that capital goods prices did not respond to bonus depreciation between 2002–2004.

[45] In Appendix I.3, we provide an explicit model consistent with Myers (1977); Bond and Meghir (1994); Bond and Van Reenen (2007) that shows that interactions with liquidity constraints amplify the effect of bonus on the cost of capital, ϕ. We interpret ϕ as the experienced reduction in the cost of capital inclusive of financing frictions.

[46] Our framework abstracts away from adjustment costs that may limit plants from adjusting their capital inputs in any given year. Since we measure the effects of bonus depreciation over a 10-year period, it is reasonable to assume that plants will be able to adjust their capital inputs over this period.

Plants also increase their capital by substituting away from other inputs J and L. The strength of this substitution effect depends on the input cost shares (s_J and s_L) and on the Allen partial elasticities of substitution (σ_{KJ} and σ_{KL}). Allen (1938) defines inputs K and J as complements in production whenever $\sigma_{KJ} < 0$, while $\sigma_{KJ} > 0$ implies that these inputs are substitutes.[47]

Consider now the model's prediction of the effect of bonus on the demands for labor

$$\beta^L = \frac{\partial \ln L}{\partial \text{Bonus}} = s_K(\sigma_{KL} - \eta) \times \phi \tag{4}$$

$$\beta^J = \frac{\partial \ln J}{\partial \text{Bonus}} = s_K(\sigma_{KJ} - \eta) \times \phi. \tag{5}$$

Equation 4 shows that bonus increases labor demand when production labor and capital are complements, i.e., $\sigma_{KL} < 0$, or when the scale effect dominates a substitution effect, i.e., $\eta > \sigma_{KL} > 0$. Finally, consider the model's prediction of the effect of bonus on plant sales

$$\beta^R = \frac{\partial \ln \text{Revenue}}{\partial \text{Bonus}} = s_K(1 - \eta) \times \phi. \tag{6}$$

Equations 3–6 provide a transparent link between our reduced-form estimates from Section 5 and the four model parameters that determine factor demands $\theta = (\sigma_{KL}, \sigma_{KJ}, \eta, \phi)$.

7.2 Reduced-Form Estimates of the Scale Effect

We first use the model to decompose the effects of bonus depreciation on labor demand into scale and substitution effects. To do so, first note that we can quantify the scale effect using our reduced-form estimates. This is because, regardless of the values of σ_{KL} and σ_{KJ}, it is always the case that:

$$\bar{\beta} \equiv s_J \beta^J + s_K \beta^K + s_L \beta^L = -s_K \eta \phi > 0. \tag{7}$$

This equation shows that the cost-weighted average of the effects of bonus on plants' inputs of production, $\bar{\beta}$, identifies the common scale effect in Equations 3–5, $-s_K \eta \phi$.

This equation makes it very easy to compute the common scale effect of the policy on the demand for plant inputs. Panel (A) of Table 7 reports estimates of the scale effect.[48] Assuming that the input cost shares are such that $s_K = 0.2$, $s_L = 0.5$, and $s_J = 0.3$, column (1) shows that the scale effect equals 0.10 (SE=0.01). Columns (2) and (3) of Table 7 show that varying the cost

[47] While any two inputs may be complements, Allen (1938) shows that second-order optimization conditions require the total substitution effect to be negative, i.e, $s_J \sigma_{KJ} + s_L \sigma_{KL} > 0$.

[48] We use the following estimates in this calculation: β^K from column (2) in Table 2, and β^L and β^J from columns (7) of Panels (B) and (C), respectively, in Table 3.

shares has very small effects on our estimate of the scale effect. The scale effect is estimated with a high degree of precision and has a natural economic interpretation: the effect of the policy on the profit-maximizing output level led to an equal increase of 10% in the demand for all inputs.[49]

We can also use this expression to evaluate whether an input is a substitute or a complement to capital. To do so, we take the ratio of Equations 4 and 7 to show that

$$\frac{\beta^L}{\bar{\beta}} = 1 - \frac{\sigma_{KL}}{\eta}. \tag{8}$$

To the extent that input L is a substitute for capital ($\sigma_{KL} > 0$), the effect of the policy on labor demand β^L would be smaller than the scale effect $\bar{\beta}$. Conversely, if an input complements capital, we would observe that the scale effect is smaller than the total effect (since $\sigma_{KL} < 0$). Recall that we estimated that bonus increased the use of non-production labor by 8.1%. Since this effect is smaller than the scale effect of 10%, it follows that non-production labor is a substitute for capital. In contrast, the estimated 11.5% increase in production labor exceeds the scale effect, suggesting that production labor complements capital in production. Panel (B) of Table 7 formally evaluates these hypotheses. Comparing β^L and $\bar{\beta}$, column (1) rejects the hypothesis that production workers are substitutes for capital with a p-value of 0.054. Columns (2)–(3) show that the p-value of this test is between 0.039 and 0.087 depending on the value of s_K.[50]

The discussion above clarifies that differences between the common scale effect and the total effect on a given input determine whether an input complements or substitutes for capital. Quantitatively, however, our calculations reveal that, for both production and non-production labor, the total effects are close to the scale effect. This result implies that the main mechanism driving the effect of bonus depreciation on labor demand is the scale effect; that is, the policy-driven reduction in the cost of capital allowed plants to expand both their output and their demand for all inputs. In the case of production labor, the scale effect was responsible for close to 90% of the total effect of the policy. These results rule out the worst fears of tax-driven automation, as the primary effect of tax policies that lower the cost of investment is not to incentivize plants to replace workers with machines.

[49] This would also be the total increase in factor demands in a Leontief production function without any substitution effects. Note that columns (4) and (5) vary η, which does not impact our estimate of the scale effect.

[50] This table also shows that we cannot reject the hypothesis that non-production workers are complements with capital at conventional levels of statistical significance.

7.3 Elasticities of Capital and Labor Demand

As we discuss in Section 2, the effects of bonus on the cost of capital depend on a number of factors that are hard to quantify, including the roles of depreciation deductions, tax losses, and financing constraints. One advantage of our model is that it allows us to recover the implied effect of the policy on the cost capital based on the estimated effects on inputs of production and the elasticity of product demand. This is because Equation 7 implies that

$$\phi = -\frac{\bar{\beta}}{s_K \eta}. \tag{9}$$

Column (1) of Panel (C) of Table 7 shows that $\phi = -0.145$ when the elasticity of product demand $\eta = 3.5$.[51] Columns (2)–(5) show that varying the capital cost share $s_K \in [0.10, 0.30]$ or the demand elasticity $\eta \in [2, 5]$ yields estimates of $\phi \in [-0.25, -0.10]$.[52]

Using our estimates of ϕ, we now estimate capital and labor demand elasticities. Column (1) of Panel (C) of Table 7 shows that the elasticity of capital demand with respect to the cost of capital is $\varepsilon^K_\phi = \frac{\beta^K}{\phi} = \frac{0.080}{-0.145} = -0.55$. This elasticity lies in the range $[-0.80, -0.32]$ across our estimates in columns (1)–(5). Since the research literature often focuses on investment flows, rather than on capital stocks, we also compute an investment elasticity: $\varepsilon^I_\phi = \frac{\beta^I}{\phi} = \frac{0.210}{-0.145} = -1.45$.[53] Finally, the cross-price elasticities of labor demand with respect to the cost of capital are $\varepsilon^L_\phi = \frac{\beta^L}{\phi} = \frac{0.116}{-0.145} = -0.80$ for production labor and $\varepsilon^J_\phi = \frac{\beta^J}{\phi} = \frac{0.090}{-0.145} = -0.62$ for non-production labor.[54] As we discuss above, the scale effect of the policy is the primary reason that increasing the cost of capital would reduce labor demand.[55]

[51] Ganapati, Shapiro and Walker (2020) estimate product demand elasticities using CM data. They report a central estimate of 3.42 and a range of estimates between 1.93 and 5.23 for selected industries.

[52] In Appendix I.3, we calibrate values of ϕ under alternative assumptions. Including a role for financing constraints implies that ϕ is 2–4 times larger than when ϕ only accounts for the present value of depreciation deductions. These calculations reconcile our results with a simplistic interpretation of the results of Zwick and Mahon (2017) that abstracts from the effect of bonus on financing constraints. These calculations are also consistent with calibrations in Zwick (2014) showing that bonus had large effects on investment due to high values of the shadow price of internal funds and high implied discounting rates.

[53] To match the capital demand elasticity, we use the long difference estimate on investment from Panel (A) of Figure 2. This elasticity lies in the range $[-2.1, -0.84]$ across our estimates in columns (1)–(5) of Table 7. In a setting where tax policy is less likely to interact with financing constraints, Chen, Jiang, Liu, Suárez Serrato and Xu (2019) estimate an investment tax elasticity of -2.2, which is comparable in magnitude to our estimates.

[54] Across our estimates in columns (1)–(5), $\varepsilon^L_\phi \in [-1.16, -0.46]$ and $\varepsilon^J_\phi \in [-0.90, -0.36]$.

[55] Figure A10 explores the dynamic patterns underlying these estimates. Panel (A) shows that the scale effect grows over time as plants respond to the cumulative effects of the policy. While Panel (B) shows that the implied effect on the cost of capital ϕ also grows over time, Panels (C) and (D) show that the investment and employment elasticities are relatively constant over time. These results are consistent with our interpretation of ϕ as the effect of the policy on cost of investment inclusive of financing constraints as well as other frictions that may prevent plants from responding to the policy.

7.4 Estimating Elasticities of Capital-Labor Substitution

Elasticities of capital-labor substitution are fundamental economic parameters. To see how our reduced-form estimates identify these elasticities, solve Equation 8 for σ_{KL} to obtain

$$\sigma_{KL} = \eta \left(1 - \frac{\beta^L}{\bar{\beta}}\right). \tag{10}$$

Notice as well that Equations 6 and 9 imply that $\eta = \frac{\bar{\beta}}{\bar{\beta} - \beta^R} > 1$. This expression, along with Equations 9–10 show that our reduced-form estimates identify the parameters of the model.[56]

We estimate the model parameters using a classical minimum distance estimator. Let $\hat{\beta} = (\hat{\beta}^K, \hat{\beta}^L, \hat{\beta}^J, \hat{\beta}^R)'$ be the vector collecting the reduced-form estimates of the effects of bonus depreciation on inputs and plant revenue, and let $h(\theta)$ be the collection of model predictions from Equations 3–6. Our estimate $\hat{\theta}$ minimizes the criterion function $[\hat{\beta} - h(\theta)]'\hat{W}[\hat{\beta} - h(\theta)]$, where $\hat{W}$ is a weighting matrix.[57]

While the equations above show that the model parameters are closely related to our reduced-form estimates, the presence of the difference $\bar{\beta} - \beta^R$ in the denominator of the formula for η raises the concern that estimates of structural parameters may be sensitive to small differences between our reduced-form estimates. For this reason, we calibrate η in our baseline estimations; we show robustness to a range of calibrated values and to estimating η. Finally, to ensure that our estimated parameters are consistent with cost minimization, we require that the substitution elasticities satisfy the constraint: $s_J\sigma_{KJ} + s_L\sigma_{KL} > 0$ (Allen, 1938).

7.4.1 Estimated Parameters

To highlight the intuition behind our model, we present structural estimates of σ_{KL} graphically in Panel (A) of Figure 10 as a function of different values of η. The dot-dashed blue line plots Equation 10, which shows that $\sigma_{KL} < 0$ regardless of the value of η. The blue dots report estimates of σ_{KL} using the full model and calibrated values of η equal to 2, 3.5, and, 5. This figure also reports a model that estimates $\eta = 4.42$ as well as models that vary the share of capital in total costs between 10% and 30%. The full model estimates lie above the line that

[56] Specifically, note that $\phi = -\frac{\bar{\beta} - \beta^R}{s_K} < 0$ and $\sigma_{KL} = \frac{\bar{\beta} - \beta^L}{\bar{\beta} - \beta^R}$. A similar expression identifies σ_{KJ}.

[57] In practice, $\hat{W}$ equals the diagonal of the inverse variance-covariance matrix $\hat{V}$ of the moments $\hat{\beta}$. Following Chamberlain (1984, §4.2), we estimate the variance of $\hat{\theta}$ with the matrix $[H(\hat{\theta})'\hat{W}H(\hat{\theta})]^{-1}H(\hat{\theta})'\hat{W}\hat{V}\hat{W}H(\hat{\theta})[H(\hat{\theta})'\hat{W}H(\hat{\theta})]^{-1}$, where $H(\hat{\theta}) = \nabla_\theta h(\theta)|_{\theta=\hat{\theta}}$ is the gradient of $h(\theta)$ at $\hat{\theta}$. We implement this procedure using code modified from Harasztosi and Lindner (2019) that relies on a finite difference approximation of $H(\hat{\theta})$.

plots Equation 10 because we impose the constraint that the model be consistent with cost minimization (i.e., that $s_J\sigma_{KJ} + s_L\sigma_{KL} > 0$). Across these different variations, we consistently estimate that $\sigma_{KL} < 0$, implying that capital and production workers are complementary inputs. Indeed, in order to obtain an estimate of $\sigma_{KL} = 1$ (i.e., Cobb-Douglas), plants would have had to increase their capital use by 38%, which is almost 5 times larger than our estimated effect. Even a Leontief production function (i.e., $\sigma_{KL} = 0$) would require that plants increase their capital by 15.5%, which is twice as large as our estimated effect.

Panel (A) of Table 8 reports these same estimates of σ_{KL} as well as all other model parameters across a range of model specifications.[58] Relative to our baseline estimate in column (1), columns (2)–(3) show that our estimates are not sensitive to calibrated cost shares, columns (4)–(5) show the effects of varying the elasticity of product demand η, and column (6) reports model estimates when we also estimate η. Across all specifications we find that non-production workers are substitutes with capital, $\sigma_{KJ} > 0$.[59] To gain intuition for these results, note that they follow directly from the fact that our estimates in Section 5 are such that $\hat{\beta}^{\mathrm{L}} > \hat{\bar{\beta}} > \hat{\beta}^{\mathrm{J}}$. Panels (B) and (C) of Table 8 show that the model predictions $h(\hat{\theta})$ are very close to our estimates $\hat{\beta}$. This result shows that the calibrated value of η and the restriction that our estimates are consistent with cost minimization are not in conflict with the reduced-form estimates of the effects of bonus depreciation.[60]

We briefly discuss additional robustness checks of our model; see Appendix J for details. Column (2) of Appendix Table A10 shows that our results are robust to using difference-in-differences estimates of $\hat{\beta}$ instead of long-differences estimates. Column (3) reports similar parameter estimates when we measure labor using production hours instead of number of workers. Column (4) shows that we also find a negative elasticity of substitution when we do not differentiate between different type of labor.[61] Columns (5)–(6) show that we estimate similar elasticitities

[58]The full model estimates are consistent with the result that the scale effect is the dominant mechanism behind the increase in labor demand. Estimates from column (1) of Table 8 imply that 90% of the increase in non-production employment is driven by the scale effect since $\frac{\eta}{\eta-\sigma_{KL}} = \frac{3.5}{3.5+0.39} = 0.90$. The complementarity effect is responsible for the remaining 10%. Similarly, these model estimates imply an elasticity of capital demand of $\varepsilon^K_\phi = -0.70$ (SE= 0.12) and an elasticity of production labor demand of $\varepsilon^L_\phi = -0.78$ (SE= 0.10). Finally, the estimated values of ϕ are also similar to those reported in Table 7.

[59]This result is economically interesting since it is opposite to the prediction of capital-skill complementarity. Griliches (1969) defines the capital-skill complementarity hypothesis using Allen elasticities of substitution as follows: $\sigma_{KL} > 0$, $\sigma_{KL} > \sigma_{KJ}$, and $\sigma_{KL} > \sigma_{LJ}$.

[60]Table A11 shows that we obtain qualitatively similar results when we do not impose this constraint.

[61]Appendix Figure A9 Panel (A) shows graphically that our reduced-form estimates imply negative substitution elasticities in two-input models; Panel (B) shows a similar result in a five-input model that includes materials,

of capital-labor substitution in models with one type of labor and that consider different roles for structures and equipment or that include materials as an additional input. Across all of our models, we consistently find that production workers complement capital in production. Finally, Appendix Figure A11 explores the dynamics of capital-labor substitution. This figure shows that capital and labor are initially very complementary ($\sigma_{KL} \ll 0$) and that σ_{KL} tends toward zero over time. This pattern is consistent with the intuition that plants can only increase production by hiring workers when capital is fixed; workers become less complementary with machines as plants adjust their capital.

Panel (B) of Figure 10 compares our estimate of σ_{KL} to others in the literature. To do so, we plot the probability that $\hat{\sigma}_{KL}$ exceeds a given value. Our baseline estimate rejects values of the elasticity of substitution between production labor and capital that are greater than 0.42 at the 95% confidence level. This test therefore rules out recent estimates of σ_{KL} from Karabarbounis and Neiman (2014) ($\sigma_{KL} = 1.3$), the elasticity of substitution implied by a Cobb-Douglas production function ($\sigma_{KL} = 1$), as well as the average value from the meta-analysis of Gechert, Havranek, Irsova and Kolcunova (2021) ($\sigma_{KL} = 0.9$). The central estimate from Raval (2019) lies at the high border of the 95% confidence interval. This figure also shows that models that only include capital and labor (orange line) or that separate capital into equipment and structures reject values greater than 0.2 at the same confidence level. Relative to most estimates in the literature, our approach benefits from using plant level data on input use and production to measure the effects of a change in the cost of capital over a 10-year period.

7.4.2 Implied Cost and Production Functions

We now relate our estimates of substitution elasticities to specific models of production. In his treatise on labor demand, Hamermesh (1996) recommends that empirical researchers specify models that allow for flexible cross-price elasticities between different inputs. One such model is the transcendental logarithmic cost function, or "translog" for short. As Christensen, Jorgenson and Lau (1971, 1973) demonstrate, this cost function is a second-order approximation to an arbitrary functional form. In Appendix J.3, we estimate the parameters of a translog cost function using our estimates from Table 8. The translog parameters are estimated with a high degree of precision, imply rich patterns of input substitution as suggested by Hamermesh (1996), and

equipment, structures, and production and non-production workers.

yield interesting economic implications. Appendix Tables A12 and A13 show that our estimated models reject the null hypotheses that our results are generated by a Cobb-Douglas function as well as the possibility that production workers or capital are separable from other inputs.

A popular but more restrictive modeling approach than the translog is the nested CES production function. For instance, Krusell, Ohanian, Ríos-Rull and Violante (2000) nest non-production labor and capital separately from production labor. This nesting choice forces $\sigma_{LJ} = \sigma_{KL}$. Given that we estimate that $\sigma_{KL} < 0$, such a production would have two (out of three) negative elasticities of substitution, which would violate second-order sufficiency conditions of cost minimization (see, e.g., Allen, 1938, p. 505). An alternative approach that is consistent with both $\sigma_{KL} < 0$ and cost minimization is to nest production labor and capital separately from non-production labor, as in the following production function:

$$F(K, L, J) = \left[\mu_1 J^{\rho_1} + (1 - \mu_1)(\mu_2 L^{\rho_2} + (1 - \mu_2)K^{\rho_2})^{\frac{\rho_1}{\rho_2}}\right]^{\frac{1}{\rho_1}},$$

where μ_1 and μ_2 are related to income shares. The fact that we estimate that $\sigma_{KJ} = \frac{1}{1-\rho_1} > 0$ and $\sigma_{KL} = \frac{1}{1-\rho_2} < 0$, implies that $\rho_1 < 1$ and $\rho_2 > 1$.[62] Indeed, Appendix Table A14 shows that we estimate that $\rho_1 = -0.55$ and $\rho_2 = 3.6$. These values are economically interesting since they are not consistent with the capital-skill complementarity hypothesis that $\rho_1 > \rho_2$. These estimates also reject the degree of capital-skill complementarity found in Krusell, Ohanian, Ríos-Rull and Violante (2000) at the 95% confidence level.

Overall, our estimated model of factor demands delivers a number of economic insights using the results of Section 5. First, the model shows that the scale effect is the main mechanism driving the increase in labor demand. Second, the implied reduction in the cost of capital delivers estimates of capital and labor demand elasticities with reasonable magnitudes. Third, we consistently estimate that capital and production workers are complements and our estimates rule out values of σ_{KL} greater than 0.4. Finally, our estimated translog and nested CES models show that our results can be generated by standard models of production and make it easy to compare our results with those of the previous literature.

[62] Lewis (2011) uses a similar nesting approach. While Arrow, Chenery, Minhas and Solow (1961) note that in two-input CES production functions, decreasing marginal returns requires that $\rho < 1$, the condition that $\rho_1, \rho_2 < 1$ is not necessary to obtain decreasing marginal returns in nested CES functions with three inputs.

7.5 Empirical Implications of Capital-Labor Complementarity

The result that capital and labor are complements in production carries interesting testable hypotheses. Specifically, we would expect to see larger investment responses when plants face lower wages.[63] We test for heterogeneous responses in three settings. First, in plants with a mostly unionized workforce. Our measure of "Union" is an indicator equal to 1 when more than 60% of workers at a plant are unionized.[64] Second, in plants located in right-to-work (RTW) states (as of 2001), where employees have less bargaining power.[65] Third, in plants that operate in local labor markets that are highly concentrated. We measure labor market concentration using a NAICS 3-digit, commuting zone level Herfindahl-Hirschmann Index (HHI) based on 2001 market conditions.[66] In settings that feature labor market monopsony, employers can strategically lower workers wages (see, e.g., Robinson, 1969; Manning, 2021). To implement these tests, we include interactions between bonus and each of these determinants of labor costs.

Table 9 presents difference-in-differences estimates of the effects of bonus on investment, employment, and mean earnings that allow for heterogeneous responses depending on proxies of labor costs. The results in Panel (A) indicate that the investment responses are concentrated in less unionized plants, where we expect wages and bargaining power to be lower. Similarly, the estimates in Panel (B) show much larger investment responses in RTW states. Finally, in Panel (C), we find larger investment responses in labor markets where wages are likely depressed due to monopsony power. Across all proxies of labor cost, we see that bonus induces more investment in plants that face lower labor costs. These results are consistent with capital and labor being complements, which validates our empirical model of factor demands. Further, these analyses

[63] This prediction follows from Equation 3, which implies that bonus depreciation will lead to stronger effects on investment when the labor cost share s_L is smaller. This implication is "Marshall's Second Law of Derived Demand," following the enumeration in Pigou (1920).

[64] Plant-level data on unionization are rare. Our measure is based on 2005 data from the Census Bureau's Management and Organizational Practices Survey (MOPS), which covers the majority of our sample.

[65] The RTW variable comes from Valletta and Freeman (1988). RTW laws allow workers to opt out of union dues and agency fees. These laws decrease the power of unions because workers can free-ride on the efforts of the union, which is obligated to bargain and obtain benefits on behalf of all workers. Researchers have also found that RTW laws codify state-level anti-union sentiments (see, e.g., Farber, Herbst, Kuziemko and Naidu, 2021, Footnote 43). For these reasons, RTW laws lower workers' bargaining power and result in lower labor costs.

[66] We construct the HHI using data from the LBD. Given that local labor concentration is highly right-skewed in our sample, we measure concentration using the log of HHI. As with other continuous interaction variables, we demean the log of HHI before interacting it with bonus. The interaction has the convenient interpretation as the differential effect of bonus depreciation between a plant located in the average labor market concentration compared to a plant that is located in a highly concentrated labor market, according to FTC/DOJ guidelines (i.e., HHI$>$ 2500).

highlight how labor market institutions can impact capital investment.

Table 9 also reports heterogeneous effects on employment and earnings. Two notable results stand out. First, negative interactions for both employment and earnings show that unions do not increase the benefits of bonus to workers. Second, bonus leads to a relative increase in average earnings in highly concentrated labor markets. This result is consistent with the notion that in monopsonistic labor markets, plants must raise wages to increase employment.

8 Conclusion

The question of whether policies that subsidize investment in physical capital help or hurt workers is pervasive in discussions about equitable and efficient fiscal policy. In this paper, we use the largest corporate tax incentive in the US in the 21st century—bonus depreciation—in conjunction with confidential data from ASM/CM to gain empirical leverage on this debate. By comparing capital and labor input usage between long- and short-duration industries around the implementation of bonus depreciation, we show that both capital and labor increased in tandem for affected plants during this period.

Our results bring up several previously unexplored phenomena in labor responses to capital investment incentives. First, we find that production labor increases more than non-production labor, and that both increase in statistically and economically important ways. We also show that the average earnings for workers at affected plants actually decrease, despite increases in labor inputs. This decrease is explained by increases in the shares of workers that are less-educated, younger, more racially diverse, and more likely to be women.

