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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 Census Data on manufacturing establishments show that tax policies increased both investment and employment, but did not stimulate wage or productivity growth. Using a structural model, we find that the primary effect of the policy was to increase the use of all inputs by lowering costs of production and that capital and production workers are complementary inputs in modern manufacturing. Our results show that tax policies that incentivize capital investment do not lead manufacturing plants to replace workers with machines.

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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)

How the adoption of capital impacts workers is one of the foundational questions of the economics discipline. This question is ever more relevant in the 21st century given widespread concerns that tax incentives for investment may unnecessarily accelerate the adoption of new machinery at the expense of workers. Empirical attempts to answer this question face a number of challenges: investment decisions are endogenous to productivity and demand shocks, capital accumulation is a slow process, and few datasets exist that can measure how capital accumulation impacts the demand for workers that interact with machinery.

This paper combines confidential data from the US Census Bureau and quasi-experimental variation in the cost of capital due to a tax policy called bonus depreciation to overcome these challenges. Bonus depreciation, or simply bonus, lowers the cost of investment by allowing plants to deduct equipment expenses more quickly. By comparing plants that benefit the most from bonus to those that benefit less, we isolate investment in capital equipment that is likely independent of other idiosyncratic shocks faced by a given plant. By following plants between 1997 and 2011, our results measuring the impact of capital adoption on workers allow plants to fully adjust along 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 stock and employment, leading them to increase their overall output. In contrast, 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. The model separates the effects of the policy into substitution and scale effects. We estimate that the scale effect—the increase in the use of all inputs due to lower production costs—accounts for 90% of the employment effects of the policy. Because production employment increased by more than the scale effect, the model shows that capital and production labor are complements in modern manufacturing. We conclude that tax policies that incentivize capital investment lead manufacturing plants to increase their scale, but do not lead these plants to replace workers with machines.

The policy we study, bonus depreciation, is one of the largest incentives for capital investment in US history and 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 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. Importantly, the benefits are determined by IRS rules and not by the useful life of any particular asset. By comparing plants that benefit the most from this incentive—those that invest more in equipment that is deducted slowly according to IRS rules—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 less. 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. Second, responses to the policy are much larger for eligible than for ineligible capital. Third, responses to the tax policy are not due to forces responsible for the recent decline in US manufacturing employment, including trends in capital intensity and skill intensity and exposure to import competition and robotization. Finally, we confirm that the effects of the policy are present in multiple datasets and are robust across a battery of specification checks.

Our baseline results use confidential data from the Census of Manufactures and the Annual Survey of Manufactures to estimate the joint effects of the policy on capital and labor demand. We estimate that treated plants increased investment flows by 15.8% relative to non-treated plants after the policy was implemented. An advantageous feature of Census data is the ability to measure capital stocks. We estimate a relative increase in overall capital of 7.8% between 2001 and 2011. These findings reject the notion that the increases in investment flows reflected a re-timing of investment. The relative increase in capital stocks among treated plants allows us to study the effects of capital accumulation on labor demand.

In contrast to the concern that capital investment displaces workers, we find concurrent increases in employment that more than match the capital investment response. By 2011, plants that benefited more from bonus had a relative employment increase of 9.5%. These gains were 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 complements labor in modern manufacturing.

The effects of bonus on employment are robust across various data sources and specification checks. First, plant-level results are robust to allowing for trends that differ by state or by pre-period measures of plant productivity, plant size, and firm size. Second, we find similar effects using employment data at the state-industry level from the Quarterly Workforce Indicators (QWI). These results based on aggregate data show that accounting for plant entry and exit does not alter our findings. We also obtain similar estimates when using alternate cutoffs to define treated units or continuous measures of treatment intensity. Our results are not driven by trends in industries facing concomitant shocks: we find similar effects when we allow for differential trends along financing costs, adoption of information and communication technology (ICT), or the production of capital goods. We also find similar effects when we exclude high-tech industries. Third, to show that our results are not driven by differential exposure to business cycles, we use NBER-CES industry-level data starting in 1990 to document that industries that benefit more from bonus did not differentially respond to past recessions. Finally, we use data from decennial Censuses and the American Community Survey (ACS) to verify that bonus has larger employment effects for workers whose occupations indicate they operate production capital. Overall, these checks limit concerns related to our identification strategy and suggest that our results measure the average effect of bonus on employment across the manufacturing sector.