In the larger context of the transformation of the US manufacturing sector, we find that bonus depreciation was less effective at stimulating manufacturing activity for industries that were more exposed to import competition from China. We also find that bonus is most effective at plants with high degrees of capital and skill intensity, which may have contributed to the increase in capital and skill intensity in the sector. Finally, we reject the hypothesis that bonus decreased employment in industries that were highly exposed to robotization; indeed, bonus had larger effects on employment in these plants. Overall, bonus does not seem to encourage plants to double-down on 20th century modes of production or to specialize in industries that are at a comparative disadvantage.

To make economic sense of our empirical results, we estimate an empirical model of factor demands that separates the effect on bonus on workers into scale and substitution effects. Because bonus lowered costs of production, the policy had statistically significant scale effects on the whole plant. While the majority of the effect on employment is driven by this scale effect, we also consistently find that capital and labor are complements in production, and we are able to rule out relatively small elasticities of substitution. We verify the complementarity between capital and labor by showing empirically that plants invest more when labor costs are low, including at non-unionized plants, RTW states, and concentrated labor markets.

Our ability to measure the effects of bonus over several margins helps us evaluate whether capital investment helps or hurts workers. While the policy did not increase workers' average earnings or plant productivity, workers benefited from increased employment opportunities, which were concentrated among traditionally marginalized groups.

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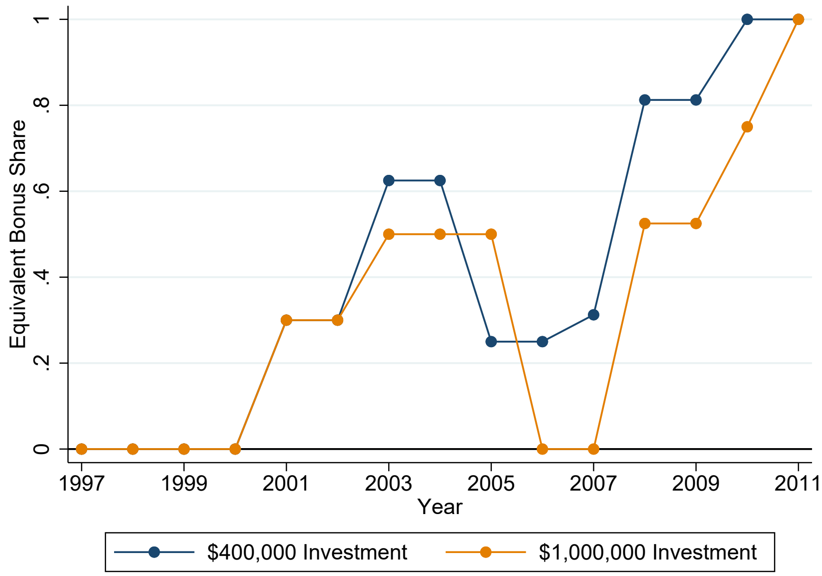
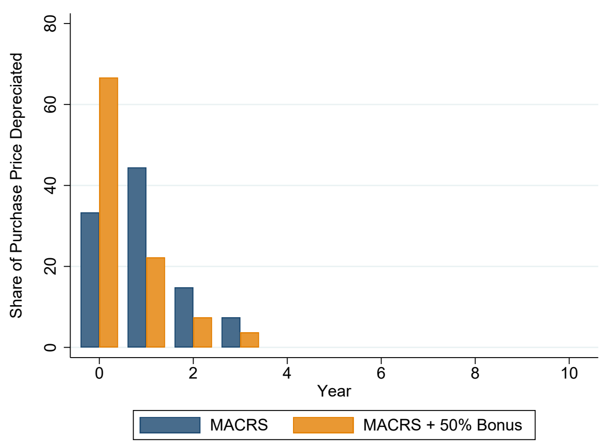
Figure 1: Bonus Depreciation Policy and Specific MACRS Assets

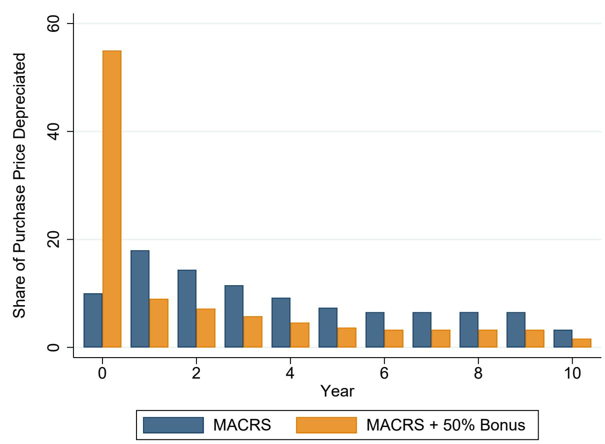
(A) Timing of Accelerated Depreciation Policies



(B) 50% Bonus on 3-Year MACRS Assets



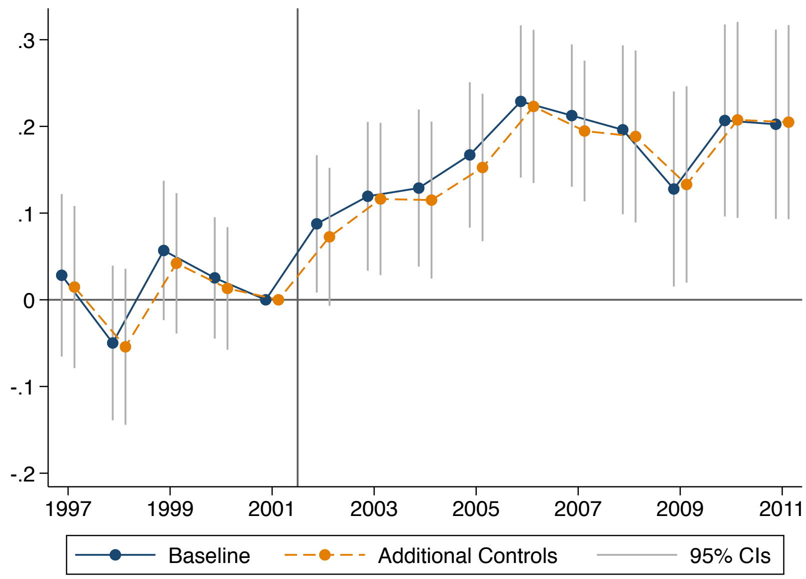
(C) 50% Bonus on 10-Year MACRS Assets



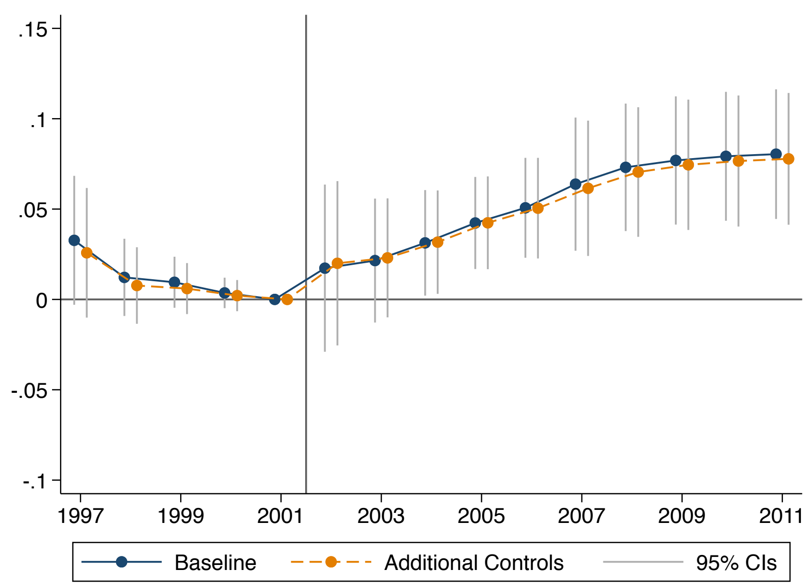
Notes: Panel (A) of Figure 1 shows how the timing of §179 and bonus depreciation incentives affect the relative share of depreciation deductions that are accelerated into the first year of the investment. The two series plot the percent of purchase price accelerated for a $400,000 investment and for a $1,000,000 investment. The $1,000,000 investment only benefits primarily from bonus depreciation. The $400,000 begins benefitting from §179 expensing starting in 2003. Panels (B) and (C) characterize how specific depreciation schedules change under bonus depreciation. See Appendix B for further explanation of these calculations. Panels (A) and (B) show how 50% Bonus changes the depreciation schedule for a 3-year asset and a 10-year asset, respectively. The Bonus depreciation provision has a much greater effect on the deduction schedule for a firm that invests in more long-duration assets. *Source:* Panel (A), Authors' calculations based on the statutory §179 and bonus rates explained in Kitchen and Knittel (2016). Panels (B) and (C), Authors' calculations based on IRS (2002) data.

Figure 2: Effects of Bonus Depreciation on Capital Investment

(A) Log Investment

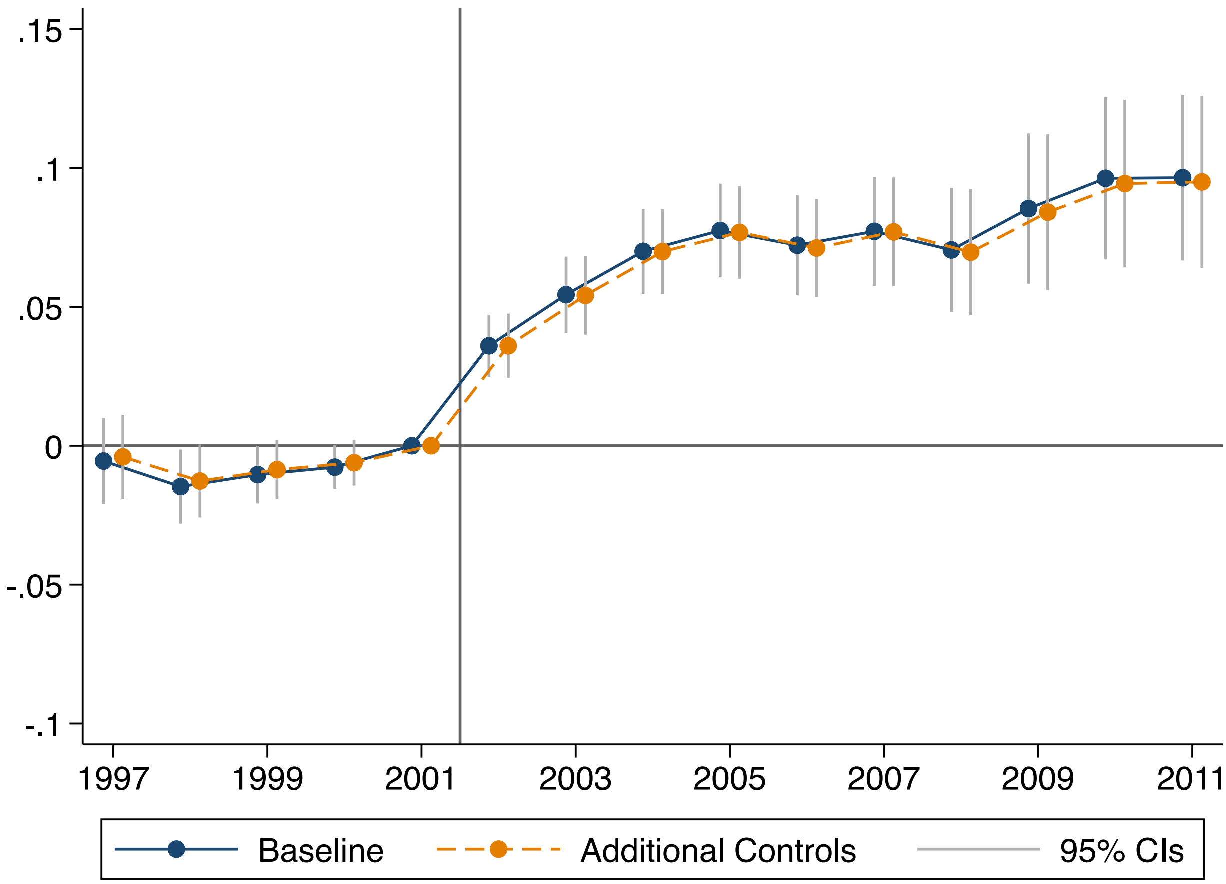


(B) Log Total Capital



Notes: Figure 2 displays estimates describing the effect of bonus depreciation on log investment in Panel (A) and log total capital in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification in each panel includes state-by-year and plant fixed effects. The specifications with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (6) and (7) of Table 1, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

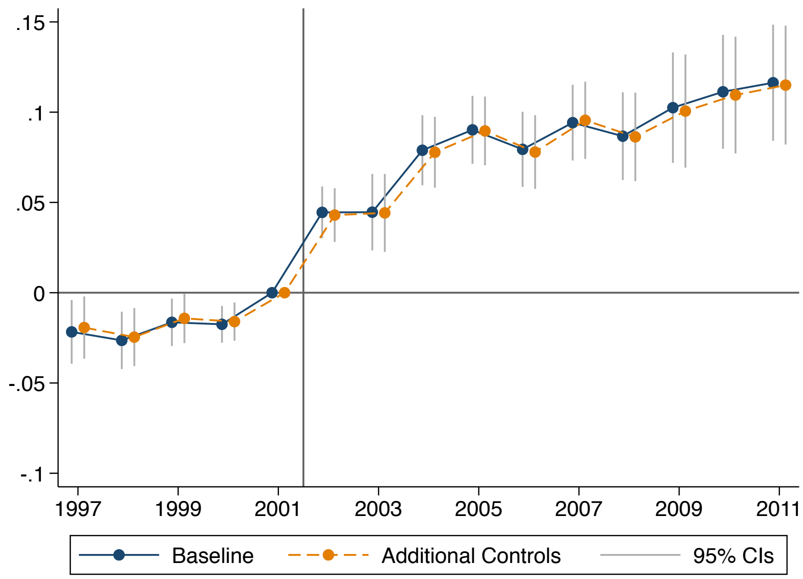
Figure 3: Effects of Bonus Depreciation on Log Employment



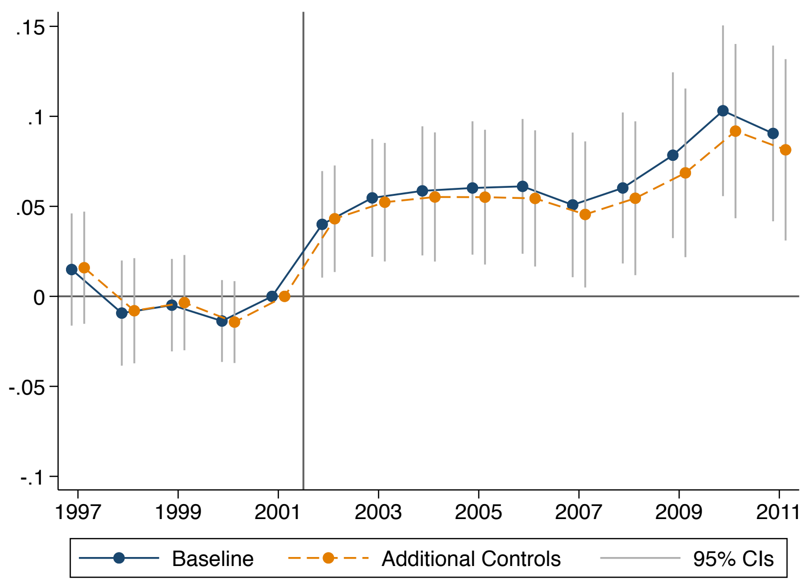
Notes: Figure 3 displays estimates describing the effect of bonus depreciation on log employment. Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification includes state-by-year and plant fixed effects. The specification with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (6) and (7) of Table 3, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure 4: Effects of Bonus Depreciation on Production and Non-production Employment

(A) Log Production Employment

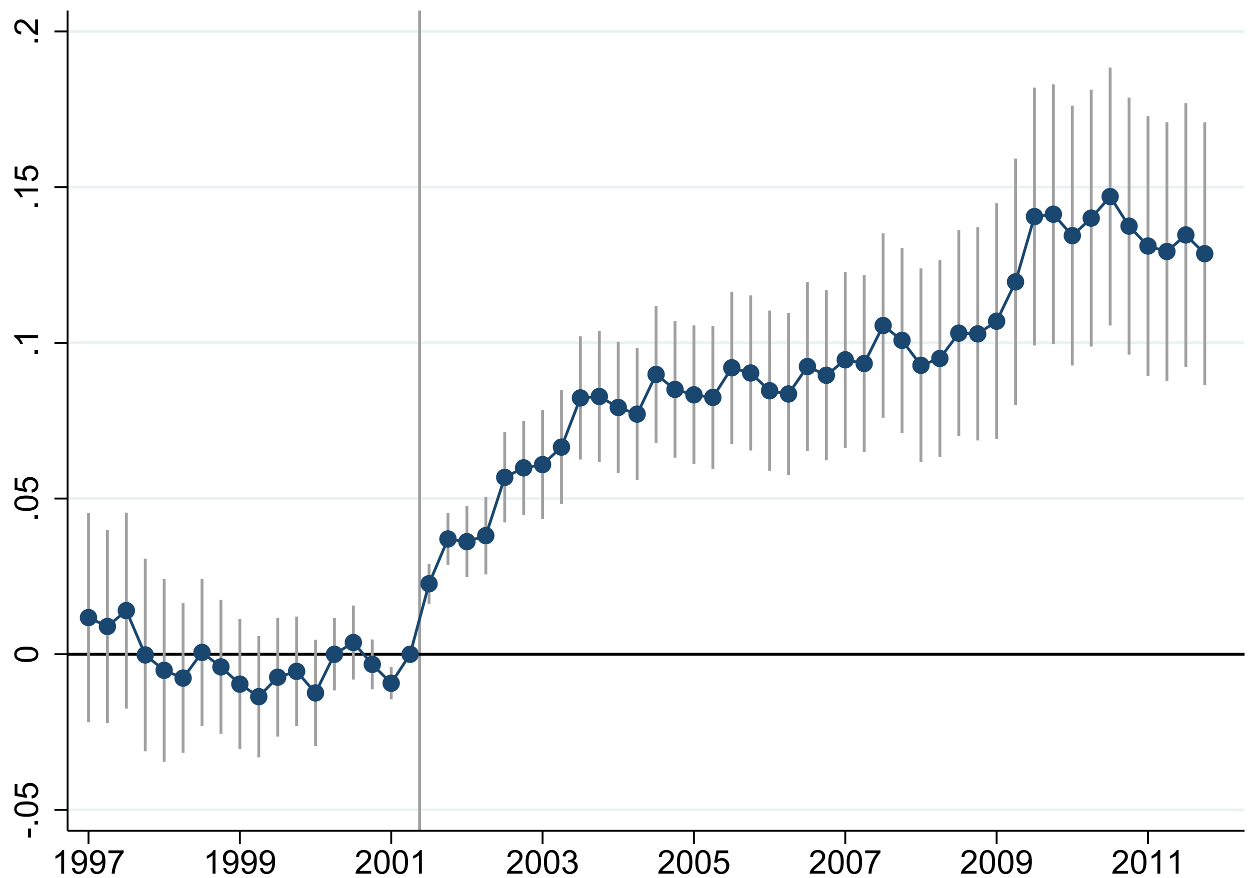


(B) Log Non-production Employment



Notes: Figure 4 displays estimates describing the effect of bonus depreciation on log production employment in Panel (A) and log non-production employment in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification in each panel includes state-by-year and plant fixed effects. The specifications with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (6) and (7) of Table 3, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

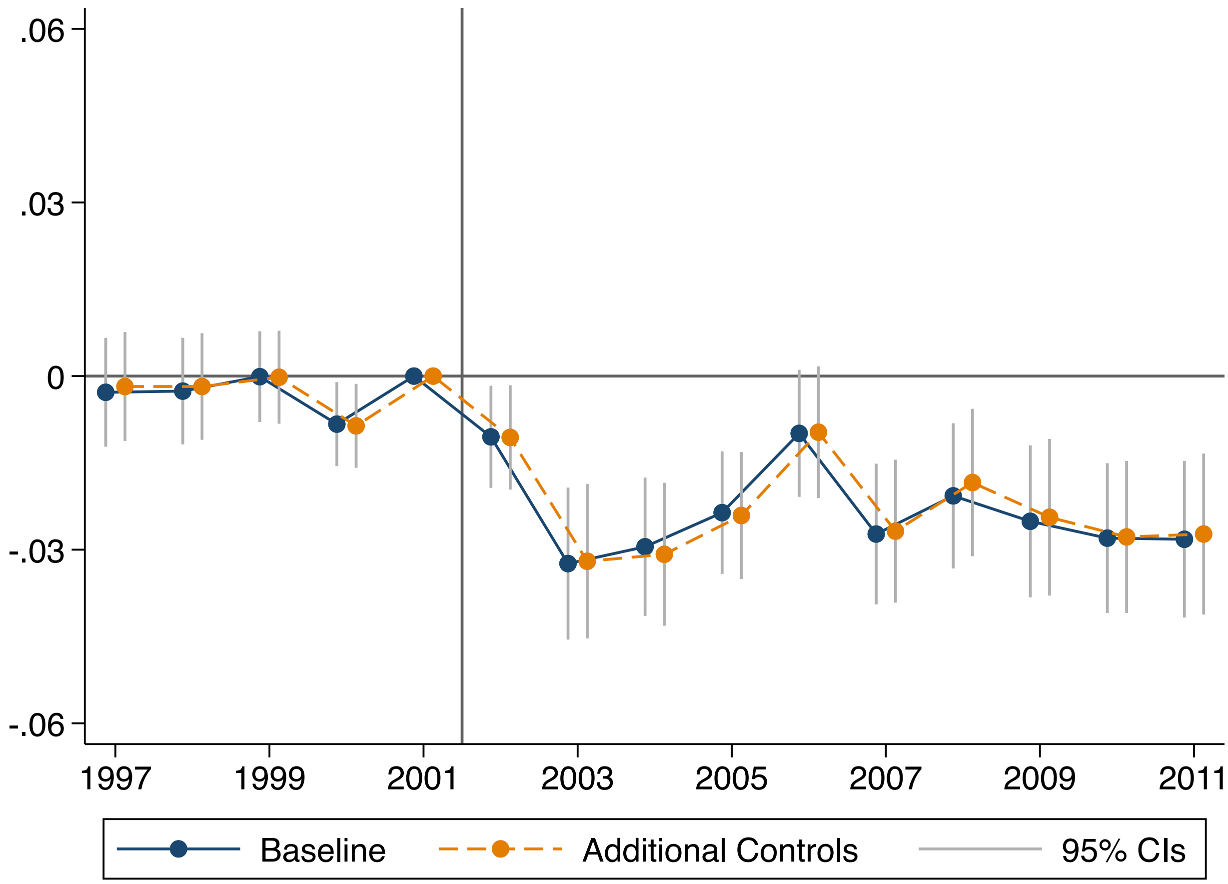
Figure 5: Effects of Bonus Depreciation on Log Employment; QWI Data



Notes: Figure 5 displays estimates describing the effect of bonus depreciation on log employment using state-by-industry QWI data. The regression estimates displayed in this figure correspond to a quarterly analogue of β_y from Equation (1), which is the change in log employment relative to 2001q2 in industries affected most by Bonus relative to industries that are less affected by Bonus. The regression includes 4-digit NAICS-by-state fixed effects and state-by-quarter fixed effects. The event study estimates in this figure correspond to column (1) of Table A5. 95% confidence intervals are included for each quarterly point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

Figure 6: Effects of Bonus Depreciation on Earnings Per Worker

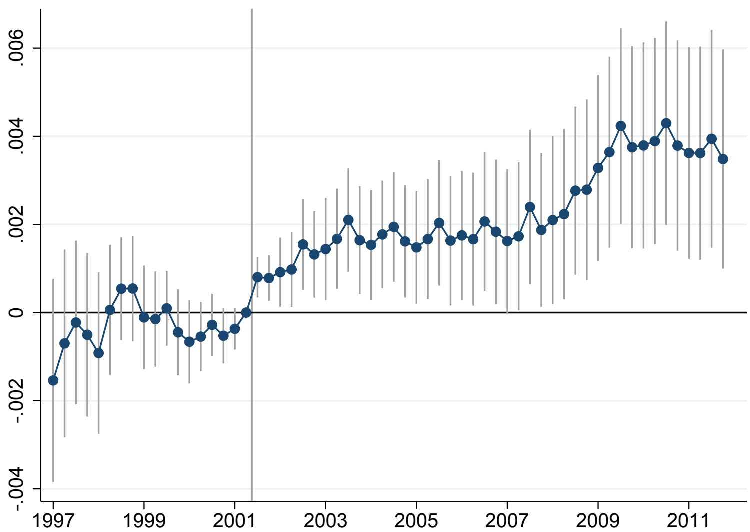
(A) Log Mean Earnings per Worker



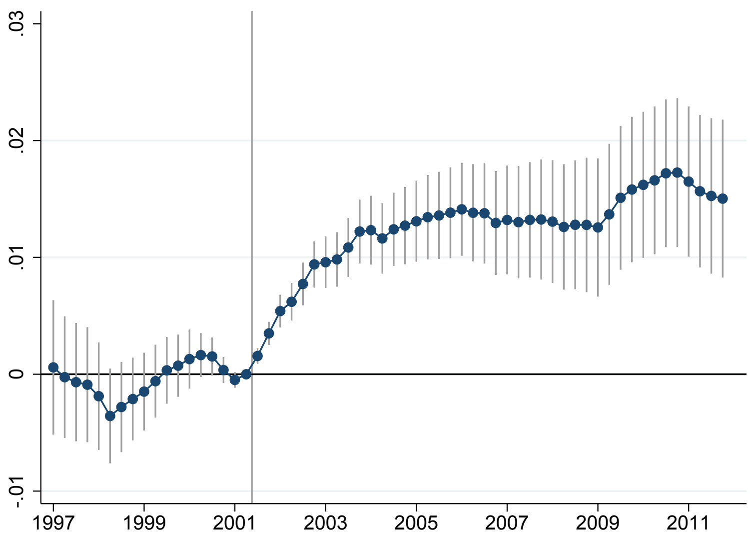
Notes: Figure 6 displays estimates describing the effect of bonus depreciation on Log Mean Earnings per Workers. Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification includes state-by-year and plant fixed effects. The specifications with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (6) and (7) of Table 4, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure 7: Effects of Bonus Depreciation on the Fractions of Employees by Education and Age

(A) Fraction of Employees with High School Education or Less

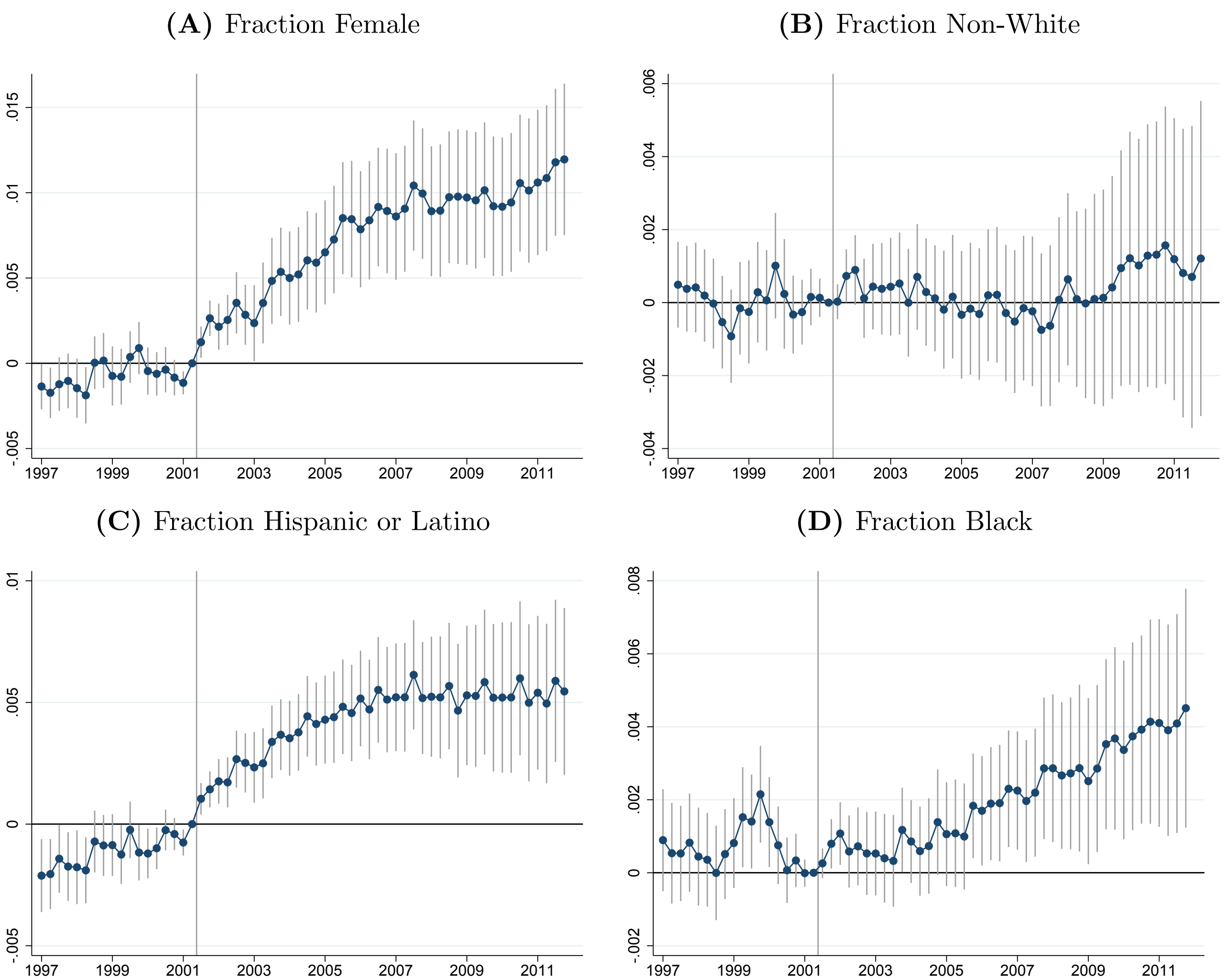


(B) Fraction of Employees 35 Years Old or Younger



Notes: Figure 7 displays estimates describing the effects of bonus depreciation on the fraction of employees with high school education or less in Panel (A) and the fraction of employees 35 years old or younger in Panel (B) using state-by-industry QWI data. The regression estimates displayed in this figure correspond to a quarterly analogue of β_y from Equation (1), which is the change in outcome relative to 2001q2 in industries affected most by bonus relative to industries that are less affected by bonus. The specification used for each panel includes 4-digit NAICS-by-state fixed effects, state-by-quarter fixed effects, and pre-period growth bins interacted with year fixed effects. The event study estimates in Panels (A) and (B) correspond to columns (3) and (4) of Table A5, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

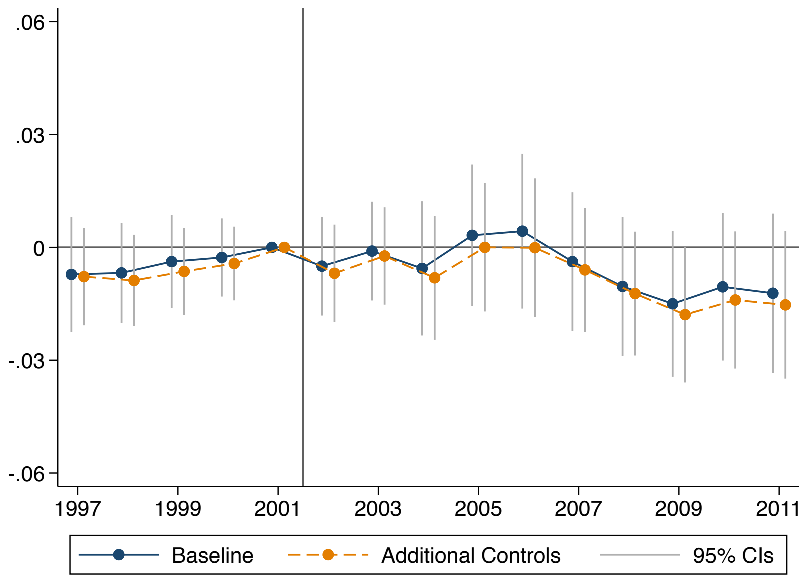
Figure 8: Effects of Bonus Depreciation on the Fractions of Employees by Gender, Race, Ethnicity



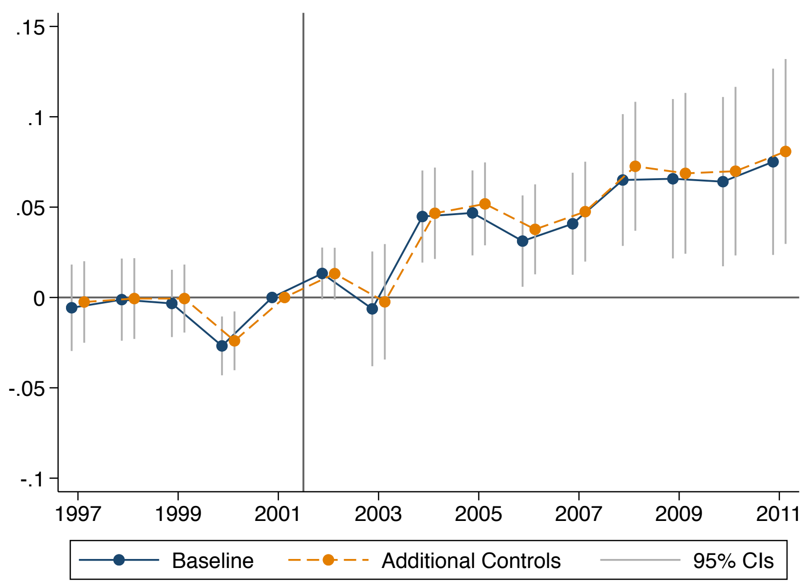
Notes: Figure 8 displays estimates describing the effects of bonus depreciation on the fraction of female employees in Panel (A), the fraction of Non-White employees in Panel (B), the fraction of Hispanic or Latino employees in Panel (C), and the fraction of Black employees in Panel (D). The regression estimates displayed in this figure correspond to a quarterly analogue of β_y from Equation (1), which is the change in outcome relative to 2001q2 in industries affected most by bonus relative to industries that are less affected by bonus. The specification used for each panel includes 4-digit NAICS-by-state fixed effects and state-by-quarter fixed effects. The event study estimates in Panels (A) through (D) correspond to columns (1) through (4) of Table A6, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

Figure 9: Effects of Bonus Depreciation on Productivity and Production

(A) Total Factor Productivity



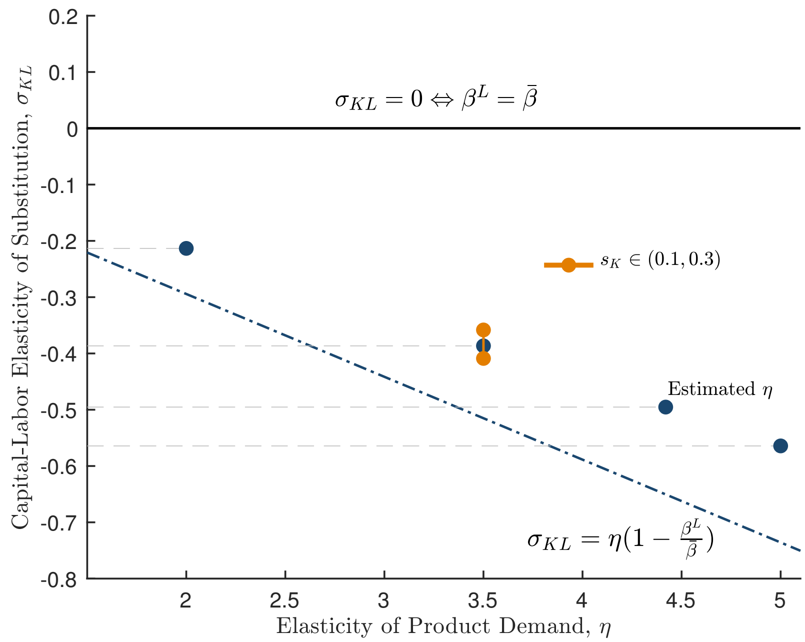
(B) Log Total Value of Shipments



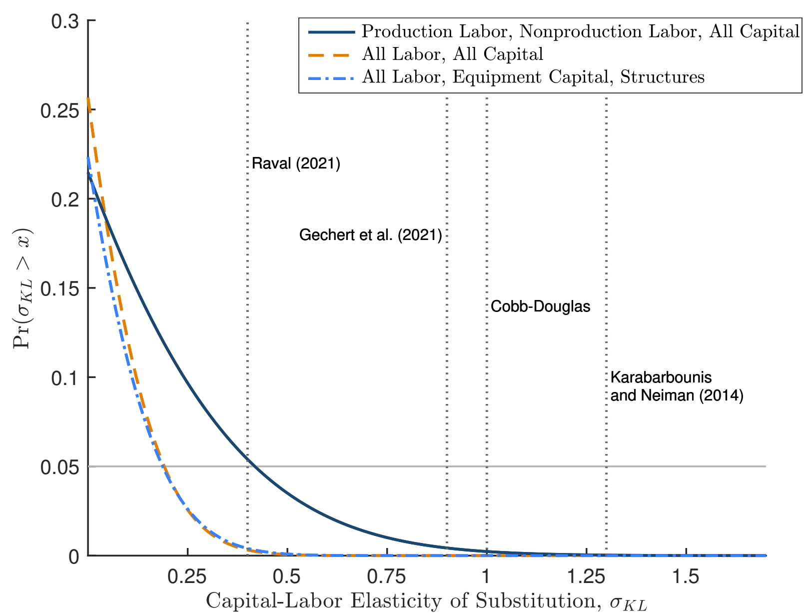
Notes: Figure 9 displays estimates describing the effects of bonus depreciation on total factor productivity in Panel (A) and log total value of shipments in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification in each panel includes state-by-year and plant fixed effects. The specifications with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (6) and (7) of Table 4, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure 10: Model Estimates of Capital-Labor Elasticity of Substitution

(A) Estimates of σ_{KL}



(B) Model Estimates of $\Pr(\sigma_{KL} > x)$



Notes: Panel (A) of Figure 10 graphically displays our estimates of σ_{KL} based on our long-differences estimates of the effects of bonus depreciation on capital and labor demand for a range of values of η. The solid blue line in Panel (B) of Figure 10 displays the probability that the estimated capital-labor substitution parameter σ_{KL} in our baseline model (Column (1), Table 8) is greater than the values along the x-axis. The dashed orange line reports a similar probability for a model with one type of labor and capital (Column (4), Table A10) and the light-blue dot-dashed line reports the case of a model with one type of labor alongside equipment and structures (Column (5), Table A10). Vertical lines correspond to σ_{KL} values from Raval (2019), from Gechert, Havranek, Irsova and Kolcunova (2021), a $\sigma_{KL} = 1$ implied by a Cobb-Douglas production function, and from Karabarbounis and Neiman (2014), respectively. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 1: Effects of Bonus Depreciation on Capital Investment

	(1)	(2)	(3)	(4)	(5)
	Panel A: Log Investment				
Bonus	0.1698***	0.1556***	0.1508***	0.1518***	0.1577***
	(0.0285)	(0.0276)	(0.0281)	(0.0279)	(0.0285)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	Panel B: IHS Investment				
Bonus	0.1675***	0.1531***	0.1486***	0.1498***	0.1561***
	(0.0298)	(0.0289)	(0.0294)	(0.0292)	(0.0298)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	Panel C: Investment over Pre-Period Capital				
Bonus	0.0309***	0.0288***	0.0267***	0.0272***	0.0278***
	(0.0044)	(0.0043)	(0.0044)	(0.0043)	(0.0045)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Year FE	✓				
Plant FE	✓	✓	✓	✓	✓
State×Year FE		✓	✓	✓	✓
PlantSize_{2001}×Year FE			✓	✓	✓
TFP_{2001}×Year FE				✓	✓
FirmSize_{2001}×Year FE					✓

Notes: Table 1 displays estimates describing the effects of bonus depreciation on log investment in Panel (A), log total capital in Panel (B), and investment over pre-period capital in Panel (C). Difference-in-differences subpanels show estimates of β from specifications in the form of Equation (2) while the long difference subpanels show estimates of β_{2011} from specifications in the form of Equation (1). Specification (1) estimates include year and plant fixed effects. Specification (2) estimates include state-by-year fixed effects and plant fixed effects. Specifications (3), (4), and (5) progressively add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects, respectively, to the controls in the preceding column. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 2: Effects of Bonus Depreciation on Capital Stocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Total Capital		Log Equipment Capital		Log Structures Capital	
Bonus	0.0804***	0.0778***	0.1047***	0.0962***	0.0413**	0.032*
	(0.0183)	(0.0186)	(0.0192)	(0.0193)	(0.0181)	(0.0189)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.023]	[0.090]
Plant FE	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE		✓		✓		✓
TFP_{2001}×Year FE		✓		✓		✓
FirmSize_{2001}×Year FE		✓		✓		✓

Notes: Table 2 displays long differences estimates describing the effects of bonus depreciation on measures of capital stocks. For each measure of capital stock, the first specification includes year and plant fixed effects and the second specification includes plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 3: Effects of Bonus Depreciation on Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A: Log Total Employment				
	Difference-in-Differences					Long Difference	
Bonus	0.0849***	0.0812***	0.0788***	0.0785***	0.0791***	0.0965***	0.095***
	(0.0097)	(0.0096)	(0.0096)	(0.0095)	(0.0097)	(0.0152)	(0.0158)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
			Panel B: Log Production Employment				
	Difference-in-Differences					Long Difference	
Bonus	0.1047***	0.1013***	0.0993***	0.0993***	0.0987***	0.1163***	0.115***
	(0.0108)	(0.0106)	(0.0106)	(0.0105)	(0.0107)	(0.0164)	(0.0168)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
			Panel C: Log Nonproduction Employment				
	Difference-in-Differences					Long Difference	
Bonus	0.0732***	0.0683***	0.064***	0.062***	0.0622***	0.0905***	0.0814***
	(0.0165)	(0.0163)	(0.0162)	(0.0163)	(0.0163)	(0.0249)	(0.0257)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]
Year FE	✓						
Plant FE	✓	✓	✓	✓	✓	✓	✓
State×Year FE		✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE			✓	✓	✓		✓
TFP_{2001}×Year FE				✓	✓		✓
FirmSize_{2001}×Year FE					✓		✓

Notes: Table 3 displays estimates describing the effects of bonus depreciation on log employment. The difference-in-differences subpanels show estimates of β from specifications in the form of Equation (2) while the long difference subpanels show estimates of β_{2011} from specifications in the form of Equation (1). Specification (1) estimates include year and plant fixed effects. Specification (2) estimates include state-by-year and plant fixed effects. Specifications (3), (4), and (5) progressively add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects, respectively, to the controls in the preceding column. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 4: Effects of Bonus Depreciation on Earnings, Productivity, and Revenue

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Log Mean Earnings						
	Difference-in-Differences					Long Difference	
Bonus	-0.0179***	-0.0208***	-0.0209***	-0.0205***	-0.0207***	-0.0282***	-0.0273***
	(0.0045)	(0.0043)	(0.0043)	(0.0043)	(0.0044)	(0.0069)	(0.0071)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	Panel B: Total Factor Productivity						
	Difference-in-Differences					Long Difference	
Bonus	-0.0007	-0.0015	-0.0011	-0.0017	-0.0028	-0.0122	-0.0153
	(0.0062)	(0.0061)	(0.0061)	(0.006)	(0.0059)	(0.0108)	(0.01)
	[0.910]	[0.806]	[0.857]	[0.777]	[0.635]	[0.259]	[0.126]
	Panel C: Log Total Value of Shipments						
	Difference-in-Differences					Long Difference	
Bonus	0.0572***	0.0514***	0.0512***	0.0517***	0.0542***	0.0751***	0.0808***
	(0.0147)	(0.0138)	(0.0138)	(0.0136)	(0.0139)	(0.0263)	(0.0261)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]	[0.002]
Year FE	✓						
Plant FE	✓	✓	✓	✓	✓	✓	✓
State×Year FE		✓	✓	✓	✓	✓	✓
$\text{PlantSize}_{2001}\times$Year FE			✓	✓	✓		✓
$\text{TFP}_{2001}\times$Year FE				✓	✓		✓
$\text{FirmSize}_{2001}\times$Year FE					✓		✓

Notes: Table 4 displays estimates describing the effects of bonus depreciation on log mean earnings in Panel (A), log TFP in Panel (B), and log total value of shipments in Panel (C). Difference-in-differences subpanels show estimates of β from specifications in the form of Equation (2) while the long differences panel shows estimates of β_{2011} from specifications in the form of Equation (1). Specification (1) estimates include year and plant fixed effects. Specification (2) estimates include state-by-year and plant fixed effects. Specifications (3), (4), and (5) progressively add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects, respectively, to the controls in the preceding column. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 5: Effects of Bonus Depreciation, Controlling for Shocks to Manufacturing Sector

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Investment		Log Employment		Log Mean Earnings	
Bonus	0.1577***	0.1566***	0.0791***	0.0691***	-0.0207***	0.0001
	(0.0285)	(0.0315)	(0.0097)	(0.0104)	(0.0044)	(0.0048)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.983]
Plant FE	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓
Plant Controls ×Year FE	✓		✓		✓	
Sector Shocks ×Year FE		✓		✓		✓

Notes: Table 5 displays difference-in-differences estimates from specifications in the form of Equation (2) on log investment, log employment, and log mean earnings. All specifications include state-by-year and plant fixed effects. To control for trends in the manufacturing sectors, all specifications also include skill intensity bins interacted with year fixed effects, capital intensity bins interacted with year fixed effects, Chinese import exposure bins interacted with year fixed effects, and robotization bins interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) data.

Table 6: Effects of Bonus Depreciation, Interactions with Shocks to Manufacturing Sector

Interaction Term	(1) Skill Intensity	(2) Capital Intensity	(3) Trade Exposure	(4) Robot Exposure
	Panel A: Log Investment			
Bonus	0.1801***	0.1565***	0.1249***	0.1584***
	(0.0337)	(0.0314)	(0.0313)	(0.0314)
	[0.000]	[0.000]	[0.000]	[0.000]
Bonus×Interaction	0.0978*	0.0316**	-0.0858***	0.0158
	(0.055)	(0.0152)	(0.0284)	(0.012)
	[0.075]	[0.038]	[0.003]	[0.188]
	Panel B: Log Total Employment			
Bonus	0.0743***	0.0691***	0.0538***	0.0705***
	(0.011)	(0.0104)	(0.011)	(0.0103)
	[0.000]	[0.000]	[0.000]	[0.000]
Bonus×Interaction	0.0215	0.0049*	-0.0415***	0.0125***
	(0.018)	(0.0029)	(0.0107)	(0.0038)
	[0.232]	[0.091]	[0.000]	[0.001]
Plant FE	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓
Skill Intensity×Year FE	✓	✓	✓	✓
Capital Intensity×Year FE	✓	✓	✓	✓
Trade Exposure×Year FE	✓	✓	✓	✓
Robot Exposure×Year FE	✓	✓	✓	✓

Notes: Table 6 displays difference-in-differences estimates and coefficients describing interactions between difference-in-differences terms and variables capturing manufacturing sector trends. The outcome variable in Panel (A) is log investment. The outcome variable in Panel (B) is log total employment. In Specifications (1)–(4), the difference-in-differences coefficient is interacted with measures of skill intensity, capital intensity, Chinese import exposure, and robotization respectively. All specifications include state-by-year and plant fixed effects. To control for trends in the manufacturing sectors, all specifications also include skill intensity bins interacted with year fixed effects, capital intensity bins interacted with year fixed effects, Chinese import exposure bins interacted with year fixed effects, and robotization bins interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) data.