A popular rationale for investment tax incentives is the belief that capital investment will raise productivity and workers' wages. We estimate that average earnings decreased by 2.7% at treated plants. Using QWI data, we show that bonus led to a relative increase in the shares of young, less educated, women, Black, and Hispanic workers. These composition shifts fully account for 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, though we do not find an increase in plant-level productivity, the policy did allow plants to increase their output.

We use our reduced-form results to estimate a structural model of factor demands that illuminates the economic mechanisms underlying the responses to the tax policy. We first implement the insight of Marshall (1890) and 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. We estimate that, by lowering costs of production, the policy increased the use of all inputs by 10% ($p < 0.001$) and that this scale effect was responsible for 90% of the overall effect of the policy on the demand for production workers. To a first-order approximation, the policy allowed plants to increase their scale; on average, plants did not replace workers with machines.

Our model shows that the elasticities of substitution between capital, production labor, and non-production labor are identified by our reduced-form estimates.[1] Using a Classical Minimum Distance approach, we estimate that the Allen elasticity of substitution between capital and non-production labor is close to 0.73.[2] 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 production labor of -0.44, implying that capital and production labor are complements.[3] We reject values greater than 0.13 for this elasticity of substitution at the 95% confidence level. In a series of empirical tests, we verify the complementarity of production labor and capital by showing that bonus increased investment more in plants with lower labor costs, as measured by plant-level unionization, location in a right-to-work state, and by local labor market concentration.

Finally, we show that our model estimates are robust to allowing for alternative policy mechanisms and to incorporating reallocation effects of the policy. First, we extend our model to allow for cash flow effects of the policy to impact labor demand. This extended model delivers similar

[1]Since the identifying variation is based on industry-level differences in the benefit of bonus, we estimate average elasticities of substitution across the manufacturing sector. As we discuss in Section 6, the benefit from bonus is not correlated with industry-level estimates of substitution elasticities.

[2]When production takes more than two inputs, there are multiple ways to define elasticities of substitution (Blackorby and Russell, 1981) and these elasticities may take negative values if inputs are complements (Hamermesh, 1996). Allen elasticities capture substitution between labor and capital relative to all other inputs. Our results are robust to using Morishima elasticities, which capture substitution between labor and capital relative to capital. We rely primarily on Allen elasticities because they separate substitution from scale effects.

[3]We show that these estimates are compatible with 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.

elasticities of substitution. Second, we show that accounting for reallocation to more capital intensive plants and industries does not substantively change our findings. Specifically, we estimate similar elasticities of substitution using industry-level data and we find similar aggregate measures of substitution using the model of Oberfield and Raval (2021).

Our results build on classic studies that 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). Using tax return data and modern causal inference methods, Zwick and Mahon (2017) made a substantial leap forward in our understanding of the effects of bonus depreciation. They showed the policy was very effective at stimulating investment, especially among small firms and those who saw immediate cash flow benefits. A subsequent literature also finds large effects of accelerated depreciation policies on investment (Ohrn, 2018, 2019; Maffini, Devereux and Xing, 2018; Fan and Liu, 2020; Guceri and Albinowski, 2021). Less attention has been paid to the effects of these policies on employment outcomes.[4,5]

This paper improves our understanding of the effects of bonus depreciation in a number of ways. While prior research studied short-term effects using consolidated firm-level data, our results capture the decade-long effects of bonus on individual production units. Our rich production data also allow for a more complete understanding of the effects of bonus on the manufacturing sector. In particular, we estimate novel responses to bonus depreciation, including on the accumulation of capital stocks, plant sales, total factor productivity, labor earnings, overall employment, employment for production and non-production workers, and workforce demographics.

Since bonus was implemented during a period of employment decline, we evaluate the concern that bonus simply props-up non-competitive plants or industries. Contrary to this concern, we find large employment effects on a balanced panel of plants, in new and younger plants that are more likely to grow, and in plants and industries with high capital and skill intensities, that are more likely to adopt robots, and that maintain an international comparative advantage. Overall, we find that the effects of bonus depreciation are concentrated on the plants and industries most likely to thrive in the 21st century.

[4]Zwick and Mahon (2017) estimate effects of bonus on payroll but not employment, Garrett, Ohrn and Suárez Serrato (2020) estimate regional employment effects, and Ohrn (2021) studies executive compensation. Tuzel and Zhang (2021) study the effects of state accelerated depreciation policies on computer purchases and the mix of occupational employment.