Table 7: Model-Based Implications of Reduced-Form Estimates

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
	Panel A: Scale Effect Estimates				
Scale Effect, $\bar{\beta}$	0.101***	0.104***	0.099***	0.101***	0.101***
	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)
	Panel B: p-values for Substitutability Tests				
Substitutability of production labor $H_0 : \bar{\beta} \geq \beta_L$	0.054	0.087	0.039	0.054	0.054
Complementarity of non-production labor $H_0 : \bar{\beta} \leq \beta_J$	0.255	0.196	0.314	0.255	0.255
	Panel C: Cost of Capital Elasticity Estimates				
Effect on cost of capital, ϕ	-0.145***	-0.296***	-0.094***	-0.253***	-0.101***
	(0.021)	(0.044)	(0.013)	(0.036)	(0.014)
Capital, ε^K_ϕ	-0.555***	-0.271***	-0.852***	-0.317***	-0.793***
	(0.109)	(0.058)	(0.149)	(0.062)	(0.155)
Investment, ε^I_ϕ	-1.398***	-0.684***	-2.146***	-0.799***	-1.997***
	(0.357)	(0.180)	(0.532)	(0.204)	(0.509)
Production Labor, ε^L_ϕ	-0.803***	-0.393***	-1.232***	-0.459***	-1.147***
	(0.067)	(0.033)	(0.109)	(0.038)	(0.096)
Non-production Labor, ε^J_ϕ	-0.625***	-0.306***	-0.959***	-0.357***	-0.893***
	(0.117)	(0.055)	(0.191)	(0.067)	(0.168)
Cost shares:					
Production labor	0.50	0.55	0.45	0.50	0.50
Nonproduction labor	0.30	0.35	0.25	0.30	0.30
Capital	0.20	0.10	0.30	0.20	0.20
Demand Elasticity, η	3.50	3.50	3.50	2.00	5.00

Notes: Table 7 presents several results relating our reduced-form estimates to model outcomes across several alternative calibrations of cost shares and η. Panel (A) displays estimates of the scale effect defined in Equation (7). Panel (B) conducts simple hypothesis tests of the substitutability and complementarity of production and non-production labor, respectively. Panel (C) presents estimates of the effect of bonus depreciation on the cost of capital using the calculated scale effects in Panel (A) and Equation (7). It also presents estimates of the elasticity of capital, investment, production labor, and non-production labor with respect to this estimated change in the cost of capital. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 8: Classical Minimum Distance Estimates of Production Elasticities

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η	(6) Est. η
	Panel A: Estimated Parameters					
Demand elasticity, η	3.500	3.500	3.500	2.000	5.000	4.420
						(4.245)
Elasticities of Substitution:						
Production labor-capital, σ_{KL}	-0.387	-0.409	-0.358	-0.213	-0.564	-0.495
	(0.489)	(0.496)	(0.500)	(0.226)	(0.857)	(0.702)
Nonproduction labor-capital, σ_{KJ}	0.644	0.642	0.645	0.356	0.940	0.825
	(0.798)	(0.791)	(0.804)	(0.378)	(1.384)	(1.136)
	Panel B: Empirical Moments					
Revenue	0.075	0.075	0.075	0.075	0.075	0.075
Production labor	0.116	0.116	0.116	0.116	0.116	0.116
Nonproduction labor	0.090	0.090	0.090	0.090	0.090	0.090
Capital	0.080	0.080	0.080	0.080	0.080	0.080
	Panel C: Model-Predicted Moments					
Revenue	0.070	0.070	0.070	0.050	0.077	0.075
Production labor	0.109	0.109	0.108	0.110	0.108	0.108
Nonproduction labor	0.080	0.080	0.080	0.082	0.079	0.079
Capital	0.098	0.097	0.098	0.099	0.097	0.097
Cost shares:						
Production labor	0.50	0.55	0.45	0.50	0.50	0.50
Nonproduction labor	0.30	0.35	0.25	0.30	0.30	0.30
Capital	0.20	0.10	0.30	0.20	0.20	0.20
Effect on Cost of Capital, ϕ	-0.14	-0.28	-0.09	-0.25	-0.10	-0.11

Notes: Table 8 presents estimates of the structural parameters of the three input model of production labor, non-production labor, and capital in Section 7. All parameters estimated using a minimum distance estimator. Column (1) represents our baseline model featuring a calibrated value of $\eta = 3.5$ and cost shares of $s_L = 0.5$, $s_J = 0.3$, and $s_K = 0.5$. Columns (2) and (3) consider lower and higher capital cost shares, columns (4) and (5) consider lower and higher calibrated demand elasticities, and column (6) presents model estimates in which we estimate the value of η. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table 9: Heterogeneity in Effects of Bonus Depreciation by Labor Market Characteristics

	(1) Log Investment	(2) Log Employment	(3) Log Mean Earnings
Panel A: Interaction with highly unionized plant indicator			
Bonus	0.1966***	0.111***	-0.0158***
	(0.0338)	(0.0107)	(0.0053)
	[0.000]	[0.000]	[0.003]
Bonus×Union	-0.0854**	-0.0619***	-0.0103*
	(0.0385)	(0.012)	(0.0062)
	[0.027]	[0.000]	[0.097]
Panel B: Interaction with Right-to-Work indicator			
Bonus	0.0622*	0.0675***	-0.0232***
	(0.0364)	(0.0131)	(0.0058)
	[0.087]	[0.000]	[0.000]
Bonus×RTW	0.200***	0.0294	0.0052
	(0.0546)	(0.0191)	(0.0086)
	[0.000]	[0.124]	[0.545]
Panel C: Interaction with local labor market concentration			
Bonus	0.1498***	0.082***	-0.022***
	(0.0275)	(0.0096)	(0.0042)
	[0.000]	[0.000]	[0.000]
Bonus×log(HHI)	0.0381**	-0.0053	0.0081***
	(0.0183)	(0.0052)	(0.0029)
	[0.037]	[0.308]	[0.005]
State×Year FE	✓	✓	✓
Plant FE	✓	✓	✓

Table 9 displays difference-in-differences estimates and coefficients describing the interaction between difference-in-differences terms and variables capturing labor market characteristics. The outcome variables in Specifications (1)–(3) are log investment, log total employment, and log mean earnings. The treatment variable is interacted with an indicator for more than 60% union presence, an indicator for state Right-to-Work laws as of 2001, and a standardized measure of local HHI in Panels (A), (B), and (C) respectively. All specifications include state-by-year and plant fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, Zwick and Mahon (2017), and Valletta and Freeman (1988) data.

Online Appendix: Not For Publication

This appendix includes several sections of supplemental information. Appendix A contains definitions for all the variables used in the paper. Appendix B describes the variation in the net present value of depreciation deductions, z_0, across time and industries. We discuss the choice of standard error calculations in Appendix C. We compare our results on investment with those of Zwick and Mahon (2017) in Appendix D, and we present additional investment responses to bonus in Appendix E. Appendix F provides additional employment results, Appendix G places our results in the context of aggregate and long-run trends in the manufacturing industry, and Appendix H decomposes the wage changes into compositional changes and other factors. Appendix I derives the complete model. Finally, Appendix J discusses variations and extensions of the structural model.

A Variable Definitions

Variable Name	**Description**
Bonus	Indicator that the NPV of investment in industry j is less than 0.875. *Source:* Zwick and Mahon (2017).
Post	Post-2001 indicator.
Log Investment	Natural logarithm of investment in plus 1. Investment is defined as the total new and used machinery and equipment expenditures in \$1,000s by plant i in year t. *Source:* ASM/CMF.
Log Total Capital	Natural logarithm of total capital plus 1. Total capital is defined as the value of total capital assets in \$1,000s of plant i in year t. Data is available in CMF years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CMF.
IHS Investment	Inverse hyperbolic sine function of investment, as defined above, by plant i in year t. *Source:* ASM/CMF.
$\Delta\text{PPENT}_t/\text{PPENT}_{1997-2001}$	Investment as Share of Pre-Period Capital. Pre-period capital defined as the average total capital, as defined above, in the 1997-2001 period. Investment in machinery and equipment as defined above by plant i in year t. *Source:* ASM/CMF.
Log Capital Equipment Stock	Natural logarithm of total capital equipment plus 1. Total capital equipment is defined as the value of total capital machinery and equipment assets of plant t in year j. Data is available in CMF years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CMF and Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2020).

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description
Log Capital Structures Stock	Natural logarithm of total capital structures plus 1. Total capital equipment is defined as the value of total capital structures assets in \$1,000s of plant i in year t. Data is available in CMF years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CMF and Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2020).
Log Employment	Natural logarithm of total employment plus 1. Total employment is defined as the total number of non-leased employees at plant i in year t. *Source:* ASM/CMF.
Log Production Employment	Natural logarithm of production employment plus 1. Production employment is defined as the total number of non-leased employees working in production at plant i in year t. *Source:* ASM/CMF.
Log Non-production Employment	Natural logarithm of non-production employment plus 1. Production employment is defined as the difference between total employment and production employment, as defined above, at plant i in year t. *Source:* ASM/CMF.
Log Mean Earnings per Worker	Natural log of average annual earnings plus 1. Average annual earnings defined as total payroll divided by total employment at plant i in year t. *Source:* ASM/CMF.
Log Total Value of Shipments	Natural log of revenue plus 1. Revenue defined as the total value of shipments from plant i in year t. *Source:* ASM/CMF.
TFP	Total Factor Productivity of plant i in year t. TFP calculated using a factor share approach following Criscuolo, Martin, Overman and Van Reenen (2019): $TFP_{it} = \tau_{it} - \bar{\tau}_{jt}$ where $\tau_{it} = r_{it} - \bar{S}_{Mjt}m_{it} - \bar{S}_{Ljt}l_{it} - (1 - \bar{S}_{mjt} - \bar{S}_{Ljt})k_{it}$. Here, r_{it} is log(total value of shipments), m_{it} is log(materials), l_{it} is log(total employment), k_{it} is log(total capital), and $\bar{S}$ terms denote average cost shares for the respective inputs in four-digit NAICS industry j. Finally, $\bar{\tau}_{jt}$ is the average value of τ_{it} in the three-digit NAICS sector. *Source:* ASM/CMF and Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2020).
RTW	Indicator that plant i operated in a state with Right-to-Work laws in 2001. *Source:* Valletta and Freeman (1988).
Unionization	Indicator that for plant i, over 60% of total employment was unionized in 2005. *Source:* MOPS.
Log HHI	Natural logarithm of local labor market Herfindahl-Hirschmann Index (HHI) in 2001. Local labor market defined as the three-digit NAICS-commuting zone in which plant i operates in 2001. For local labor market m, HHI $= 10,000 \sum_{f \in F_t(m)} \left(\frac{l_{ft}}{L_{F(m)t}}\right)^2$, where l_{ft} is employment of firm f, $F_t(m)$ is the set of all firms operating in labor market m in time t, and $L_{F(m)t}$ is total employment in labor market m. *Source:* LBD.

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Table A.1 – *Continued from previous page*

Variable	**Description**
Skill Intensity	Skill intensity of plant i defined as share of total employment classified as non-production employment in 2001. Skill intensity fixed effects defined as quartiles of skill intensity across plants in estimating sample. *Source:* ASM/CMF.
Capital Intensity	Capital intensity of plant i defined as total capital assets divided by employment in 2001. Capital intensity fixed effects defined as quartiles of capital intensity across plants in estimating sample. *Source:* ASM/CMF.
ADH Exposure	ADH exposure for plant i defined as the change in exposure to Chinese import competition at the six-digit NAICS industry level from 2000 to 2007. *Source:* Acemoglu, Autor, Dorn, Hanson and Price (2016).
AR Robotization	AR Robotization for plant i defined as the change in robotization at the three-digit NAICS sector level from 1993 to 2007. *Source:* Acemoglu and Restrepo (2020).
Plant Size Fixed Effect	Plant size of plant i defined as total capital assets in year 2001. Plant size fixed effects defined as quartiles of plant size across plants in estimating sample. *Source:* ASM/CMF.
Firm Size Fixed Effect	Firm size of plant i defined as total employment of firm to which plant is attached in year 2001. Firm Size fixed effects defined as quartiles of firm size across plants in estimating sample. *Source:* ASM/CMF.
TFP Fixed Effects	TFP of plant i defined above. TFP fixed effects defined as quartiles of TFP in 2001 across plants in estimating sample. *Source:* ASM/CMF.
Log Employment, QWI	Natural logarithm of total employment in each four-digit NAICS industry $\times$ state $\times$ year. *Source:* QWI.
Log Mean Earnings, QWI	Natural logarithm of mean earnings in each four-digit NAICS industry $\times$ state $\times$ year. *Source:* QWI.
Fraction of Employees with High School Education or Less	Fraction of employees in each four-digit NAICS industry $\times$ state $\times$ year that report having a high school education or less. Reported education is observed for approximately one-seventh of the sample that completed the census long-form and is imputed for all other workers. *Source:* QWI.
Fraction of Employees 35 Years Old or Younger	Fraction of employees in each four-digit NAICS industry $\times$ state $\times$ year that are 35 years old or younger. *Source:* QWI.
Fraction of Female Employees	Fraction of employees in each four-digit NAICS industry $\times$ state $\times$ year that are female. *Source:* QWI.
Fraction of Non-White Employees	Fraction of employees in each four-digit NAICS industry $\times$ state $\times$ year with a reported race other than White. *Source:* QWI.
Fraction of Hispanic or Latino Employees	Fraction of employees in each four-digit NAICS industry $\times$ state $\times$ year whose reported ethnicity is Hispanic or Latino. *Source:* QWI.
Fraction of Black Employees	Fraction of employment in each four-digit NAICS industry $\times$ state $\times$ year whose reported race is Black. *Source:* QWI.

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Table A.1 – *Continued from previous page*

Variable	**Description**
Log Employment, Small Firms	Natural logarithm of employment in firms with 50 or fewer employees in each four-digit NAICS industry × state × year. *Source:* QWI.
Log Employment, Young Firms	Natural logarithm of employment in firms that are five or fewer years old in each four-digit NAICS industry × state × year. *Source:* QWI.
Log Employment, NBER-CES	Natural logarithm of total employment in each four-digit NAICS industry × year. *Source:* NBER and CES.
Log Investment, NBER-CES	Natural logarithm of total investment in each four-digit NAICS industry × year. *Source:* NBER and CES.
Log Capital Stock, NBER-CES	Natural logarithm of total capital stock in each four-digit NAICS industry × year. *Source:* NBER and CES.
ICT Asset Shares	Share of fixed assets in information and communication technology at the three- and four-digit NAICS industry level. Shares calculated as average over 1997-2001 period. *Source:* BEA.
Capital Producer Indicator	Indicator for whether a four-digit NAICS industry reports any sales of capital goods to other industries in 2002. *Source:* BEA.
Cost of External Capital	Average cost of borrowing, defined as interest divided by debt, for publicly traded firms for each four-digit NAICS industry averaged over the 1997-2001 period. *Source:* Compustat.

B Context for the Present Value of Depreciation Deductions

The tax subsidy to long-duration capital investment during our sample period comes from both bonus depreciation and §179 incentives. The original round of 30% bonus depreciation applied to equipment installed after September 11, 2001 and was intended to be temporary. Bonus was increased to 50% in mid 2003. The policy was phased out beginning on January 1, 2005, but many large investments in long-lived assets qualified through January 1, 2006. In response to the 2008 financial crisis, bonus was reinstated at 50% and has continued with temporary extensions through the Tax Cuts and Jobs Act of 2017, which increased the policy to 100% bonus depreciation, also known as full expensing. §179 expensing began with a limit of $24,000 in 2001 increasing to $100,000 in 2003, $250,000 in 2008, and $500,000 in 2010. The §179 incentives begin being phased out dollar for dollar at four times the investment limit.

We display the time variation in how these incentives affected two different investments—one for $400,000 and one for $1,000,000—and calculate the effective bonus rate in Panel (A) of Figure 1. First, §179 allows for investments under certain thresholds to be immediately deducted or expensed, which makes the present value of deductions for $1 of investments to be equal to one. After claiming any relevant §179 incentives, a firm can claim an additional "bonus" percentage of the remaining investment cost that wasn't covered, which is 38% on average during the sample period. For instance in 2004, the §179 threshold was \$100,000 phasing out at \$400,000 and the bonus rate was 50%. For a \$400,000 investment, one first claims \$100,000 of §179 incentives and then claims 50% bonus for the remainder of the investment cost. This leads to \$250,000 of investment immediately deducted ($100,000 + 0.5 \times (400,000 - 100,000)$), which is equivalent to 62.5% bonus. Further, sometimes bonus is larger for larger investments such as the extension of 50% bonus for investments larger than one million dollar in 2005. The accelerated depreciation policies are mostly driven by §179 for smaller investments and by bonus for larger investments.

We rely on Zwick and Mahon (2017) replication data to measure which plants are most impacted by accelerated depreciation. They provide estimates of the net present value of depreciation deductions for non-bonus years derived from IRS Form 4562. The data provide variation at the 4-digit NAICS industry level. We plot the replication data in a histogram in Panel (A) of Figure A1 for manufacturing industries (NAICS 3111 to 3399). We find there is a structural break around 0.875, the scale of which is a function of several modeling assumptions regarding the appropriate discount factors. We use this structural break as the threshold to be considered treated by bonus. Plants with a NPV of depreciation deductions below the threshold are considered long duration industries and we count those industries as relatively treated and the rest as controls.

IRS SOI sector-level corporation depreciation data are used to calculate the NPV of depreciation deductions at the IRS sector level. The total sum of assets placed in service during the previous tax year for each sector and for each depreciation is available in Table 13 of the "Corporation Complete Report" through IRS (2017). As further evidence that firms are relatively unable to adjust the tax-duration of their investment, we plot the aggregate net present value of depreciation deductions for \$1 of equipment investment by IRS sectors, which don't have perfect NAICS analogs. We show the results of these calculations in Panel (B) of Figure A1. The longest duration businesses, the bottom tercile of firms weighted by equipment investment, always have z_0 calculations that are around 10%-15% lower than the medium and short duration firms. We show that the levels of these differences in IRS SOI data are stable from 2000 to 2011 before accounting for bonus depreciation incentives.

C Standard Error Clustering

Throughout the paper, we cluster standard errors at the level of treatment variation (e.g., Bertrand, Duflo and Mullainathan, 2004; Cameron and Miller, 2015). To define this level, consider the impact of bonus on a firm's investment decision. The firm sets the marginal product of capital $f'(K)$ equal to the cost of capital as follows

$$f'(K) = r + \delta + \frac{1 - \tau z}{1 - \tau},$$

where r is the interest rate, δ is the economic rate of depreciation, and τ is the firm's combined corporate income tax rate. As we discuss in Section 2, the policy has differential benefits across industries since

$$z = b + (1 - b) \times z_0,$$

where z_0 is industry-specific. Additionally, the tax benefit from bonus depreciation depends on τ, which is a function of state and federal tax policies. Specifically,

$$\tau = \tau_f \times (1 - \tau_s) + \tau_s \times (1 - \tau_f \times \mathbb{I}[D_s]),$$

where τ_f and τ_s are the federal and state corporate income tax rates, respectively. The first term accounts for the fact that corporations are able to deduct state taxes from federal taxes. The second term in this equation captures the fact that some states allow for federal taxes to be deducted from state taxes, an event we denote by $\mathbb{I}[D_s]$. In this case, we assume that states allow for bonus depreciation at the state level and rely on the same tax base. Additional interactions between state tax systems and bonus depreciation arise when states depart from using the federal tax base or when they additionally provide further depreciation incentives (see, e.g. Ohrn, 2019; Suárez Serrato and Zidar, 2018)

The equations above clarify that the benefit from bonus depends on interactions between the federal bonus policy and federal and state tax systems. This motivates us to cluster standard errors at the industry-state level. Moreover, as we show in Table A2, our primary investment, capital, employment, earnings, and productivity results have similar levels of statistical significance when we instead cluster standard errors at the industry level. Finally, we note that these levels of clustering are more conservative than those of previous papers that cluster at the firm level (e.g., Zwick and Mahon, 2017).

D Comparison to Investment Effects from Zwick and Mahon (2017)

This section compares our estimated effects of bonus on log investment with those reported by Zwick and Mahon (2017, ZM, henceforth). ZM discuss their identifying variation in their §III.B on page 228. In a direct analogue to the exercise in this paper, this section of ZM compares investment outcomes in the 30% of firms in industries with the longest duration investment to the 30% of firms in the shortest duration of investment. Below we describe how we compare our results to those of ZM.

In Panels (A) and (B) of their Figure 1, ZM report yearly averages of log investment for both treated and control firms. We obtain the numerical values of these data points using the program

WebPlotDigitizer (see https://apps.automeris.io/wpd/). Columns (1)–(4) of Table A1 report the extracted data. This table then creates a series that mirrors our event study estimates. To do so, we compute the difference between the average values of treated and control groups by year. We then normalize this difference to be zero in the year 2000 and we combine the data from the two times periods in ZM by making the assumption that differences in investment between these two groups are constant between 2004 and 2005. Table A1 details these operations.

Figure A2 plots the series in column (7) of Table A1 along with our estimates from the additional controls series in Panel (A) of Figure 2.[67] Similar to our results, ZM show that investment at treated firms increases immediately after the implementation of the policy. In the 2002-04 period and among those who had some positive investment, ZM show that treated firms had investment that was 11.8% higher than control firms. This corresponds to our event study estimates for the same time period which show an average increase in investment of 10.1%. This figure shows that we are not able to reject the hypothesis that the estimates in the orange line differ from those in the blue line for most years.

Overall, Figure A2 shows that our estimated effects of bonus on log investment are quite comparable with those reported by ZM. The similarity in these results is remarkable for several reasons. First, while we use census and survey data, ZM rely on data from corporate tax returns. Second, while we focus on plants in the manufacturing sector, ZM study data on firms in the overall economy. Third, while our results focus on a balanced panel that includes mostly larger plants, ZM study a non-balanced panel that includes many small firms. Finally, while our estimates only rely on the controls mentioned in Section 4, ZM produce the estimates in their Figure 1 using a two step process that first re-weights observations to address sampling changes over time and then residualizes the effects of a host of variables, including splines in assets, sales, profit margin, and age. Despite all these differences, Figure A2 shows that our investment results have a comparable magnitude to those of ZM.

E Additional Investment Results

This section shows two event studies for different constructions of the investment outcome variable as discussed in Section 5. Estimates for the first additional outcome, the inverse hyperbolic sine of investment ($\ln(x + \sqrt{x^2 + 1})$), are shown in Panel (A) of Figure A3. This outcome allows both the intensive and extensive margins to respond to bonus and has the same scale for interpretatoin as the natural log. The estimates are almost identical to the primary variable definition of log investment, which suggests the extensive margin is is not behaving differently than the intensive margin.

[67]We normalize years to the survey year in ASM which is derived from a survey during the year while the tax data are retrospective from the following year. This means we plot 2000 in ZM as equivalent to 2001 in the ASM data.

The third construction of the investment outcome is capital expenditure divided by pre-period capital. The interpretation of these coefficients are a change in investment as a share of original assets. The event study coefficients are shown in Panel (B) of Figure A3. The time patterns and increases are qualitatively similar to the other definitions. Difference-in-differences estimates for both of these variable definitions are shown in Panels (B) and (C) of Table 1.

F Additional Employment Results

This Appendix extends the employment results discussed in Section 5. In that section, we introduce state-industry level variation using QWI data to measure employment responses in settings that may not be well covered by the ASM sample that is balanced. First, the ASM sample can be tilted toward large and old plants by construction, so we use QWI state-industry variation to see whether the same trends show up in small and young firms.

We show QWI event study estimates for firms with 1-50 employees in Panel (A) of Figure A4. This sample restricts on plants being very small and aggregates up to the state level, so if a plant grows beyond 50 employees it will leave the sample and aggregate state employment in this category would decrease. This sample restriction still shows that long duration plants experienced more employment growth than short duration counterparts even selecting on being very small plants. Further, we replicate the employment analysis again restricting to plants that are in the first 5 years of operation. We still find that employment in plants treated by bonus is increasing relative to untreated plants. Quarterly coefficients are shown in Panel (B) of Figure A4.

We also show extended robustness to a variety of industry level characteristics that could be correlated with the tax duration of investment. We do this using QWI data and state-industry variation instead of with ASM/CM data to limit the number of disclosures we have to make with the confidential Census data. The most important of these tests deals with our discrete definition of treatment. The variable z_0, which is defined as the PV of depreciation deductions for each dollar of investment, can be used as a continuous treatment instead of a discrete treatment. In Figure A6, we present results where we define treatment continuously as $(1\text{-}z_0)\tau^{*}0.0375$, which is the average treatment of accelerated depreciation due to bonus from 2002 to 2011. In Panel (A), we show that the event study has the same sign and statistical significance as the discrete version. Panel (B) displays a binscatter of changes in employment as a function of z_0, where we see the continuous treatment does not show any effect driven by outliers, but a smooth decreasing of employment as industries enjoyed shorter depreciation schedules historically (i.e. higher z_0). Our formulation of the treatment as a discrete variable does not appear to have a material impact on our results.

We present additional robustness checks in Figure A5. Many industries have differing reliance on Information and Communications Technology (ICT) capital, which is undergoing a technological transformation during our sample. We gather data from the BEA Detail Data for Fixed Assets and Consumer Durable Goods tables from 1997-2001 and calculate the average intensity in ICT assets in each industry. We interact quintiles of this intensity measure and interact with year fixed effects as a control in Panel (A) of Figure A5. We find this additional control does not materially impact our log employment regression estimates. Second, it could be the case that the producers of capital goods have increased earnings and productivity related to demand for their goods and not due to their cost of investment. We also use the 2002 BEA Input-Output tables to identify industries that sell capital goods to other industries. We control for an indicator equal to one if an industry reports any capital goods sales and interact this indicator with year fixed effects. Panel (B) shows that our estimates are larger in magnitude with the inclusion of this control, although the results are qualitatively similar.

Third, one could be concerned that the different mixes of assets and capital intensity across industries could lead to different costs of accessing external finance that requires some sort of collateral. As a proxy for the cost of external capital, we calculate the average cost of borrowing (interest divided by debt) for publicly traded firms in Compustat. We also create quintile bins of this external cost measure and interact with year fixed effects to allow for differential time paths for firms with different costs of capital. We include this control in Panel (C) and similarly find that our results do not change. Finally, we note that our decision to cut the z_0 distribution at the 33^{rd} percentile is not material to our estimates. We also show that cutting the z_0 distribution at the 25^{th} or 40^{th} percentile finds very similar effects. These results are shown in Panel (D).

We also use QWI data to present extended results on workforce composition corresponding to Figures 7 and 8. The diff-in-diff and long difference coefficients are reported in Tables A5 and A6, respectively.

G Aggregate and Long-Run Manufacturing Trends

This Appendix provides additional context to the employment and capital investment results presented in Section 5. Figure A8 demonstrates that the positive effects of Bonus Depreciation on U.S. manufacturing plants that we estimate can be interpreted in the context of large sector-level declines in employment and an overall shift toward more capital-intensive production. We utilize data from the NBER-CES Manufacturing Industry Database to obtain sector-wide manufacturing time series. We then apply our event study estimates from Section 5 to these series to illustrate the aggregate effects implied by our results. Panel (A) demonstrates that manufacturing capital stock grew steadily for both long and short duration industries in the pre-period, but stagnated for short duration industries after

2001. On the other hand, long duration industry capital stock continued to grow in the treatment period, though less dramatically than in the pre-period. Panel (B) demonstrates that manufacturing employment experienced a stable post-2001 decline across both long and short duration industries. Long duration industries thus experienced relatively more positive employment growth than short duration industries, despite an overall decline in employment. Taken together, these figures demonstrate the well-established fact that U.S. manufacturing became more capital intensive over the 1997-2011 period.

Figure A8 replicates our main investment and employment event study regressions using data from the NBER-CES Manufacturing Industry Database over the 1990-2011 period to demonstrate that our results are not explained by long-run business cycle trends that the 1997-2011 sample period in our main analysis could otherwise mask. Event study coefficient estimates are obtained from regressions similar to Equation (1) using 4-digit NAICS industry-year level data. Panel (A) shows that despite some short-run fluctuations, log investment in our pre-period reveals no statistically significant differences across long and short duration industries in the 1990-2000 period. This coarse regression also produces post-2001 effects that are very similar to those derived from our plant-level regressions. Panel (B) shows that log employment in the pre-period was very stable across long and short duration industries, while we again find large positive effects in the post-2001 period.

H Worker Composition and Wage Decomposition

This section provides two complementary methods of assessing the impact of worker composition on the observed decrease in labor earnings at plants treated by bonus, relative to control plants. First, we replicate the Log Earnings regression with QWI data while controlling for the various measurements of workforce composition at the state-industry level. The results of these regressions are presented in Appendix Table A7. This table begins with the original Log Earnings regression coefficient indicating that earnings decrease in Bonus plants in the post period by 3.1 log points relative to control plants. The next four specifications sequentially add controls for each of the endogenous workforce characteristics that we find respond to bonus incentives: share young workers, share workers with highschool education or less, share of non-white workers, and share of female workers.[68] In the final column with all controls, we find that bonus is associated with a 0.7 log point increase in earnings instead of a decrease, although the effect is statistically insignificant. This indicates that the change in workforce composition explains more than the entire decrease in earnings.

Second, we apply a formal decomposition to measure the effect of each margin of workforce composi-

[68] The workforce characteristics are included in each regression interacted with year fixed effects to allow them to have different effects over time in an evolving market.

tion directly. The Kitagawa-Oaxaca-Blinder decomposition follows the literature by estimating separate earnings regressions before and after bonus for the treatment and control samples to separate changes in observable characteristics from the changes in the predicted marginal effects associated with those characteristics (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973). To begin the composition, we begin with the fact that the wages in treated and control industries before and after the implementation of bonus can be described by a system of 4 equations, with each describing the relationship of wages to workforce characteristics for a different sample:

$$\begin{aligned}
wage_{jst}^{\text{bonus, pre}} &= \alpha_{js}^{\text{bonus, pre}} + \gamma_{st}^{\text{bonus, pre}} + \beta^{\text{bonus, pre}} X_{jst}^{\text{bonus, pre}} + \varepsilon_{jst} \\
wage_{jst}^{\text{bonus, post}} &= \alpha_{js}^{\text{bonus, post}} + \gamma_{st}^{\text{bonus, post}} + \beta^{\text{bonus, post}} X_{jst}^{\text{bonus, post}} + \varepsilon_{jst} \\
wage_{jst}^{\text{control, pre}} &= \alpha_{js}^{\text{control, pre}} + \gamma_{st}^{\text{control, pre}} + \beta^{\text{control, pre}} X_{jst}^{\text{control, pre}} + \varepsilon_{jst} \\
wage_{jst}^{\text{control, post}} &= \alpha_{js}^{\text{control, post}} + \gamma_{st}^{\text{control, post}} + \beta^{\text{control, post}} X_{jst}^{\text{control, post}} + \varepsilon_{jst}.
\end{aligned}$$

The controls X_{jst} in each regression include the share of young employees, share of employees with less than a high school education, share of non-white employees, and share of employess that are female. All regressions include state-by-year and industry-by-state fixed effects. In expectation under the assumption that $\text{E}(\varepsilon_{jst}|X_{jst}) = 0$, we can restate these equations as OLS estimates. Taking differences of the first two equations describes the change in average wages for bonus plants to be the difference in estimated fixed effects (Δ FE) plus the difference in average effects of workforce composition.

$$\Delta w\bar{a}ge^{\text{bonus}} = \Delta \text{FE}^{\text{bonus}} + \hat{\beta}^{\text{bonus, post}} \bar{X}^{\text{bonus, post}} - \hat{\beta}^{\text{bonus, pre}} \bar{X}^{\text{bonus, pre}}.$$

Adding and subtracting the estimated value of $\hat{\beta}^{\text{bonus, post}} \bar{X}^{\text{bonus, pre}}$ to the right hand side of this equation allows us to separate "quantity" or "composition" effects, changes in shares holding prices constant, from everything else that is going on.

$$\Delta w\bar{a}ge^{\text{bonus}} = \underbrace{\Delta \text{FE}^{\text{bonus}} + \Delta \hat{\beta}^{\text{bonus}} \bar{X}^{\text{bonus, pre}}}_{\text{Everything Else}} + \underbrace{\hat{\beta}^{\text{bonus, pre}} \Delta \bar{X}^{\text{bonus}}}_{\text{Composition}}.$$

To find the relative wage effects for treated plants relative to control plants, we must do the same calculation for the control equations and then take a difference between the wage decomposition for Bonus plants and control plants. Estimates of the four regressions explaining Log Earnings are shown in Columns (1)-(4) of Appendix Table A8. The impact of the change in workforce composition is simply the difference between the quantity term for treated plants and for control plants and can be calculated separately for each characteristic:

- The increase in young workers accounts for 0.46 log points of the decrease,
- the increase in less educated workers accounts for 1.40 log points of the decrease,
- the increase in non-white workers accounts for 0.12 log points of the decrease,
- and the increase in female workers accounts for 0.85 log points of the decrease.

Taken in its entirety, this decomposition suggests that 2.83 log points of the 3.1 log point effect is explained by changes in composition. Conservatively, composition in this exercise explains 91% of the wage effect by this method instead of the entire effect in the previous method. That is, we continue to find that it is the change in the share of less educated workers and the share of female workers that explain most of the variation as in the regressions including the endogenous controls.

I Structural Model Derivation

Below we derive the model predictions presented in section 7. The following exposition follows closely that in Harasztosi and Lindner (2019), which in turn follows Hamermesh (1996) to derive the output demand elasticity.

I.1 Consumer Problem

Consider a differentiated goods market and consumer preferences given by the constant elasticity of substitution function

$$U = \left(a \left[\left(\int_0^1 q(\omega)^{\frac{\kappa-1}{\kappa}} d\omega \right)^{\frac{\kappa}{\kappa-1}} \right]^{\frac{\theta-1}{\theta}} + (1-a) X^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$

where consumption of a variety ω from the differentiated goods market is given by $q(\omega)$ and X is spending on outside goods. Let $Q = \left(\int_0^1 q(\omega)^{\frac{\kappa-1}{\kappa}} d\omega \right)$. The consumer budget constraint is given by

$$\int_0^1 p(\omega) q(\omega) d\omega + X = I,$$

where consumer income is I and expenditures on the outside good X is set as a numeraire. Demand for variety ω may be derived by first solving the consumer's constrained optimization problem as represented by the Lagrangian below:

$$\mathcal{L} = \left(a \left[\left(\int_0^1 q(\omega)^{\frac{\kappa-1}{\kappa}} d\omega \right)^{\frac{\kappa}{\kappa-1}} \right]^{\frac{\theta-1}{\theta}} + (1-a) X^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} - \lambda \left[\int_0^1 p(\omega) q(\omega) d\omega + X - I \right].$$

Taking first-order conditions with respect to $q(\omega)$ and X

$$\frac{\partial L}{\partial q(\omega)} = \left(a\big(Q^{\frac{\kappa}{\kappa-1}}\big)^{\frac{\theta-1}{\theta}} + (1-a)X^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} a\big(Q^{\frac{\kappa}{\kappa-1}}\big)^{\frac{\theta-1}{\theta}-1} Q^{\frac{\kappa}{\kappa-1}-1} q(\omega)^{\frac{\kappa-1}{\kappa}-1} - \lambda p(\omega) = 0, \tag{11}$$

$$\frac{\partial L}{\partial X} = \left(a\big(Q^{\frac{\kappa}{\kappa-1}}\big)^{\frac{\theta-1}{\theta}} + (1-a)X^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}-1} (1-a)X^{\frac{\theta-1}{\theta}-1} - \lambda = 0. \tag{12}$$

Relative demand for a given variety can be derived by taking the ratio of FOCs of two varieties ω_1 and ω_2, and rearranging:

$$q(\omega_1) = \left(\frac{p(\omega_1)}{p(\omega_2)}\right)^{-\kappa} q(\omega_2).$$

This expression may be further manipulated by multiplying both sides by $p(\omega_1)$ and integrating with respect to $p(\omega_1)$:

$$\int_0^1 p(\omega_1)q(\omega_1)d\omega_1 = p(\omega_2)^{\kappa} q(\omega_2) \int_0^1 p(\omega_1)^{1-\kappa} d\omega_1.$$

The left-hand side of this expression is equal to total expenditures on all varieties (that is, $(I-X)$). Defining the composite price index $P \equiv \Big(\int_0^1 p(\omega_2)^{1-\kappa} d\omega_2\Big)^{\frac{1}{1-\kappa}}$, we write this equation as

$$(I-X) = p(\omega_2)^{\kappa} q(\omega_2) P^{1-\kappa}.$$

We then solve for the optimal choice of $q(\omega_2) = (I-X)P^{\kappa-1}p(\omega_2)^{-\kappa}$. Utilizing this simplified expression, it is convenient to express $Q^{\frac{\kappa}{\kappa-1}}$ as

$$Q^{\frac{\kappa}{\kappa-1}} = \left(\int_0^1 q(\omega_2)^{\frac{\kappa-1}{\kappa}} d\omega_2\right)^{\frac{\kappa}{\kappa-1}} = (I-X)P^{\kappa-1}\Big(\int_0^1 p(\omega_2)^{1-\kappa} d\omega_2\Big)^{\frac{\kappa}{\kappa-1}} = (I-X)P^{-1}.$$

To derive the optimal quantity of X, combine the two FOCs:

$$a\Big(Q^{\frac{\kappa}{\kappa-1}}\Big)^{\frac{\theta-1}{\theta}-1} Q^{\frac{\kappa}{\kappa-1}-1} q(\omega)^{\frac{\kappa-1}{\kappa}-1} = (1-a)X^{\frac{\theta-1}{\theta}-1} p(\omega)$$

Multiplying both sides by $q(\omega)$ and integrating over ω simplifies the expression to

$$a\Big(Q^{\frac{\kappa}{\kappa-1}}\Big)^{\frac{\theta-1}{\theta}} = (1-a)X^{\frac{\theta-1}{\theta}-1} \int_0^1 p(\omega)q(\omega)d\omega.$$

Using the expressions $Q^{\frac{\kappa}{\kappa-1}} = (I-X)P^{-1}$ and $\int_0^1 p(\omega)q(\omega)d\omega = (I-X)$ implies that

$$X = \frac{\big(\frac{1-a}{a}\big)^{\theta} P^{\theta-1}}{1+\big(\frac{1-a}{a}\big)^{\theta} P^{\theta-1}} I \quad \text{and} \quad I - X = \frac{1}{1+\big(\frac{1-a}{a}\big)^{\theta} P^{\theta-1}} I.$$

We may now express the firm level demand for good $q(\omega)$ as

$$q(\omega_2) = I \frac{1}{1+\big(\frac{1-a}{a}\big)^{\theta} P^{\theta-1}} P^{1-\kappa} p(\omega_2)^{-\kappa}. \tag{13}$$

As a result, we can derive the elasticity of demand for a given variety ω with respect to its own price as

$$\frac{\partial \log q(\omega)}{\partial \log p(\omega)} = -\kappa.$$

I.2 Firm Problem

Firms first minimize production costs subject to constant returns to scale technology; let $c(w, R, p_j)$ denote the firm's unit cost function, which depends on the wage rate w, the rental rate of capital R, and the price of an arbitrary third input p_j. Given the elasticity of output demand derived in the previous section, we may utilize firm optimality conditions to derive the expressions in the main text that relate our empirical elasticities to structural parameters of interest. With constant returns to scale production technology, profit maximization for a firm producing variety ω is determined by the following expression:

$$\max_{q(\omega)} \quad p(q(\omega), \omega)q(\omega) - c(w, R, p_j)q(\omega).$$

Solving and rearranging yields the following first order condition:

$$\left(\frac{\partial p(\omega)}{\partial q(\omega)}\frac{q(\omega)}{p(\omega)} + 1\right)p(\omega) - c(w, R, p_j) = 0.$$

From the consumer problem, the inverse elasticity of demand is $\frac{\partial p(\omega)}{\partial q(\omega)}\frac{q(\omega)}{p(\omega)} = -\frac{1}{\kappa}$, which allows us to express the optimal price for ω as a function of a fixed mark-up μ and input prices:

$$p(\omega) = \underbrace{\frac{\kappa}{\kappa - 1}}_{\equiv \mu} c(w, R, p_j).$$

Using this expression, we first consider the effects of bonus depreciation on firm production. First, consider the effect of an arbitrary change in the cost of capital R on prices charged by affected firms. Taking logarithms and differentiating with respect to R gives

$$\frac{\partial \log p(\omega)}{\partial R} = \frac{\partial \log c(w, R, p_j)}{\partial R} + \frac{\partial \log \mu}{\partial R}$$

Given that the mark-up μ is constant, $\frac{\partial \log \mu}{\partial R} = 0$. Shephard's lemma $\left(c_R = \frac{K}{q}\right)$ then implies that the elasticity of output prices with respect to capital input prices is equal to the share of capital cost in total cost, s_K:

$$\frac{\partial \log p(\omega)}{\partial \log R} = \frac{R \times c_R}{c} = \frac{R \times K}{cq(\omega)} \equiv s_K.$$

We then utilize this expression to derive the analogous effect on total revenue:

$$\frac{\partial \log p(\omega)q(\omega)}{\partial \log R} = \frac{\partial \log p(\omega)}{\partial \log R} + \frac{\partial \log q(\omega)}{\partial \log p(\omega)}\frac{\partial \log p(\omega)}{\partial \log R}.$$

Letting $-\eta \equiv \frac{\partial \log q(\omega)}{\partial \log p(\omega)}$, the effect on total revenue of an arbitrary change in the cost of capital is

$$\frac{\partial \log p(\omega)q(\omega)}{\partial \log R} = (1 - \eta)s_K.$$

The scale effect, ηs_K, depends on the degree to which bonus depreciation impacts the quantity sold by a given firm, $q(\omega)$. Under the assumption that bonus depreciation only impacts one firm, Equation 13 shows that $\eta = \kappa$. To the extent that bonus impacts the sector-level price index P, Equation 13 shows that the relevant η also depends on substitution toward consumption on outside goods X.

Letting $\phi = \frac{\partial \log R}{\partial \text{Bonus}} < 0$ denote the effect of bonus on the cost of capital, we arrive at Equation 6:

$$\frac{\partial \log p(\omega)q(\omega)}{\partial \text{Bonus}} = (1-\eta)s_K \times \phi.$$

Next, we derive the effect of bonus on the input decisions of affected firms. For each input, we use Shepards' lemma to express the optimal choice of each input as a function of the optimal output quantity and the first derivative of the cost function. Taking logs and differentiating with respect to an arbitrary change in the cost of capital, we may arrive at expressions for the effect of bonus on optimal input decisions as a function of input elasticities of substitution, the output demand elasticity, and input cost shares. For the optimal choice of capital, Shephard's lemma gives $K = c_R q$. Therefore,

$$\frac{\partial \log K(\omega)}{\partial R} = \frac{c_{RR}}{c_R} + \frac{\partial \log q(\omega)}{\partial R}. \tag{14}$$

Multiplying both sides of this expression by $\frac{\partial R}{\partial \log R} = R$ and substituting for the previously derived expression for input cost shares yields

$$\frac{\partial \log K(\omega)}{\partial \log R} = R\frac{c_{RR}}{c_R} - \eta s_K.$$

To write $R\frac{c_{RR}}{c_R}$ in terms of elasticities of substitution, note that constant returns to scale and Shephard's lemma imply that:

$$\begin{aligned} qc(w,R,p_j) &= wL + RK + p_j J \\ qc(w,R,p_j) &= wc_w q + Rc_R q + p_j c_{p_j} q \\ c(w,R,p_j) &= wc_w + Rc_R + p_j c_{p_j}. \end{aligned}$$

Differentiating with respect to the cost of capital implies

$$\begin{aligned} c_R &= wc_{wR} + c_R + Rc_{RR} + p_j c_{p_j R} \\ R\frac{c_{RR}}{c_R} &= -w\frac{c_{wR}}{c_R} - p_j\frac{c_{p_j R}}{c_R} \\ R\frac{c_{RR}}{c_R} &= -\frac{wL}{L}\frac{c_{wR}}{c_R} - \frac{p_j J}{J}\frac{c_{p_j R}}{c_R} \\ R\frac{c_{RR}}{c_R} &= -\frac{wL}{qc}\frac{cc_{wR}}{c_w c_R} - \frac{p_j J}{qc}\frac{cc_{p_j R}}{c_{p_j} c_R} \\ R\frac{c_{RR}}{c_R} &= -s_L\sigma_{KL} - s_J\sigma_{KJ}, \end{aligned}$$

where the second line solves for $R\frac{c_{RR}}{c_R}$, the third line manipulates each ratio by multiplying and diving by the respective input, and the fourth line uses Shephard's lemma and further multiplies and divides by c. The last line uses the definitions of cost shares $s_L = \frac{wL}{qc}$ and $s_J = \frac{p_j J}{qc}$ and of the Allen partial elasticity of substitution between inputs i and j, which is given by $\sigma_{ij} = \frac{cc_{ij}}{c_i c_j}$. Again letting $\phi = \frac{\partial \log R}{\partial \text{Bonus}} < 0$, we combine this expression with Equation 14 to derive Equation 3 from the main text:

$$\frac{\partial \log K(\omega)}{\partial \text{Bonus}} = (-s_J \sigma_{KJ} - s_L \sigma_{KL} - \eta s_K) \times \phi.$$

We follow a similar procedure to derive Equation 4, the effect of bonus on the optimal labor choice. Taking logarithms of Shephard's lemma ($L = c_w q$) and differentiating with respect to R,

$$\frac{\partial \log L(\omega)}{\partial R} = \frac{c_{wR}}{c_w} + \frac{\partial \log q(\omega)}{\partial R}.$$

As before, we can write this expression as

$$\begin{aligned} \frac{\partial \log L(\omega)}{\partial \log R} &= \frac{Rc_R}{c} \frac{cc_{wR}}{c_R c_w} - \eta s_K \\ \frac{\partial \log L(\omega)}{\partial \log R} &= \frac{RK}{qc} \frac{cc_{wR}}{c_R c_w} - \eta s_K \end{aligned}$$

where the first line multiplies and divides by $\frac{c_R}{c}$ and the second line uses Shephard's lemma. Using definitions of the Allen partial elasticity of substitution and the share of capital in total costs, together with $\phi = \frac{\partial \log R}{\partial \text{Bonus}} < 0$, we arrive at Equation 4

$$\frac{\partial \log L(\omega)}{\partial \text{Bonus}} = s_K(\sigma_{KL} - \eta) \times \phi.$$

Equation 5 can be derived in a similar fashion.

I.3 Effects of Bonus under Financing Constraints

This section describes a simple model that shows that financing constraints can amplify the effects of bonus on the cost of capital. As in Domar (1953), suppose that plants would like to finance new investments, I, through a combination of retained earnings, RE, and the cash flow plants get from bonus, BCF. When $I \leq RE + BCF$ the firm pays $\frac{r(1-\tau z)}{1-\tau}$ to finance investment. Note that $BCF = \tau b I$, so that plants pay the interest rate $\frac{r(1-\tau z)}{1-\tau}$ if $I \leq \frac{RE}{1-\tau b}$. That is, retained earnings can finance larger investments when b is larger, since this allows plants to claim a larger share of the total tax deductions associated with the investment in the year the investment is made. Additionally, we consider that plants face uncertainty regarding the retained earnings that will be available at the time of investment, so that $RE \sim G(\cdot)$. As in Myers (1977); Bond and Meghir (1994); Bond and Van Reenen (2007), we assume that plants pay a transaction cost f when accessing financing mechanisms (e.g., by issuing stock) when investment costs exceed retained earnings.

The expected financing cost for an investment I is then

$$\text{Cost of Capital} \equiv \frac{r(1-\tau z)}{1-\tau} + \frac{f}{1-\tau}\mathbb{P}r\left(I \geq \frac{RE}{1-\tau b}\right) = \frac{r(1-\tau(b+(1-b)z_0))}{1-\tau} + \frac{f}{1-\tau}G\left(I(1-\tau b)\right).$$

The effect of bonus on the cost of capital is then:

$$-\frac{\tau}{1-\tau}\left[r(1-z_0) + fIG'(I(1-\tau b))\right].$$

Note that, since $G(\cdot)$ is a C.D.F., $G'(\cdot) \geq 0$. This expression shows that bonus lowers the cost of capital both by decreasing the standard user cost of capital term from Hall and Jorgenson (1967) and by reducing the likelihood that plants will pay transaction costs to access other forms of finance.

Let $\varepsilon_G = \frac{IG'}{G} \geq 0$ be the elasticity of the likelihood that the firm is constrained with respect to the size of the investment. We can then write ϕ as follows:

$$\begin{aligned}\phi &\equiv \frac{\partial \ln(\text{Cost of Capital})}{\partial \text{Bonus}} = \frac{-1}{\text{Cost of Capital}} \times \frac{\tau}{1-\tau}\left[r(1-z_0) + fG(I(1-\tau b))\varepsilon_G\right] \\ &= -\tau\left[s_r\frac{(1-z_0)}{(1-\tau z)} + (1-s_r)\varepsilon_G\right],\end{aligned}$$

where s_r is the share of financing costs explained by the opportunity cost of retained earnings.

When $s_r = 1$, $\phi = \frac{\partial \ln \frac{r(1-\tau z)}{1-\tau}}{\partial \text{Bonus}} = -\frac{\tau(1-z_0)}{(1-\tau z)}$. As an illustrative calculation, assume $\tau = 0.35$, $z_0 = 0.9$, and that $b = 0.5$. For investments financed with retained earnings (i.e., when $s_r = 1$), we calculate that $\phi = -0.052$. Assuming that about half of the investment cost is due to additional financing costs and that $\varepsilon_G = 0.25$ implies that $\phi = -0.15$, while assuming that $\varepsilon_G = 0.5$ and $s_r = 0.5$ implies that $\phi = -0.276$.

J Additional Model Results

This section presents various model results in greater detail. These results demonstrate that our conclusion that capital and labor are complements in production holds up across several alternative models. This section also presents estimates of both translog cost functions and constant elasticity of substitution production functions. These estimated functions allow us to test several hypotheses of interest. Finally, we utilize our event study estimates over the 2002-2011 period to calculate several model parameters over time.

J.1 Two-Input Model Results

To motivate the three input model presented in the main text, we first consider a two input model with capital and labor. Solving for σ_{KL} in Equation 8 allows us to write the elasticity of capital-labor substitution as:

$$\sigma_{KL} = \eta\left(1 - \frac{\beta^L}{s_L\beta^L + s_K\beta^K}\right). \tag{15}$$

To implement this equation, we set input cost shares so that $1 - s_K = s_L = 0.8$. Panel A of Figure A9 plots this equation using the estimated effects of bonus on capital and labor for a range of values of η. This figure shows that, regardless of the value of η, the fact that $\hat{\beta}^L > \hat{\beta}^K$ implies that capital and labor are complements, i.e., $\sigma_{KL} < 0$.[69] Column (4) of Table A10 implements the classical minimum distance approach to estimate σ_{KL}, finding an estimate of $\sigma_{KL} = -0.12$. In two input models, a negative elasticity of substitution is not consistent with cost minimization. One interpretation of these results is that the data are not consistent with a large degree of substitution between capital and workers.[70] A second interpretation is that plants in our data are not well approximated by a two input model.