[5]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. LaPoint and Sakabe (2021) estimate responses to a geographically targeted Japanese version of bonus depreciation.

Our paper also contributes to the literature estimating elasticities of substitution between capital and different types of labor, which are fundamental economic parameters. Prior estimates suggest that capital and labor are highly substitutable, implying that policies that lower the cost of capital may increase income inequality (e.g., Zucman and Piketty, 2014).[6] Inequality may also increase if production workers are more substitutable with capital than non-production workers, as per the "capital-skill complementarity hypothesis" (Griliches, 1969; Goldin and Katz, 1998; Krusell, Ohanian, Ríos-Rull and Violante, 2000; Lewis, 2011). We contribute to this literature by using quasi-experimental variation in the cost of capital over a 10-year period, detailed plant-level data, and a multi-input structural model to estimate substitution elasticities between capital and different types of labor. Our estimates show that workers are not highly substitutable with machines and are not compatible with the capital-skill complementarity hypothesis.[7]

Our findings are consistent with the recent literature exploring the effects of technologically-advanced capital on labor demand. Multiple studies 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).[8,9] Hirvonen, Stenhammar and Tuhkuri (2022) find that, in response to a technology subsidy, Finnish firms increased their technologically-advanced capital and employment in the same way as we find that US firms responded to bonus depreciation. Aghion, Antonin, Bunel and Jaravel (2022*b*) find that French firms that invested in modern manufacturing capital and automation also increased their employment due to gains in productivity and consumer demand. Consistent with these studies, we show in heterogeneity analyses that bonus had larger employment effects in industries that were more likely to adopt industrial

[6] Recent studies focusing on a single type of labor include Karabarbounis and Neiman (2014), Doraszelski and Jaumandreu (2018), Raval (2019), Benzarti and Harju (2021), and Oberfield and Raval (2021). Chirinko (2008) concludes that this parameter is between 0.4 and 0.6. A recent meta-analysis yields an average estimate of 0.9 (close to Cobb-Douglas), but shows that correcting for publication bias lowers the estimate to 0.3 (Gechert, Havranek, Irsova and Kolcunova, 2021).

[7] Our results are consistent with the finding of Beaudry and Green (2003), that faster capital accumulation could have tempered the rise in income inequality experienced in the US since the 1980s.

[8] Using industry-level variation, Klenert, Fernandez-Macias and Antón Pérez (2020) show that the adoption of robots led to increases in employment without substantially changing the share of low-skill workers. Using similar methods, Graetz and Michaels (2018) conclude robot adoption did not decrease employment.

[9] Acemoglu and Restrepo (2020) and Dauth, Findeisen, Suedekum and Woessner (2021) 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. Acemoglu, Manera and Restrepo (2020) show that, due to bonus depreciation, the US tax code has increasingly favored capital over labor, raising the concern that bonus could reduce employment and wages. Garrett, Ohrn and Suárez Serrato (2020) find bonus depreciation increased employment in local labor markets suggesting capital investments stimulated by the policy, which may include robots, do not lead to similar effects. See Aghion, Antonin, Bunel and Jaravel (2022*a*) for a survey of research on the effects of automation on labor demand.

robots.[10,11]

Section 1 describes accelerated depreciation policies. Section 2 discusses our data sources. Sections 3 and 4 present our research design and results. We place our results in the context of the transforming US manufacturing sector in Section 5. Section 6 estimates our model of factor demands and Section 7 extends our model to explore the roles of reallocation and cash-flow effects of the policy. Section 8 concludes.

1 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.[12] 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 cost of equipment investment 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 depreciation policy referred to as §179 ("Section 179"), which allowed for full expensing of investment costs below a dollar limit.[13] Throughout the paper, we interpret our results as the combined effect of these policies.

[10] Benmelech and Zator (2022) show robots account for less than 0.3% of equipment investment worldwide during our sample period. That robots likely account for only a small amount of all capital investment stimulated by bonus likely explains the divergence between our results and those of Lewis (2011) that suggest workers without high school degrees are substitutes for automative technologies.