J.2 Alternative Model Inputs

We consider several alternative models in which different inputs are used in production. Table A10 presents several three input alternatives to the baseline model estimates presented in the text, which we reproduce in column (1). Columns (2) and (3) of Table A10 again consider a three input production technology comprising production labor, non-production labor, and capital, but instead estimate labor relying on estimates of effects on employment using difference-in-differences (instead of long differences) and hours (instead of number of workers), respectively. In both cases, we estimates very similar values of σ_{KL}, suggesting that the finding that production labor and capital are complements is not driven by mismeasurement of labor inputs, nor by focusing on the long-run effect of bonus depreciation on inputs. Column (5) of Table A10 considers an alternative production function that combines (all) workers with equipment capital, and structures. As discussed in the main text, structures were generally not eligible for bonus depreciation. This model finds that workers are complementary to equipment and that structures are substitutes with equipment. Since the model perfectly matches the estimated effect on capital structures, we interpret the estimated 4% increase in structures as being driven by a scale effect, though it is diminished by a substitution away from structures. Finally, column (6) considers a model with workers, capital, and materials. In this model, workers continue to be complements with capital, and we also find that materials and capital are substitutes.

We also estimate a five input model that combines production labor, non-production labor, materials, capital structures, and capital equipment. Panel B of Figure A9 reports values of σ_{KL} implied by a five-input analogue of Equation 15 across values of η. Once again, our estimates imply negative values of σ_{KL}.

[69] To be consistent with a Cobb-Douglas production function, Equation 15 implies that $\hat{\beta}^K$ would have to be 2.25-times as large as $\hat{\beta}^L$, assuming $\eta = 5$; and 6-times as large if $\eta = 2$.

[70] Gechert, Havranek, Irsova and Kolcunova (2021) conduct a meta-analysis of estimates of σ_{KL} and show that, correcting for publication bias, one should expect to find a large number of negative estimates of σ_{KL}.

J.3 Translog Cost Function Estimation

Following Hamermesh (1996) and Berndt and Christensen (1973), we estimate translog cost function parameters implied by the estimated substitution elasticities presented in Table 8. The translog cost function can accommodate an arbitrary number of inputs, is a second-order approximation to a general cost function, and nests several alternative production technologies. The general form is given by:

$$\log C = \log Y + a_0 + \sum_i a_i \log w_i + 0.5 \sum_i \sum_j b_{ij} \log w_i \log w_j, \tag{16}$$

where

$$\sum_i a_i = 1; \quad b_{ij} = b_{ji}; \quad \sum_i b_{ij} = 0, \ \forall j, \tag{17}$$

where the parameters b_{ij} are the parameters of interest. For factor inputs i and j and associated cost shares s_i and s_j, the partial elasticities of substitution we estimate can be expressed as

$$\sigma_{ij} = [b_{ij} + s_i s_j]/s_i s_j, \quad i \neq j. \tag{18}$$

We can then estimate b_{lk} and b_{jk} using our estimated elasticities of substitution, σ_{KL} and σ_{JK}. In order to identify b_{lj}, we consider two values of σ_{LJ} relative to our estimates of σ_{KL} and σ_{JK} in Table 8. Specifically, first consider that properties of cost minimization imply a lower-bound value of σ_{LJ} :

$$s_J \sigma_{LJ} + s_K \sigma_{KL} > 0,$$

$$\sigma_{LJ} > -(s_K/s_J)\sigma_{KJ}.$$

As a second alternative, we consider the assumption that σ_{LJ} is as large as our largest estimated elasticity: $\max = \{\hat{\sigma}_{KL}, \hat{\sigma}_{JK}\} = \hat{\sigma}_{JK}$. Below, we present results using these two alternative values of σ_{LJ}, which we use to estimate b_{lj}.

To identify the parameters b_{ii} then requires values of σ_{LL}, σ_{JJ}, and σ_{KK}. These values can be obtained from the following identities:

$$s_L \sigma_{LL} + s_J \sigma_{LJ} + s_K \sigma_{LK} = 0,$$

$$s_L \sigma_{JL} + s_J \sigma_{JJ} + s_K \sigma_{JK} = 0,$$

$$s_L \sigma_{KL} + s_J \sigma_{KJ} + s_K \sigma_{KK} = 0.$$

Rearranging the first of these expressions, $\sigma_{LL} = [-s_J \sigma_{LJ} - s_K \sigma_{LK}]/s_L$. Equation (3) demonstrates that for an input j, σ_{jj} can be interpreted as the negative of the total substitution effect with respect to other inputs divided by the cost share s_j. We can then relate these parameters to their translog counterparts through the following equation:

$$\sigma_{ii} = [b_{ii} + s_i^2 - s_i]/s_i^2. \tag{19}$$

Equations (18) and (19) demonstrate that the partial elasticities of substitution we estimate are linear functions of the analogous translog parameters b_{ij}. Panels A of Tables A12 and A13 report translog parameter estimates for our two assumed values of σ_{LJ}.

An advantage of estimating these translog cost parameters is that we may derive simple testable restrictions on these parameters that correspond to different production technologies. We test the following hypotheses:

$$H_0 : b_{kl} = b_{kj} = b_{jl} = 0 \quad \text{(Cobb-Douglas)},$$
$$H_0 : b_{kl} = b_{kj} = 0 \quad \text{(Capital Separability)},$$
$$H_0 : b_{kj} = b_{lj} = 0 \quad (J \text{ Separability}),$$
$$H_0 : b_{kl} = b_{lj} = 0 \quad (L \text{ Separability}),$$
$$H_0 : b_{ij} = -s_i s_j \quad \forall i \neq j \quad \text{(Leontief)}.$$

Panels B of Tables A12 and A13 report p-values associated with the F-tests corresponding to these null hypotheses across the 3-input model estimates presented in Table 8. For both bounds on σ_{LJ}, we are generally able to reject the Cobb-Douglas production technology as well as capital and production labor separability at the 5% level and in many cases at the 0.1% level.

We also reject non-production labor separability when assuming $\sigma_{LJ} = -(s_K/s_J)\sigma_{KJ}$. This result makes intuitive sense since the lower bound that implies this value of σ_{LJ} corresponds to null total elasticity of substitution, which is closer to a Leontief production technology than a separable one. In contrast, we do not reject that non-production labor may be separable when we assume that $\sigma_{LJ} = \sigma_{KJ}$. This result also makes intuitive sense since $\sigma_{LJ} = \sigma_{KJ}$ implies that $b_{lj} = b_{kj}$, which by construction satisfies half of the conditions of test of J-separability.

In both cases, we are unable to reject a Leontif production technology across all models. This result is consistent with our finding in Section 7 that the most of the effect of the policy on factor demands was driven by the scale effect.

J.4 Constant Elasticity of Substitution Parameter Estimates

The model estimates in Table 8 can be easily transformed into estimates of substitution parameters from a nested constant elasticity of substitution (CES) production function. For the partial elasticities of substitution σ_{KJ} and σ_{KL}, the analogous CES substitution parameters are given by $\rho_1 = (\sigma_{KJ}-1)/\sigma_{KJ}$ and $\rho_2 = (\sigma_{KL}-1)/\sigma_{KL}$, respectively. Estimates of these parameters are presented in Table A13 across the models in Table 8.

Following the CES framework of Krusell, Ohanian, Ríos-Rull and Violante (2000), these estimates naturally lead to the question of whether our estimated effects on production and non-production labor are consistent with a capital-skill complementarity hypothesis that $\rho_1 > \rho_2$, or, equivalently, $\sigma_{KL} > \sigma_{KJ}$. Given the fact that our estimates of ρ_1 are uniformly negative and those of ρ_2 are uniformly positive, it would appear that our results are inconsistent with this hypothesis. However, due to the relative imprecision of our CES estimates, we cannot rule out this hypothesis formally. Instead, we test whether we can reject the finding of Krusell, Ohanian, Ríos-Rull and Violante (2000) that $\sigma_{KL} > \sigma_{KJ}+1$. Table A13 presents p-values from these statistical tests. With the exception of a model with a large calibrated value of η, we reject this hypothesis at the 10% level for all other models.

J.5 Model Estimates over Time

Our existing model results utilize either difference-in-differences or long difference estimates to recover estimates of scale effects, effects on the cost of capital, input elasticities with respect to changes in the cost of capital, and capital-labor substitution elasticities. Alternatively, we may utilize the event study estimates from Section 5 to recover these estimates for the entire 2002-2011 treatment period. Due to disclosure restrictions, we impute the covariances between reduced-form estimates in the 2002-2010 period where necessary by assuming that the correlations between any two regression estimates are constant and equal to their correlation in 2011.

Panels (A) and (B) of Figure A10 presents estimates of the scale effect and the effect on the cost of capital, respectively, over time. We estimate both the scale effect, $\bar{\beta}$, and the effect on the cost of capital, ϕ, by applying Equation (7) year-by-year. Consistent with the increasing effects over time across most outcomes in Section 5 we find that both of these effects increase in magnitude over time. Panels (C) and (D) display estimates of the investment and production employment elasticities presented in Table 7 over time. As in the main text, we define these elasticities as $\varepsilon^I_\phi = \beta^I/\phi$ and $\varepsilon^L_\phi = \beta^L/\phi$, respectively. These estimates are relatively stable over time. This result suggests that our estimates of ϕ capture the effects of the policy on the cost of capital, inclusive of financing and adjustment constraints that may prevent plants from adjusting their capital.

Lastly, we estimate σ_{KL} for each year over the 2004-2011 period by combining our event study estimates of the effect of bonus depreciation on production labor, an annualized long-difference estimate of the effect on total revenue, and Equations (4) and (6):

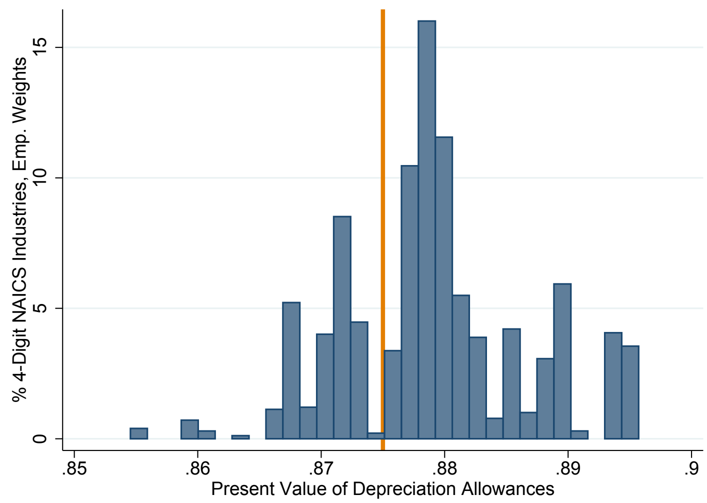
$$\sigma_{KL}^t = (1-\eta)\frac{\beta_t^L}{\beta_t^R} + \eta.$$

Figure A11 presents these estimates. While somewhat imprecise, these point estimates suggest a much larger, negative estimate of σ_{KL} that gradually attenuates over time. This pattern is consistent with labor being a more flexible input than capital in the short run, whereas over time, capital adjustments imply smaller degrees of complementary between labor and capital.

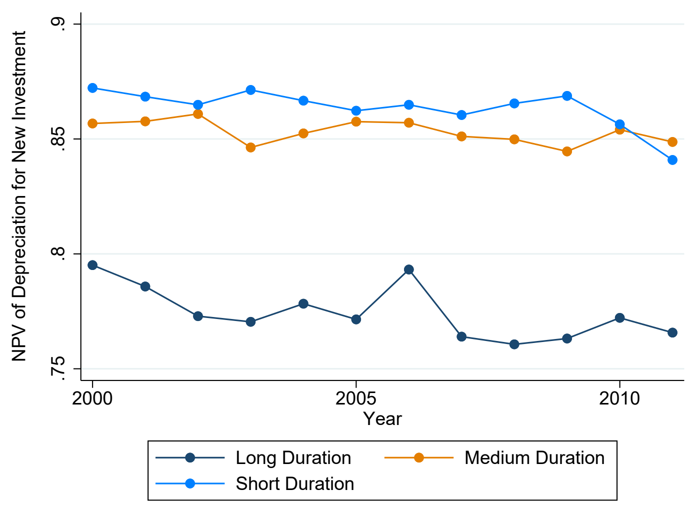
Appendix Figures

Figure A1: Distribution and Stability of Depreciation Net Present Value without Bonus

(A) Distribution of Depreciation NPV without Bonus

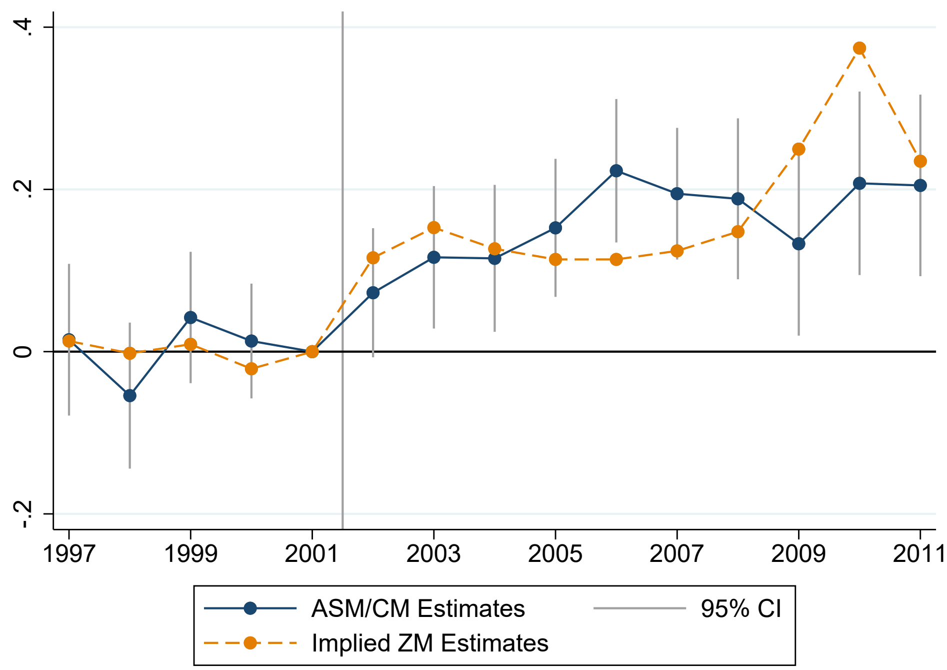


(B) Stability of Depreciation NPV Over Time



Notes: Panel (A) of Figure A1 shows the distribution of the present value of depreciation deductions across manufacturing industries according to estimates in Zwick and Mahon (2017). The vertical red line in this graph at 0.875 highlights the structural break that we take advantage of for defining plants that benefit most from Bonus. Panel (B) of Figure A1 displays the aggregate net present value of depreciation deductions for $1 of new investment in each year from 2000 to 2011 with an assumed discount rate of 7% without applying bonus depreciation. These represent annual estimates of z_0 discussed in Section 2. IRS sectors are aggregated into thirds based on weighted total investment in 2000 with the trends for each third graphed separately. The graph highlights that the sectors that invest in the longest tax-duration assets always have z_0 estimates less than 0.8 while the other two terciles have similarly stable z_0 estimates that are much higher. It does not appear that the non-bonus depreciation values of new investment are changing over time in response to Bonus. *Source:* Authors' calculations based on Zwick and Mahon (2017) replication data and IRS SOI sector-level corporation depreciation data, derived from Form 4562.

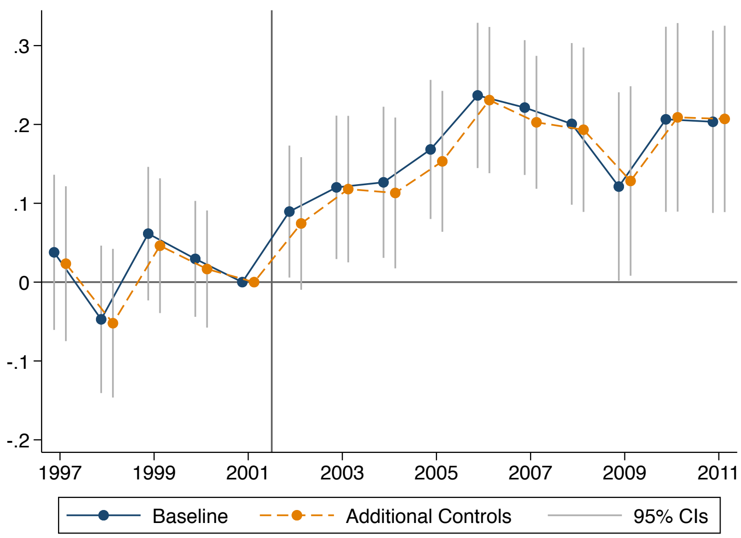
Figure A2: Comparison of Investment Event Study Results with Zwick and Mahon (2017)



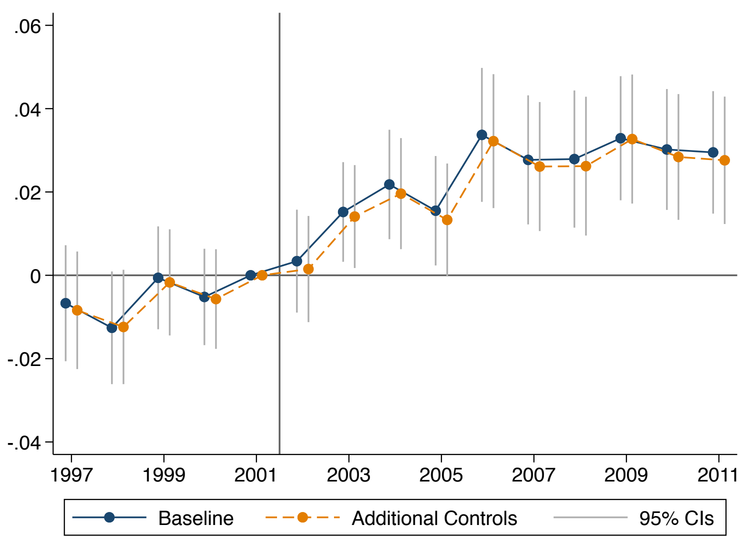
Notes: Figure A2 compares our investment results to those of Zwick and Mahon (2017). As we discuss in Section 4, we define exposure to treatment as a binary variable that takes the value of one when for firms with z_0 in the first three terciles of the distribution of z_0. Zwick and Mahon (2017) use the same definition of treated firms in their Figure 1 (see their §III.B, p.228). Using the reported values in their Figure 1, we construct a combined event study that mirrors our estimates. We describe this procedure in Appendix D. Table A1 lists the data and operations used to generate the orange series. Because IRS tax data report results from previous years and the ASM/CM data report production data in March of the current year, we align these two series to match economic activity in the same year. The blue series reproduce our estimates of the effects of bonus on log investment from Figure 2. This figure shows that our estimated effects of bonus on log investment are quite comparable with those reported in Zwick and Mahon (2017).
Source: Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure A3: Effects of Bonus Depreciation on Alternative Investment Outcomes

(A) IHS Investment



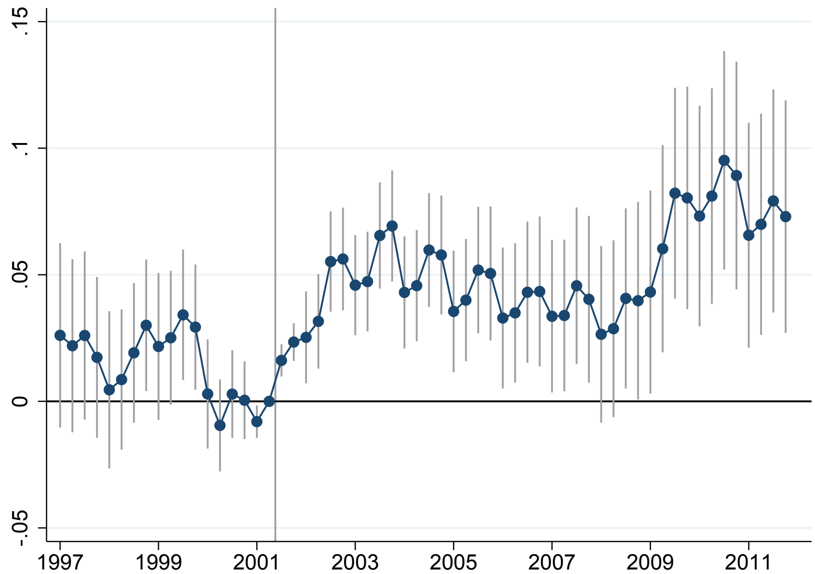
(B) $(\Delta \text{PPENT}_t / \text{PPENT}_{1997-2001})$



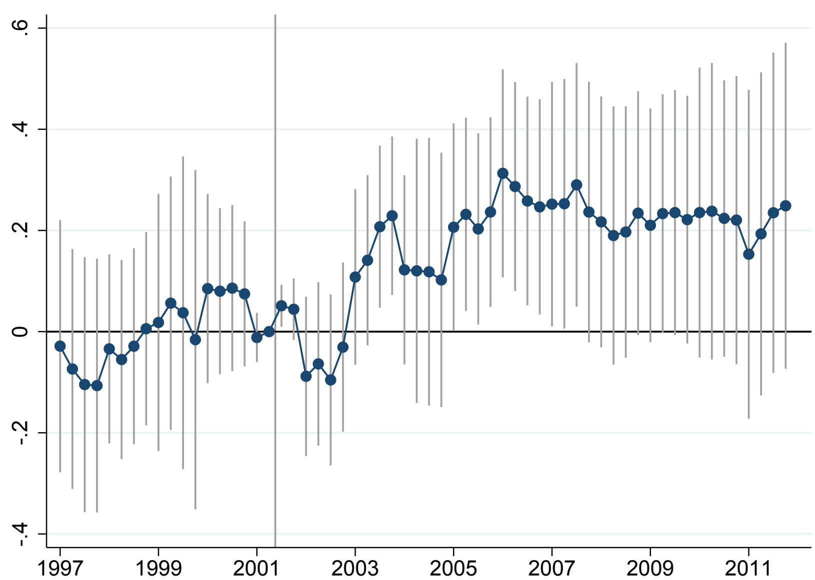
Notes: Figure A3 displays estimates describing the effect of bonus depreciation on the Inverse Hyperbolic Sine of Investment in Panel (A) and PPENT expenditures divided by previous PPENT stock in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with Bonus. The baseline specification in each panel includes state-by-year and plant fixed effects. The specifications with additional controls add plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects to the baseline specifications. These specifications correspond to columns (2) and (5) of Table 1, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level.
Source: Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure A4: Effects of Bonus Depreciation on Smaller and Younger Firm Employment; QWI

(A) Firms with 1-50 Employees

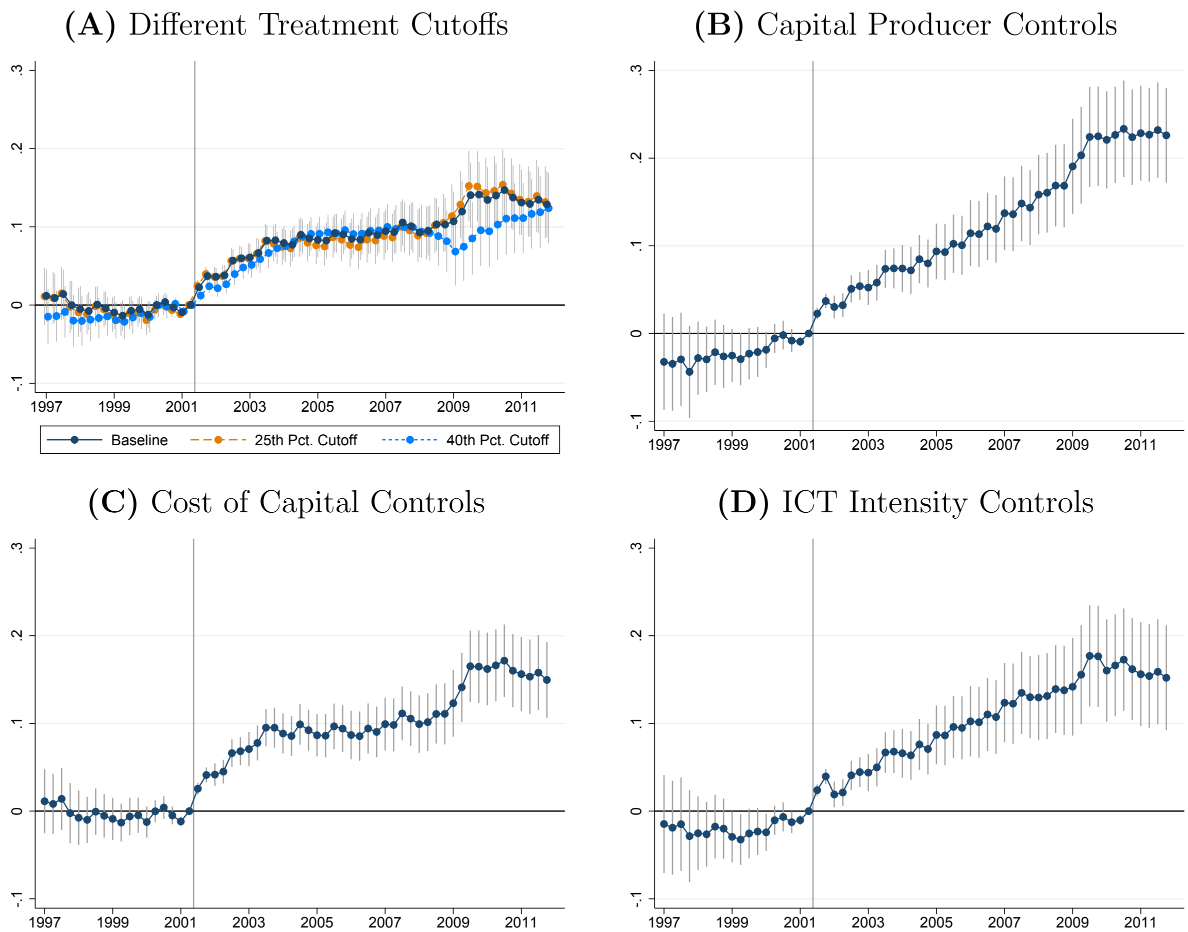


(B) Firms 0-5 Years Old



Notes: Figure A4 displays estimates describing the effect of bonus depreciation on Log Employment for small and young firms using state-by-industry QWI data. Panel (A) restricts the sample to firms with 50 or fewer employees. Panel (B) restricts the sample to firms that are five or fewer years old. The regression estimates displayed in this figure correspond to a quarterly analogue of β_y from Equation (1), which is the change in log employment relative to 2001q2 in industries affected most by Bonus relative to industries that are less affected by Bonus. The regression includes 4-digit NAICS-by-state fixed effects and state-by-quarter fixed effects. 95% confidence intervals are included for each quarterly point estimate with standard errors clustered by the 4-digit NAICS-by-state level. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

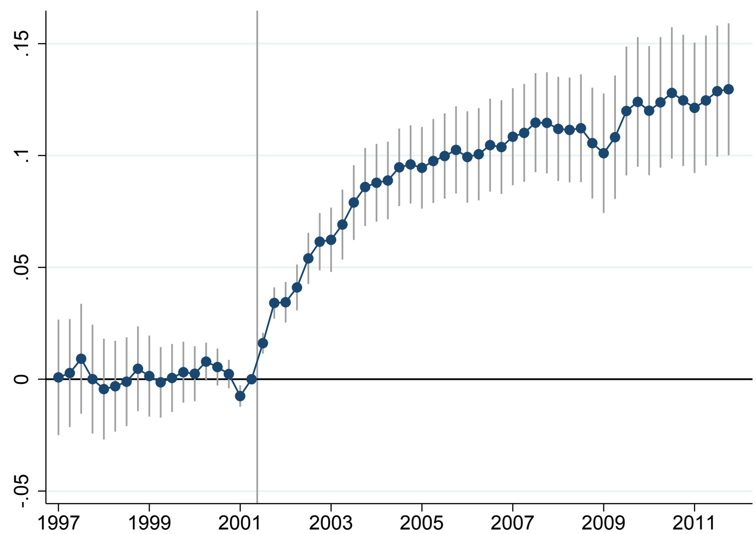
Figure A5: Effects of Bonus Depreciation, QWI Employment Robustness Checks



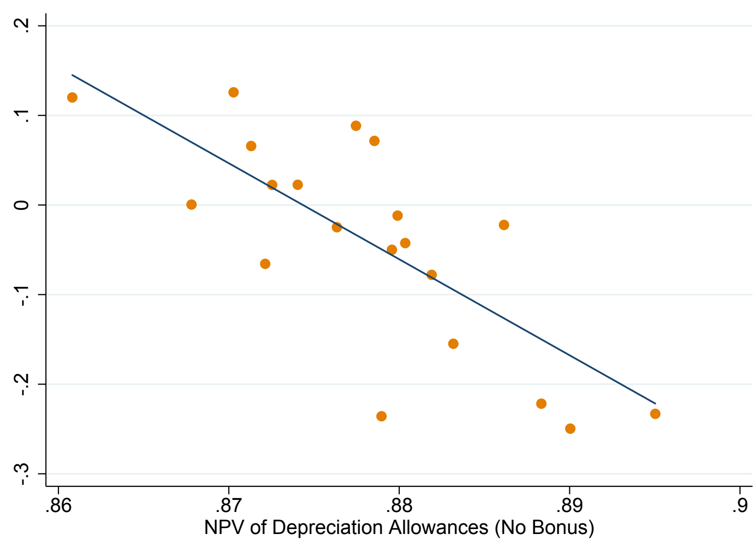
Notes: Figure A5 presents additional estimates of the effect of depreciation incentives on log employment in the state-by-industry QWI data as in Figure 5. Panel (A) shows the effects of bonus on employment using three different cutoffs in the z_0 distribution to determine treatment: 25^{th} percentile, 33^{rd} percentile, and 40^{th} percentile. Panel (B) includes an indicator for capital producing industries interacted with year fixed effects. Capital producing industries are identified using 2002 BEA Input-Output tables. Panel (C) includes quintile indicators for the cost of capital interacted with year fixed effects. We proxy for the cost of capital by taking the industry average of the cost of borrowing from Compustat, defined as xint / (dltt + dlc). Panel (D) includes quintile indicators for industry-level information and communications technology (ICT) capital intensity interacted with year fixed effects. ICT capital intensity was calculated during the period 1997–2001 as a share of capital stock in ICT goods using BEA Detailed Data for Fixed Assets and Consumer Durable Goods. *Source:* Authors' calculations based on QWI, BEA, Compustat, and Zwick and Mahon (2017) data.

Figure A6: Effects of Bonus Depreciation on Employees, Continuous Treatment

(A) Effect of Bonus Depreciation on QWI Log Employment, Continuous Treatment



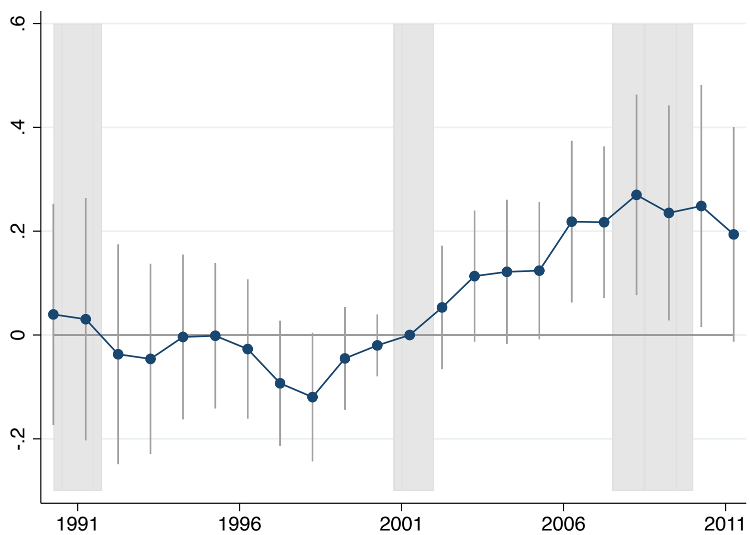
(B) Binscatter; Industry Level Changes in Employment vs. z_0



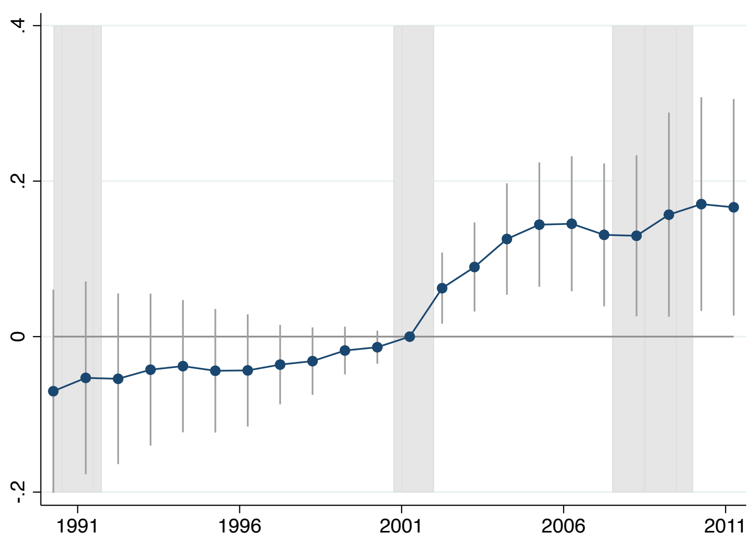
Notes: Panel (A) of Figure A6 displays estimates describing the effect of bonus depreciation on log employment using state-by-industry QWI data as in Figure 5, but using the continuous (1-z_0)τ*0.0375 in place of the treatment indicator. Panel (B) presents a binned-scatter plot of industry-level changes in QWI Log Employment against $z - 0$. Each industry-level change is derived from a regression in the form of Equation including an interaction term for the industry of focus. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

Figure A7: U.S. Manufacturing Over the Business Cycle

(A) Log Investment



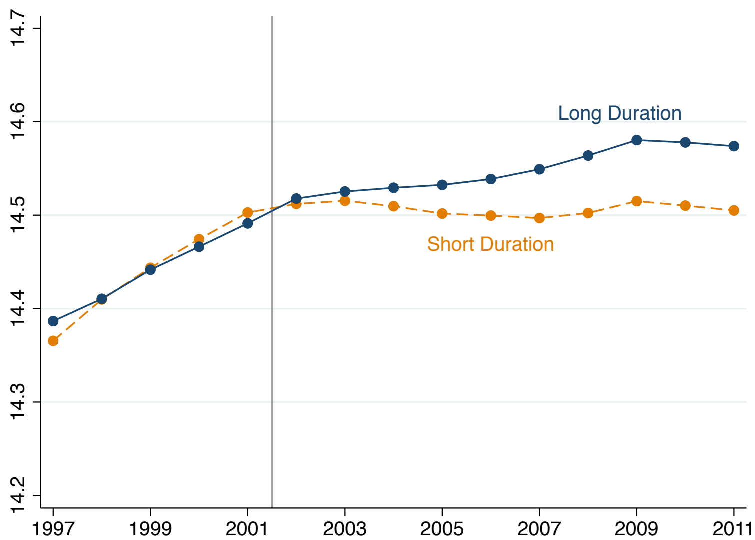
(B) Log Employment



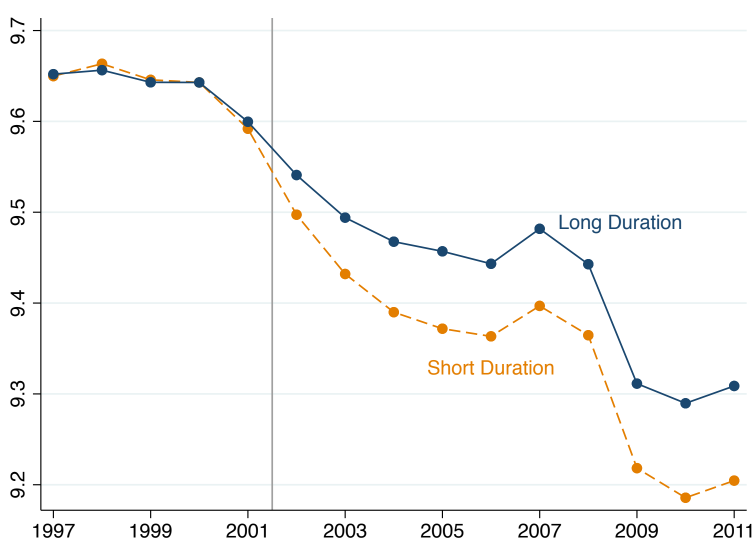
Notes: Figure A7 presents event study regression coefficients summarizing the effect of bonus depreciation on log employment and log investment in 4-digit NAICS industries over the 1990 to 2011 period. Coefficients obtained from industry-year level regressions akin to Equation (1) with observations weighted by 2001 industry employment levels. Industry and year fixed effects are included in estimating equations, and standard errors are clustered at the 4-digit NAICS level. Shaded regions correspond to dates classified as business cycle contractions by the National Bureau of Economic Research. *Source:* Authors' calculations based on NBER-CES Manufacturing Industry Database, NBER Business Cycle Expansions and Contractions, and Zwick and Mahon (2017) data.

Figure A8: Effects of Bonus Depreciation on Aggregate Trends

(A) Log Capital Stock



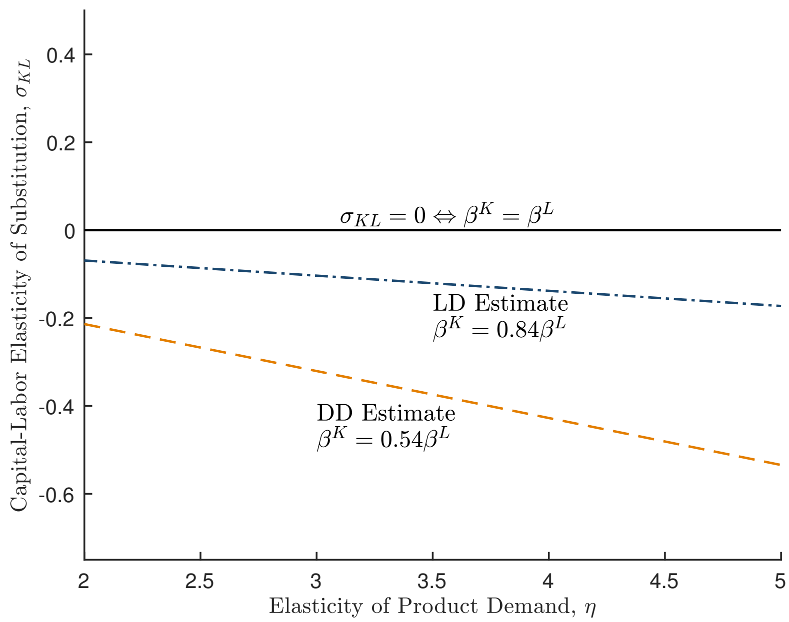
(B) Log Employment



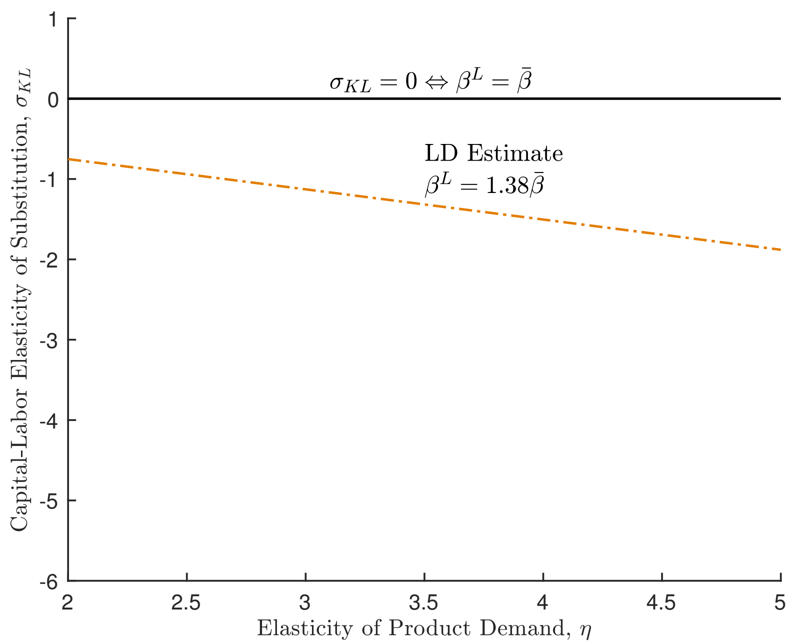
Notes: Figure A8 presents the effect of bonus depreciation on aggregate trends over log employment and log capital stock over the 1997-2011 implied by our reduced form estimates. We construct aggregate series across bonus treatment by calculating aggregate time series of log capital stock and log employment, respectively, for all manufacturing industries and applying estimates of event study coefficients from Equation (1) to the resulting series. *Source:* Authors' calculations based on NBER-CES Manufacturing Industry Database, ASM, CMF, and Zwick and Mahon (2017) data.

Figure A9: Additional Estimates of Capital-Labor Substitution

(A) σ_{KL} in a Two Input Model

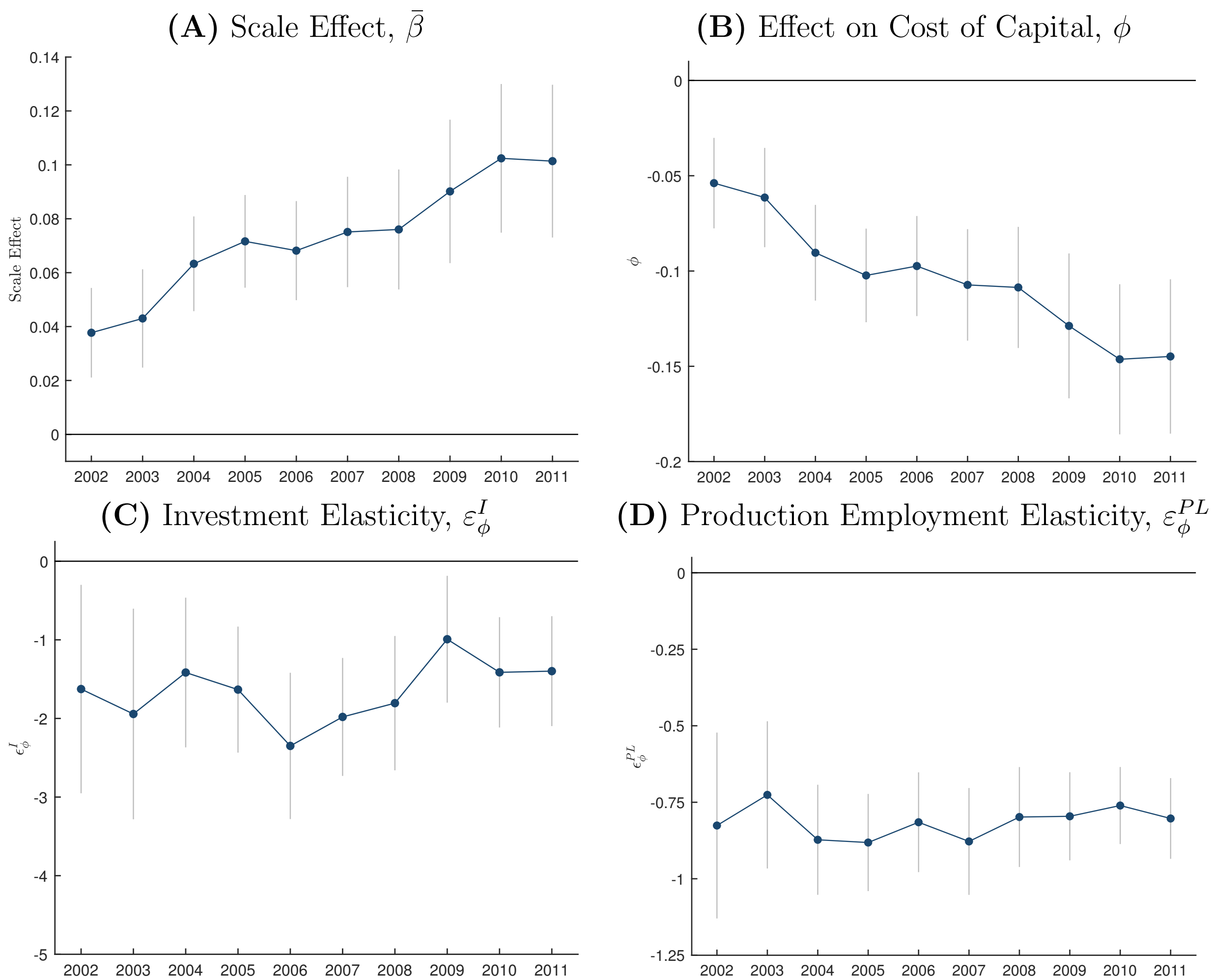


(B) σ_{KL} in a Five Input Model



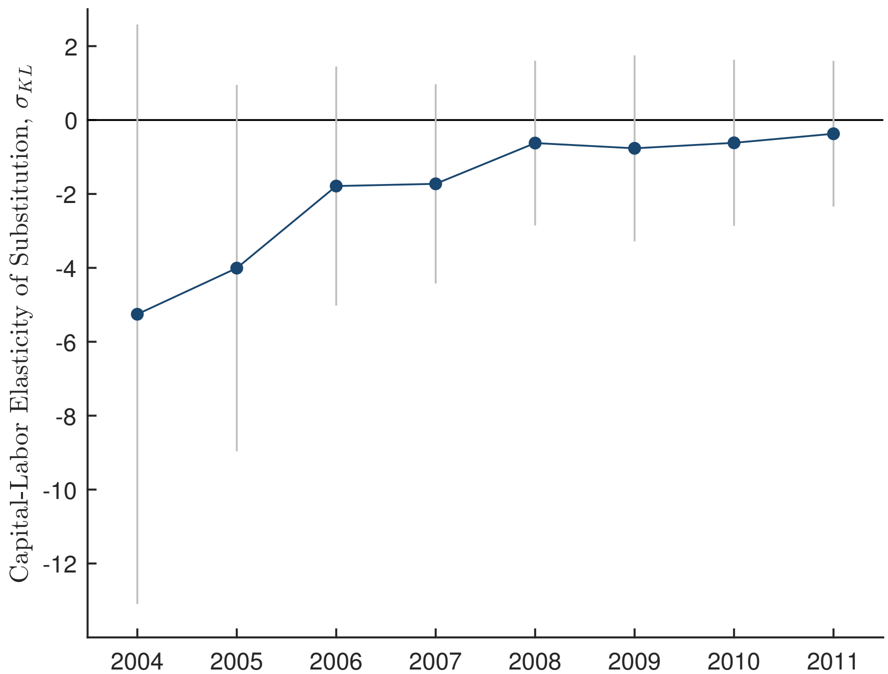
Notes: Figure A9 implements versions of Equation 15 across two- and five-input models and for a range of values of η. Panel (A) shows that both our long-differences and difference-in-differences reduced-form estimates are not consistent with large degrees of substitution between capital and labor in a two-input model. This figure also motivates the estimation of three-input models since profit maximization requires a non-negative value of σ_{KL}. Panel (B) implements a five-input analogue of Equation 15 using our long-differences estimates of the effects of bonus depreciation on capital and labor demand for a range of values of η. The inputs included are production labor (cost share $c_{l_1} = 0.15$), non-production labor (cost share $c_{l_2} = 0.10$), equipment capital (cost share $c_{k_1} = 0.06$), structures capital (cost share $c_{k_2} = 0.04$), and materials (cost share $c_m = 0.65$). *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure A10: Scale, Cost of Capital, and Elasticity Estimates over Time



Notes: Figure A10 displays select model estimates over the 2002-2011 period using event study regression estimates from Equation (1). Panel (A) presents the scale effects implied by our reduced form estimates over the 2002-2011 period. Scale effects for year t are defined using equation 7 as $\bar{\beta}_t = s_J\beta^J_t + s_K\beta^K_t + s_L\beta^L_t$. Panel (B) displays estimates of the effect on the cost of capital. Effects for year t are defined using equation 7 as $\phi = -\hat{\beta}_t/(s_K\eta)$. Panels (C) and (D) present estimates of the elasticity of investment and production labor, respectively, with respect to changes in the cost of capital over time. Elasticities are calculate as $\varepsilon^I_\phi = \beta^I/\phi$ and $\varepsilon^L_\phi = \beta^L/\phi$, respectively. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Figure A11: Capital-Production Labor Substitution over Time



Notes: Figure A11 estimates σ_{KL} over the 2004-2011 period. For each year t, σ_{KL} estimates are obtained using the estimated effects of bonus depreciation from Equation (1), an annualized long-differences estimate of the effect of bonus depreciation on revenue, and equations 4 and 6. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Appendix Tables

Table A1: Graph Data from Zwick and Mahon (2017)

	Figure 1, Panel A		Figure 1, Panel B		Differences (Bonus-Control)		Combined
	Control	Bonus	Control	Bonus	Panel A	Panel B	Event Study
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1996	6.553	6.553			0.013		0.013
1997	6.602	6.587			-0.002		-0.002
1998	6.482	6.478			0.009		0.009
1999	6.488	6.454			-0.021		-0.021
2000	6.480	6.467			0.000		0.000
2001	6.243	6.346			0.116		0.116
2002	6.078	6.218			0.153		0.153
2003	6.119	6.233			0.127		0.127
2004	6.251	6.352			0.114		0.114
2005			6.455	6.455		0.000	0.114
2006			6.604	6.614		0.010	0.124
2007			6.599	6.633		0.034	0.148
2008			6.569	6.705		0.136	0.250
2009			6.259	6.519		0.261	0.374
2010			6.398	6.519		0.121	0.235

Notes: Table A1 uses graph data from Zwick and Mahon (2017) as a way to compare our investment results. To construct this table, we first use the program WebPlotDigitizer (see `https://apps.automeris.io/wpd/`) to extract data points from Figure 1 in Zwick and Mahon (2017). Columns (1)–(4) report the extracted data. Column (5) reports the differences between the first bonus and control series (i.e., column 2 minus column 1) normalizing the difference to 2000. Column (6) reports the differences between the second bonus and control series (i.e., column 4 minus column 3). Column (7) joins these two series making the assumption that there is no relative change between 2004 and 2005. We make this assumption given differences in how data are normalized between Panels A and B of Figure 1 in Zwick and Mahon (2017). Figure A2 plots the series in column (7) of this table along with our estimates from Panel (A) of Figure 2. *Source:* Authors' calculations based on Zwick and Mahon (2017) graph data.