[11] A number of studies show that adoption of ICT increased the relative demand for "skilled" workers who typically engage in non-routine, cognitive tasks (Autor, Katz and Krueger, 1998; Autor, Levy and Murnane, 2003; Akerman, Gaarder and Mogstad, 2015; Gaggl and Wright, 2017). Interpreting our results in light of these findings suggests that bonus did not shift investment towards ICT or other types of skill-complementing capital.

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

[13] 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).

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 tax rate of 35% that purchases a computer for \$1,000, which would normally depreciate over five years.[14] 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 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 asset that is depreciated more slowly according to IRS rules (i.e., the barge) 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

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

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 capital that is depreciated more slowly according to IRS rules. 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 depending on the useful life of a specific asset.[15] 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 3, 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 2001 while the \$1,000,000 investment benefits in all years after 2002 with the exception of 2006 and 2007. The average bonus rate between 2001 and 2011 was 45%.[16] Using this bonus rate and estimates from Zwick and Mahon (2017) based on IRS data, we calculate that by increasing the

[15] 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. The assignment of class lives were initially intended to approximate average useful lives of assets, but the historical assignment was imperfect at the time and has not been regularly updated to reflect changes in manufacturing technologies.

[16] 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.

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 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) and Zwick and Mahon (2017) provide evidence that financing constraints help shape the response of investment to bonus depreciation.[17] The total impact of bonus on the cost of capital is therefore likely to significantly exceed the value of depreciation deductions alone.

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 6, we recover the implied effect of bonus on the cost of capital using our reduced form estimates that incorporate these factors.

After 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

[17] 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.

pandemic.[18] These trends highlight the importance of bonus depreciation and related policies in shaping investment and potentially labor demand in the 21st century.

2 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' 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 allows us to study how plants adjust production in response to the policy and our measure of output captures the scale effect 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

[18] 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).

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).[19] 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. 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.[20] Chen (2019) and Giroud and Rauh (2019) relied 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).

In a number of analyses, we 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 ex-

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

[20] 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).

plore 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. Third, 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.

Finally, we also use the NBER-CES Manufacturing Industry Database. These data rely on ASM/CM data to construct industry-level measures of employment and capital stocks. Relative to our balanced plant-level sample, our estimates using these data incorporate the effects of the policy inclusive of entry, exit, and reallocation across plants within industries.

3 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 benefited the most from bonus depreciation. We then describe our event study, difference-in-differences framework that uses this classification to identify how US manufacturing plants responded to the policy.

3.1 Treatment Variation in Bonus Depreciation

Recall from Section 1 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.[21] Relying on the z_0 distribution also captures variation in the cost of capital due to §179 expensing. Like bonus, §179 most benefits plants that invest in assets that are depreciated more slowly according to IRS tax rules.

[21] 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.

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 less-treated units.[22]

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.[23] 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, because their use is unaffected by the policy.

3.2 Empirical Specifications

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

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

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. The coefficients β_{1997} through β_{2011} describe the relative outcome changes 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

[22] 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 or when using the continuous variation in z_0.

[23] 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.

differences in z_0 are generated by the assignment of IRS depreciation schedules to different types of assets generally defined by their use rather than their useful lives. 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 a number 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 including state-by-year fixed effects and 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.[24] These controls ensure that the effects of bonus are not confounded by trends that affect plants or firms of different sizes or productivity. Finally, in Section 5, 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

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

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

[24] 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.

2002–2011.[25] 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).[26]

4 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 earnings per worker. Finally, we characterize how the policy affects plant output and productivity.

4.1 Investment and Capital Stock Responses

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 the validity of our empirical strategy. Second, log investment for the treated group jumps by nearly 10% 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.[27]

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

[26] Appendix C describes these interactions and shows that our results are generally robust to clustering at the industry level, which is more conservative.

[27] 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 a detailed comparison to earlier estimates.

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%.[28]

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. 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.[29] In sum, across all three investment outcomes we find large, positive, and statistically significant 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 bonus de-

[28]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."

[29]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 Figure A3.

preciation mostly applied to equipment investment during our period, 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 6, bonus may influence investment in structures through both a scale effect and a substitution effect.

4.2 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 effects 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, 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 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.[30] As we show in Panels (B) and (C) of Table 3, the point estimate of the effect of bonus on production employment is larger than that on non-production employment across all our specifications.[31] 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.[32] 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 2, 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.[33] Importantly, these aggregated data capture extensive margins of response, such as plant exit or entry, that our balanced panel omits by construction. Figure 4 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.[34] These results suggest that entry and exit margins do not substantially alter our estimates of the effects of bonus depreciation on employment.