Table A2: Effects of Bonus Depreciation, Industry-Level Clustering

	(1) Log Investment	(2) Log Total Capital	(3) Log Employment	(4) Log Mean Earnings	(5) Log Total Revenue	(6) TFP
	Difference-in-Differences					
Bonus	0.1577**	0.0445	0.0791***	-0.0207**	0.0542	-0.0028
	(0.0642)	(0.0329)	(0.0224)	(0.0087)	(0.0344)	(0.0082)
	[0.014]	[0.176]	[0.000]	[0.017]	[0.115]	[0.733]
	Long Differences					
Bonus	0.2049	0.0778*	0.095**	-0.0273**	0.0808	-0.0153
	(0.1246)	(0.0416)	(0.04)	(0.0126)	(0.0717)	(0.0162)
	[0.100]	[0.061]	[0.018]	[0.030]	[0.260]	[0.345]
Plant FE	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE	✓	✓	✓	✓	✓	✓
TFP_{2001}×Year FE	✓	✓	✓	✓	✓	✓
FirmSize_{2001}×Year FE	✓	✓	✓	✓	✓	✓

Notes: Table A2 displays estimates describing the effect of bonus depreciation on various outcomes with standard errors clustered at the 4-digit NAICS level. Differences-in-differences subpanels show the Bonus×Post coefficient estimates from specifications in the form of Equation (2) while the Long Differences panel shows Bonus×$[t = 2011]$ coefficient estimates from specifications in the form of Equation (1). Outcome variables in Specifications (1)–(6) are Log Investment, Log Total Total Employment, Log Mean Earnings, Log Total Capital, Log Total Value of Shipments, and TFP. All Specifications include plant fixed effects, state-by-year fixed effects, plant size in 2001 bins interacted with year fixed effects, TFP in 2001 bins interacted with year fixed effects, and firm size in 2001 interacted with year fixed effects. Standard errors are presented in parentheses. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table A3: Effects of Bonus on Hours Worked and Materials

	(1) Log Prod. Hours	(2) Log Nonprod. Hours	(3) Log Materials
Bonus	0.0863***	0.0582*	0.0832**
	(0.0181)	(0.0311)	(0.0344)
	[0.000]	[0.061]	[0.016]
Plant FE	✓	✓	✓
State×Year FE	✓	✓	✓

Notes: Table A3 displays long differences estimates describing the effect of bonus depreciation on hours measures of labor demand and on plants' use of materials. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table A4: Effects of Bonus Depreciation, Interactions with Local Bonus Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Investment		Log Employment		Log Mean Earnings	
Bonus	0.1535**	0.1531**	0.0789***	0.0756***	-0.0206**	-0.0204**
	(0.0601)	(0.0642)	(0.0219)	(0.0222)	(0.0086)	(0.0087)
	[0.011]	[0.017]	[0.000]	[0.001]	[0.017]	[0.019]
Local Exposure	0.0349*	0.0407**	0.0127**	0.0149***	-0.0037	-0.0037
	(0.018)	(0.0178)	(0.0055)	(0.0049)	(0.0031)	(0.003)
	[0.053]	[0.022]	[0.021]	[0.002]	[0.233]	[0.217]
Bonus × Exposure	-0.0417	-0.0389	-0.0074	-0.0049	0.0045	0.0043
	(0.0283)	(0.0276)	(0.0083)	(0.0078)	(0.0037)	(0.0036)
	[0.141]	[0.159]	[0.373]	[0.530]	[0.224]	[0.232]
Plant FE	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE		✓		✓		✓
TFP_{2001}×Year FE		✓		✓		✓
FirmSize_{2001}×Year FE		✓		✓		✓

Notes: Table A4 displays difference-in-differences estimates and coefficients describing the interaction between difference-in-differences terms and variables capturing the share of local commuting zone exposure to bonus depreciation in 2001. Local exposure is defined as the percent of manufacturing employment in long duration industries in a given plant's commuting zone. Exposure variables are demeaned and standardized such that reported coefficients express the effect of moving from the 25th to the 75th percentile exposure across plants in our estimating sample. Due to disclosure restrictions, reported standard errors, displayed in parentheses, are clustered at the 4-digit NAICS level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) data.

Table A5: Effect of Bonus Depreciation, QWI Sample

	(1) Log(Emp)	(2) Log(Earn)	(3) % < HS	(4) % < 35 years
	Difference-in-Differences			
Bonus	0.097***	-0.031***	0.00259***	0.01285***
	(0.0156)	(0.00547)	(0.000605)	(0.0024862)
	[0.000]	[0.000]	[0.000]	[0.000]
	Long Differences			
Bonus	0.135***	-0.0314***	0.00394***	0.0306***
	(0.0216)	(0.0078)	(0.000724)	(0.00679)
	[0.000]	[0.000]	[0.000]	[0.000]
Share2001			0.25	0.3
State×NAICS FE	✓	✓	✓	✓
State×Quarter FE	✓	✓	✓	✓

Notes: Table A5 shows the effect of bonus depreciation on outcomes based on state-industry data from QWI. Difference-in-differences subpanels show the estimates of β from specifications in the form of Equation (2) while the long differences subpanels show estimates of β_{2011q3} from specifications in the form of Equation (1). The outcomes across Specifications (1)–(4) are the Log of Total Employment, the Log of Mean Earnings, the fraction of employees with a high school degree or less Education, and the fraction of employees who are 35 years or younger. All specifications include 4-digit NAICS-by-state and State-quarter fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* QWI and Zwick and Mahon (2017) data.

Table A6: Effect of Bonus Depreciation on Fraction of Different Race and Ethnicity

	(1) % Female	(2) % Nonwhite	(3) % Black	(4) % Hispanic
	Difference-in-Differences			
Bonus	0.00822***	0.000267	0.0012	0.00536***
	(0.00151)	(0.000958)	(0.00074)	(0.000969)
	[0.000]	[0.780]	[0.105]	[0.000]
	Long Differences			
Bonus	0.0118***	0.000678	0.00409***	0.00589***
	(0.0022)	(0.00211)	(0.00153)	(0.0017)
	[0.000]	[0.748]	[0.008]	[0.001]
Share2001	0.25	0.26	0.07	0.06
State×NAICS FE	✓	✓	✓	✓
State×Quarter FE	✓	✓	✓	✓
Pre-Period Growth FE	✓	✓	✓	✓

Notes: Table A6 shows the effect of bonus depreciation on demographic characteristics of the workforce based on state-industry data from QWI. Differences-in-differences subpanels show the Bonus×Post coefficient estimates from specifications in the form of Equation (2) while the long difference subpanels show Bonus×$[t = 2011q3]$ coefficient estimates from specifications in the form of Equation (1). The outcomes across Specifications (1)–(4) are the fraction of female employees, the fraction of non-white employees, the fraction of Black employees, and the fraction of Hispanic employees. All specifications include 4-digit NAICS-by-state fixed effects, State-quarter fixed effects, and pre-period growth rate bins in the outcome variable interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* QWI and Zwick and Mahon (2017) data.

Table A7: Effect of Bonus on Earnings, Controlling for Endogenous Worker Composition

	(1)	(2)	(3)	(4)	(5)
	Difference-in-Differences				
Bonus	-0.031***	-0.028***	-0.003	-0.003	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	[0.000]	[0.000]	[0.495]	[0.549]	[0.126]
Industry × State FE	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓
Age Shares		✓	✓	✓	✓
Education Shares			✓	✓	✓
Race Shares				✓	✓
Sex Shares					✓

Notes: Table A7 Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented below. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* QWI and Zwick and Mahon (2017) data.

Table A8: Effect of Worker Composition on Observed Earnings, Decomposition Regressions

	(1)	(2)	(3)	(4)
	Treat Pre	Treat Post	Control Pre	Control Post
Share Young	-0.548***	0.189**	-0.505***	-0.102
	(0.124)	(0.093)	(0.105)	(0.071)
	[0.000]	[0.043]	[0.000]	[0.149]
Share Highschool or Less	-3.298***	-3.683***	-4.436***	-3.810***
	(0.324)	(0.328)	(0.520)	(0.230)
	[0.000]	[0.000]	[0.000]	[0.000]
Share Nonwhite	0.096	0.078	0.893***	0.259***
	(0.132)	(0.080)	(0.247)	(0.082)
	[0.465]	[0.327]	[0.000]	[0.002]
Share Female	-0.549***	-0.644***	-0.904***	-0.390***
	(0.141)	(0.108)	(0.160)	(0.070)
	[0.000]	[0.000]	[0.000]	[0.000]
Industry × State FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Mean Share Young	0.308	0.254	0.303	0.236
Mean Share Highschool or Less	0.259	0.255	0.223	0.218
Mean Share Nonwhite	0.167	0.171	0.173	0.175
Mean Share Female	0.262	0.261	0.334	0.318

Notes: Table A8 Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented below. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* QWI and Zwick and Mahon (2017) data.

Table A9: Effects of Bonus Depreciation and Manufacturing Trends

	(1) Log Investment	(2) Log Employment
Bonus	0.1457***	0.0577***
	(0.0339)	(0.0117)
	[0.000]	[0.000]
Treat×Skill Intensity	0.0577	0.0097
	(0.0541)	(0.0181)
	[0.286]	[0.592]
Treat×Capital Intensity	0.0259*	0.0028
	(0.0155)	(0.003)
	[0.095]	[0.351]
Treat×Trade Exposure	-0.0723**	-0.0413***
	(0.0296)	(0.0111)
	[0.015]	[0.000]
Treat×Robot Exposure	0.0187	0.0137***
	(0.012)	(0.0038)
	[0.119]	[0.000]
Plant FE	✓	✓
State×Year FE	✓	✓
Skill Intensity×Year FE	✓	✓
Capital Intensity×Year FE	✓	✓
Trade Exposure×Year FE	✓	✓
Robot Exposure×Year FE	✓	✓

Notes: Table A9 displays difference-in-differences estimates and coefficients describing the full set of interactions between the DD term and variables capturing all four manufacturing sector trends: Skill Intensity, Capital Intensity, Chinese Import Exposure, and Robotization. The outcome variable in Specification (1) is the Log of Investment. The outcome variable in Specification (2) is the Log of Total Employment. All specifications include state-by-year and plant fixed effects. To control for trends in the manufacturing sectors, both specifications include skill intensity bins interacted with year fixed effects, capital intensity bins interacted with year fixed effects, Chinese import exposure bins interacted with year fixed effects, and robotization bins interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ *Source:* Authors' calculations based on ASM, CMF, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) data.

Table A10: Classical Minimum Distance Estimates of Production Elasticities

	(1) Baseline	(2) DD	(3) Hours	(4)	(5)	(6)
	Panel A: Estimated Parameters					
Demand elasticity, η	3.500	3.500	3.500	3.500	3.500	3.500
Elasticities of Substitution:						
Labor-capital, σ_{KL}	-0.387	-0.405	-0.618	-0.126	-0.161	-0.433
	(0.489)	(0.659)	(0.516)	(0.193)	(0.212)	(0.911)
Nonproduction labor-capital, σ_{KJ}	0.644	0.721	1.030			
	(0.798)	(1.187)	(0.802)			
Equipment-structures, σ_{KS}					1.949	
					(1.697)	
Materials-capital, σ_{KM}						0.167
						(0.472)
	Panel B: Empirical Moments					
Revenue	0.075	0.051	0.075	0.075	0.075	0.075
Labor	0.116	0.101	0.086	0.097	0.097	0.097
Nonproduction labor	0.090	0.068	0.058			
Structures					0.041	
Materials						0.083
Capital	0.080	0.042	0.080		0.105	0.080
	Panel C: Model-Predicted Moments					
Revenue	0.070	0.057	0.056	0.068	0.067	0.061
Labor	0.109	0.089	0.092	0.098	0.098	0.096
Nonproduction labor	0.080	0.064	0.055			
Structures					0.042	
Materials						0.082
Capital	0.098	0.082	0.078	0.081	0.105	0.086
Cost shares:						
Labor	0.50	0.50	0.50	0.80	0.80	0.25
Nonproduction labor	0.30	0.30	0.30			
Structures					0.09	
Materials						0.65
Capital	0.20	0.20	0.20	0.20	0.11	0.10
Effect on Cost of Capital, ϕ	-0.14	-0.11	-0.11	-0.14	-0.24	-0.25

Notes: Table A10 presents classical minimum distance estimates across several alternative models. Column (1) reproduces column (1) of Table 8 for reference. Columns (2) and (3) demonstrate that these baseline results are robust to using difference-in-differences estimates and estimates on labor hours, respectively. Column (4) estimates a two input model of total labor employment and capital. Columns (5) and (6) consider three input models with either two types of capital or materials, respectively. Capital-labor substitution elasticities corresponds either to that of total capital and total labor, the elasticity of capital and production labor, or the elasticity of substitution between equipment capital and production labor.

Table A11: Unconstrained Classical Minimum Distance Estimates of Production Elasticities

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η	(6) Est. η
	Panel A: Estimated Parameters					
Demand elasticity, η	3.500	3.500	3.500	2.000	5.000	3.858
						(3.115)
Elasticities of Substitution:						
Production labor-capital, σ_{KL}	-0.513	-0.425	-0.605	-0.287	-0.743	-0.568
	(0.541)	(0.474)	(0.639)	(0.235)	(0.982)	(0.633)
Nonproduction labor-capital, σ_{KJ}	0.370	0.442	0.297	0.194	0.556	0.414
	(0.651)	(0.650)	(0.665)	(0.335)	(1.049)	(0.738)
	Panel B: Empirical Moments					
Revenue	0.075	0.075	0.075	0.075	0.075	0.075
Production labor	0.116	0.116	0.116	0.116	0.116	0.116
Nonproduction labor	0.090	0.090	0.090	0.090	0.090	0.090
Capital	0.080	0.080	0.080	0.080	0.080	0.080
	Panel C: Model-Predicted Moments					
Revenue	0.073	0.074	0.071	0.052	0.080	0.075
Production labor	0.117	0.116	0.117	0.119	0.115	0.116
Nonproduction labor	0.091	0.091	0.091	0.094	0.089	0.090
Capital	0.081	0.080	0.081	0.082	0.080	0.080
Cost shares:						
Production labor	0.50	0.55	0.45	0.50	0.50	0.50
Nonproduction labor	0.30	0.35	0.25	0.30	0.30	0.30
Capital	0.20	0.10	0.30	0.20	0.20	0.20
Effect on Cost of Capital, ϕ	-0.15	-0.30	-0.09	-0.26	-0.10	-0.13

Notes: Table A11 reproduces Table 8 from the main text by implementing an unconstrained classical minimum distance estimation procedure. Estimation is identical to that conducted in Table 8 with the exception that we do not impose the cost-minimization constraint $s_L\sigma_{KL} + s_J\sigma_{KJ} > 0$.

Table A12: Translog Cost Function Estimation: σ_{LJ} Lower Bound

	(1) Baseline	(2) DD	(3) Hours	(4) Low s_K	(5) High s_K	(6) Low η	(7) High η
	Panel A: Estimated Parameters						
b_{ll}	0.250	0.250	0.250	0.247	0.247	0.250	0.250
b_{jj}	0.133	0.086	0.126	0.183	0.091	0.167	0.097
	(0.094)	(0.097)	(0.134)	(0.055)	(0.120)	(0.043)	(0.165)
b_{kk}	0.160	0.160	0.157	0.090	0.210	0.160	0.160
	(0.023)	(0.023)	(0.031)	(0.007)	(0.046)	(0.013)	(0.034)
b_{kl}	-0.139	-0.162	-0.141	-0.077	-0.183	-0.121	-0.156
	(0.049)	(0.052)	(0.066)	(0.027)	(0.068)	(0.023)	(0.086)
b_{kj}	-0.021	0.002	-0.017	-0.013	-0.027	-0.039	-0.004
	(0.048)	(0.048)	(0.071)	(0.028)	(0.060)	(0.023)	(0.083)
b_{lj}	-0.111	-0.088	-0.109	-0.170	-0.064	-0.129	-0.094
	(0.049)	(0.052)	(0.066)	(0.027)	(0.068)	(0.023)	(0.086)
	Panel B: Production Function F-test p-values						
Cobb-Douglas	0.000	0.000	0.011	0.000	0.243	0.000	0.015
K Separability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J Separability	0.000	0.001	0.004	0.000	0.587	0.000	0.027
L Separability	0.005	0.002	0.033	0.005	0.007	0.000	0.068
Leontif	0.712	0.435	0.821	0.711	0.714	0.616	0.791
σ_{LJ}	0.26	0.41	0.27	0.12	0.43	0.14	0.38
	(0.22)	(0.23)	(0.29)	(0.04)	(0.72)	(0.10)	(0.38)
Demand elasticity	3.50	3.50	3.50	3.50	3.50	2.00	5.00
Cost shares:							
Production labor	0.50	0.50	0.50	0.55	0.45	0.50	0.50
Nonproduction labor	0.30	0.30	0.30	0.35	0.25	0.30	0.30
Capital	0.20	0.20	0.20	0.10	0.30	0.20	0.20
Effect on Cost of Capital, ϕ	-0.14	-0.11	-0.11	-0.28	-0.09	-0.25	-0.10

Notes: Table A12 presents estimates of translog cost parameters implied by estimated substitution elasticities corresponding to the columns in Table 8 and tests whether various production functions are consistent with the associated translog parameters. Panel A displays estimated translog cost parameters where σ_{LJ} is assumed to be equal to the lower bound implied by the model estimates in Table 8, $\hat{\sigma}_{LJ} = -(s_K/s_J)\hat{\sigma}_{KL}$. Panel B displays p-values from F-tests in which the null hypotheses are sets of conditions on the estimated translog parameters implying the specified production technologies. The null hypotheses tested are $H_0 : b_{kl} = b_{kj} = b_{jl} = 0$ (Cobb-Douglas), $H_0 : b_{kl} = b_{kj} = 0$ (Capital Separability), $H_0 : b_{kj} = b_{lj} = 0$ (J Separability), $H_0 : b_{kl} = b_{lj} = 0$, ($L$ Separability), and $H_0 : b_{ij} = -s_i * s_j \forall i \neq j$ (Leontif). *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table A13: Translog Cost Function Estimation: $\sigma_{LJ} = \max\{\sigma_{KJ}, \sigma_{KL}\}$

	(1) Baseline	(2) DD	(3) Hours	(4) Low s_K	(5) High s_K	(6) Low η	(7) High η
	Panel A: Estimated Parameters						
b_{ll}	0.192	0.157	0.182	0.146	0.223	0.218	0.165
	(0.080)	(0.078)	(0.122)	(0.126)	(0.060)	(0.040)	(0.133)
b_{jj}	0.075	-0.006	0.059	0.081	0.067	0.135	0.013
	(0.168)	(0.168)	(0.249)	(0.180)	(0.151)	(0.079)	(0.291)
b_{kk}	0.160	0.160	0.157	0.090	0.210	0.160	0.160
	(0.023)	(0.023)	(0.031)	(0.007)	(0.046)	(0.013)	(0.034)
b_{kl}	-0.139	-0.162	-0.141	-0.077	-0.183	-0.121	-0.156
	(0.049)	(0.052)	(0.066)	(0.027)	(0.068)	(0.023)	(0.086)
b_{kj}	-0.021	0.002	-0.017	-0.013	-0.027	-0.039	-0.004
	(0.048)	(0.048)	(0.071)	(0.028)	(0.060)	(0.023)	(0.083)
b_{lj}	-0.053	0.005	-0.042	-0.069	-0.040	-0.097	-0.009
	(0.120)	(0.120)	(0.178)	(0.152)	(0.090)	(0.057)	(0.208)
	Panel B: Production Function F-test p-values						
Cobb-Douglas	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K Separability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J Separability	0.656	0.970	0.814	0.651	0.659	0.088	0.966
L Separability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Leontif	0.712	0.435	0.821	0.711	0.714	0.616	0.791
σ_{LJ}	0.64	1.03	0.72	0.64	0.64	0.36	0.94
	(0.80)	(0.80)	(1.19)	(0.79)	(0.80)	(0.38)	(1.38)
Demand elasticity	3.50	3.50	3.50	3.50	3.50	2.00	5.00
Cost shares:							
Production labor	0.50	0.50	0.50	0.55	0.45	0.50	0.50
Nonproduction labor	0.30	0.30	0.30	0.35	0.25	0.30	0.30
Capital	0.20	0.20	0.20	0.10	0.30	0.20	0.20
Effect on Cost of Capital, ϕ	-0.14	-0.11	-0.11	-0.28	-0.09	-0.25	-0.10

Notes: Table A13 presents estimates of translog cost parameters implied by estimated substitution elasticities corresponding to the columns in Table 8 and tests whether various production functions are consistent with the associated translog parameters. Panel A displays estimated translog cost parameters where σ_{LJ} is assumed to be equal the upper bound implied by the model estimates in Table A10, $\hat{\sigma}_{LJ} = \hat{\sigma}_{KJ}$. Panel B displays p-values from F-tests in which the null hypotheses are sets of conditions on the estimated translog parameters implying the specified production technologies. The null hypotheses tested are $H_0 : b_{kl} = b_{kj} = b_{jl} = 0$ (Cobb-Douglas), $H_0 : b_{kl} = b_{kj} = 0$ (Capital Separability), $H_0 : b_{kj} = b_{lj} = 0$ (J Separability), $H_0 : b_{kl} = b_{lj} = 0$, ($L$ Separability), and $H_0 : b_{ij} = -s_i * s_j \forall i \neq j$ (Leontif). *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.

Table A14: Constant Elasticity of Substitution Parameter Estimates

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η	(6) Est. η
	Panel A: CES Parameter Estimates					
Nonproduction Labor, ρ_1	-0.552	-0.556	-0.551	-1.812	-0.063	-0.211
	(2.152)	(2.155)	(2.156)	(4.863)	(1.330)	(1.564)
Production Labor, ρ_2	3.587	3.446	3.791	5.687	2.772	3.019
	(4.682)	(4.213)	(5.510)	(10.450)	(2.907)	(3.415)
	Panel B: p-values for Skill Complementarity Test					
$H_0 : \sigma_{KL} - \sigma_{KJ} - 1 > 0$	0.052	0.054	0.051	0.003	0.127	0.098
Cost shares:						
Production labor	0.50	0.55	0.45	0.50	0.50	0.50
Nonproduction labor	0.30	0.35	0.25	0.30	0.30	0.30
Capital	0.20	0.10	0.30	0.20	0.20	0.20
Effect on Cost of Capital, ϕ	-0.14	-0.28	-0.09	-0.25	-0.10	-0.11
Demand Elasticity, η	3.50	3.50	3.50	2.00	5.00	4.42

Notes: Panel (A) of Table A14 presents estimates of substitution parameters from a constant elasticity of substitution (CES) production function implied by our estimates of σ_{KL} and σ_{KJ} in Table 8. Panel (B) tests a null hypothesis of $H_0 : \sigma_{KL} - \sigma_{KJ} - 1 > 0$, consistent with the presence of skill complementarity of capital, across these models. *Source:* Authors' calculations based on ASM, CMF, and Zwick and Mahon (2017) data.