[30] We follow Berman, Bound and Griliches (1994) in using the production/non-production task dichotomy in the ASM data when estimating labor demand. As we show below, we find similar results using Census data and task definitions related to manufacturing production in Acemoglu and Autor (2011).

[31] Using the DD specification in column (2), we reject the hypothesis that $\beta^{\text{Prod}} < \beta^{\text{Non-Prod}}$ with a p-value of 0.0214. We obtain a p-value of 0.14 for the same test using our LD estimates in column (6).

[32] Panels (A) and (B) of Figure A4 present event study graphs of the effects of bonus on production and non-production employment. 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.

[33] All QWI regressions are weighted according to 2001 state-industry employment.

[34] Column (1) of Table A4 reports corresponding regression coefficients.

Due to the balanced panel nature of our ASM/CM data, our baseline results are not representative of smaller or younger firms. Panel (A) of Figure A5 estimates the effects of bonus depreciation 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. 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.[35]

4.2.1 Additional Robustness Checks

Before analyzing the impact of bonus on labor earnings and productivity, we demonstrate the robustness of the effects on employment.[36] First, in Panel (A) of Figure A6, we also show that we obtain similar results using the continuous variation in z_0.[37] We also estimate the effects of bonus on employment using alternative treatment cutoffs. Panel (A) of Figure A7 shows that we find similar employment effects when we define treatment using the 25th and 40th percentiles of the z_0 distribution.

We now show that our results are robust to controlling for a number of potential confounding 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. To assess this possibility, we measure the share of each industry's output that is used in non-residential investment in 2001. In Panel (B) of Figure A7, we show that we find almost identical effects of bonus on employment when we include interactions of this measure with year fixed effects. Second, an additional concern is that plants that benefit most from bonus have different costs of capital, which could potentially bias our results. Panel (C) of Figure A7 shows that our results are robust to controlling for industry-level quintiles of

[35]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.

[36]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.

[37]Additionally, Panel (B) of 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.

effective interest rates from COMPUSTAT interacted with year fixed effects.

In Figure A8, we show that our results are not driven by growth in ICT intensive industries or "tech" industries. We use two separate measures of ICT intensity. First, we use BEA data to construct the share of ICT capital in the pre-period. Second, we use a measure of the share of workers engaging in ICT-related tasks during the period 2002–2016 from Gallipoli and Makridis (2018). Panel (A) shows that we continue to find large employment effects when controlling for tercile bins of either measure interacted with year fixed effects. In Panel (B), we present event study plots after dropping "tech" industries.[38] All three series of estimates continue to show bonus depreciation has a large and statistically significant effect on employment, suggesting growth in ICT-intensive or high-tech industries does not substantially bias our estimates.

The result that the employment effect of bonus is concentrated on workers that interact with machinery relies on correctly identifying production tasks. In Appendix F, we map occupation data from the decennial Census and the American Community Survey to the routine/non-routine and cognitive/non-cognitive classifications from Acemoglu and Autor (2011). As we show in Figure A9, when we use this definition of production occupations, we continue to find that bonus has larger effects on the employment of production workers, who are primarily engaged in routine, manual tasks. We also find large effects for all routine-task workers, further reinforcing the conclusion that the benefits of modern capital investments are not solely absorbed by professional workers (i.e., those in non-routine, cognitive occupations).

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 Figure A10, industries that benefit most from bonus 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 Table A6, we show that we obtain similar plant-level effects of bonus on employment and investment when we

[38] Based on Heckler (2005), "tech" industries have more than 25% of workers in technology oriented occupations.

additionally control for local exposure to bonus depreciation.[39] 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.

4.3 Labor Earnings

Policymakers often motivate the use 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 5 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.[40] 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. We use QWI data to show that this is the case. As in previous analyses using QWI data, we include state-by-industry and state-by-quarter fixed effects. In addition, we include flexible controls that ensure that our estimates are not contaminated by ongoing changes in the demographic composition of the manufacturing workforce during the period. Specifically, we include bins of changes in employment between 1997–2001 for a given demographic group at the state-industry-level interacted with year fixed effects.

Figure 6 presents event studies showing the effects of bonus on the employment of different demographic groups. Panel (A) presents two series of estimates, one for workers with a high school-level education or fewer years of education and another for workers with more than a high school-level education. This plot shows a stronger response for workers with fewer years of education. The difference-in-differences estimate on workers with fewer years of education is larger by 3.7 percentage points (p=0.001). These differential effects alter the composition of

[39] 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.

[40] We find a similar negative effect when we estimate the impact of bonus on average earnings using QWI data; see column (2) of Table A4.

the workforce, increasing the share of lower education workers by 1.0%.[41] Panel (B) of Figure 6 presents analyses for workers above and below 35 years of age. We estimate larger employment effects on younger workers. The employment effects of bonus are larger by 6 percentage points (p=0.004), which increases the share of younger workers by 3.8%. Panels (C) and (D) also show stronger and statistically distinct responses to bonus depreciation for women (relative to men) and for Black and Hispanic workers (relative to white workers). We also find that bonus increased the share of female workers by 3.2%, the share of Hispanic or Latino workers by 8.5%, and the share of Black workers by 1.6%. Overall, we find that bonus had larger employment effects for workers that are paid, on average, relatively less. These results provide the first piece of evidence that the estimated decrease in average earnings per worker may be due to changes in workforce demographics induced by the tax policy.

We now use two methodologies to show that the decrease in average wages is due to compositional changes in the workforce. 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. 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 employ workers with fewer years of formal education as well as more young, racially diverse, and female workers. Appendix I provides a detailed description of these analyses.

Overall, our results show that bonus depreciation did not increase average earnings per worker.[42] However, our employment results show that bonus depreciation disproportionately helped disadvantaged workers at a time when their employment prospects in the manufacturing

[41] Table A4 presents estimates of bonus on different demographic shares. For instance, column (3) of Table A4 shows that the fraction of workers with fewer years of education increased by 0.00259. We calculate the 1.0% increase by dividing this estimate by the base fraction of less educated workers of 25.3%.

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

sector were dwindling (Gould, 2018).[43]

4.4 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 7 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.[44] 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%.[45]

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 7 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 7 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. These findings suggest that bonus helped treated plants increase their overall scale. In Section 6, we show that the scale effect explains most of the capital and labor responses.

5 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

[43] Appendix F shows that the pattern of stronger employment effects for disadvantaged workers is most prevalent in production occupations (i.e., those primarily engaged in manual, routine tasks).

[44] We also rule out increases in labor productivity since the revenue effect does not exceed the effect on labor.

[45] 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 the tax policy and not by sector-level trends. Crucially, we explore whether bonus depreciation simply propped-up dying industries or whether it stimulated investment and employment in the industries most likely to thrive in the 21st century.

Charles, Hurst and Schwartz (2019) identify four main factors that led to significant transformation in the manufacturing sector between 2000–2017. First, they identify a marked increase in "skill intensity," as measured by the share of employment in non-production roles. Second, they note that this change is paired with an increase in "capital intensity," i.e., an increase in the share of productivity attributable to capital. The last two factors are the dramatic increase in import competition from China (e.g., Autor, Dorn and Hanson, 2013; Acemoglu, Autor, Dorn, Hanson and Price, 2016; Autor, Dorn and Hanson, 2016; Pierce and Schott, 2016) and the increased adoption of automated production processes (e.g., Acemoglu and Restrepo, 2020).[46]

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 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 of 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 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

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

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.[47] 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.[48]

While our estimated effects of bonus depreciation are not generated by the major drivers of transformation in the manufacturing sector, it is still important to understand our results given this context. As Charles, Hurst and Schwartz (2019) note, the US manufacturing sector lost 5.5 million jobs from 2000-2017. Figure A11 helps place our estimates in this context by comparing the magnitude of the effects of bonus depreciation to aggregate trends (see Appendix H for details). This figure shows that, while bonus attenuated the employment decline, it also stimulated positive growth in capital accumulation.

This context motivates the salient policy concern that bonus depreciation simply props-up non-competitive plants or industries. Contrary to this hypothesis, a number of our results suggest that the policy stimulated absolute increases in capital investment and labor demand for some plants. First, recall that we find that new and young firms—which are more likely to be growing—also respond to bonus depreciation by increasing employment. Second, our baseline results rely on a balanced sample of plants that survive through our analysis period. Whether bonus propped-up these plants is therefore not at the core of these results. Finally, the fact that we find similar results on our balanced sample of plants and when using the aggregate QWI data suggests that plant deaths are not a major component of the employment responses we observe.

To more directly explore this hypothesis, we estimate whether bonus had larger effects on plants and industries that are least likely to thrive in the future. We implement this analysis by including 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

[47] 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 4.3.

[48] 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.

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.[49] 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 benefit the most from accelerated depreciation policies.

Column (3) of Table 6 estimates interaction effects of bonus and import competition. Increased import competition depresses the effects of bonus depreciation on both investment and employment. These results are intuitive; investment incentives have the least impact on 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.

The results of Table 6 show that bonus depreciation did not simply prop-up non-competitive industries. Instead, we find that the policy has the largest impacts on the plants and industries that are 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 the US manufacturing sector.

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

6 Estimating Factor Demands Using Tax Policy Variation

While our reduced-form results yield novel insights into the effects of one of the largest tax incentives for investment in US history, these results alone are not sufficient to understand the economic mechanisms by which the policy impacts capital accumulation and labor demand. We uncover these mechanisms by estimating a structural model of factor demands. We incorporate 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 allows us to estimate the relative importance of these mechanisms. The model also allows us to recover the implied effects of the policy on the cost of capital, which we use to compute cost of capital elasticities of capital and labor demand inclusive of financing and other constraints. Finally, the model leverages tax policy variation to estimate elasticities of substitution between capital and different types of labor.

6.1 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 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). Bonus depreciation lowers the cost of capital, which we denote by $\phi \equiv \frac{\partial \ln(\text{Cost of Capital})}{\partial \text{Bonus}} < 0$.[50] ϕ includes both the increased present value of depreciation deductions and reductions in financing and other frictions.[51] Since our identification strategy relies on cross-industry variation, our estimates of substitution elasticities capture the average value

[50] 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); Basu, Kim and Singh (2021) show that capital goods prices did not increase in response to bonus depreciation.

[51] Appendix J.3 provides a model consistent with Myers (1977); Bond and Meghir (1994); Bond and Van Reenen (2007) that shows that interactions with financing frictions amplify the effect of bonus on the cost of capital, ϕ. An alternative assumption is that bonus both lowers the cost of capital and provides additional cash flow that relaxes a financing or capacity constraint, which directly impacts labor demand. In Appendix J.4, we extend our model to allow for this possibility and show that our results are robust to allowing for cash flow effects.

across the manufacturing sector.[52] Appendix J provides a detailed derivation of the model.[53]

These simple assumptions allow us to characterize the effects 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. 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. Both the scale and substitution effects depend on the degree to which bonus lowers the overall cost of capital, including financing and other frictions. We therefore interpret ϕ as the experienced reduction in the cost of capital inclusive of these frictions.

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

[52] A potential concern is that industries with lower elasticities of substitution (σ_{KL}) benefit more from bonus. This concern is unlikely to impact our estimates since Table 5 and Figure A8 show that our reduced-form results are not sensitive to (1) controlling for capital intensity, (2) controlling for industry trends in ICT adoption, or to (3) removing high-tech industries, which are short duration industries with potentially high degrees of substitution. In addition, Panel (A) of Figure A12 shows that the benefit from bonus, z_0, is uncorrelated with industry-level estimates of σ_{KL} from Raval (2019). Panel (B) further shows that we obtain similar effects on employment when we control for differential trends based on these industry-level estimates of σ_{KL}.

[53] 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.

complements, i.e., $\sigma_{KL} < 0$, or when the scale effect dominates the substitution effect, i.e., $\eta > \sigma_{KL} > 0$. Finally, consider the model's prediction of the effect of bonus on plant sales

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

Equation 6 shows that the effect of bonus on revenue combines a price decrease of $s_K\phi$ with an increase in the quantity sold of $-\eta s_K \phi$.

As Blackorby and Russell (1981) discuss, there are alternative ways to define substitution elasticities when production takes more than two inputs. The elasticities of substitution in Equations (3)–(5) are Allen partial elasticities, which capture substitution between capital and a given input, relative to all other inputs. Our analyses require Allen elasticities for a number of reasons. First, they allow us to separate the scale and substitution effects of the policy and determine whether inputs are complements or substitutes.[54] Second, this framework provides a transparent link between our reduced-form estimates from Section 4 and the four model parameters that determine factor demands $\theta = (\sigma_{KL}, \sigma_{KJ}, \eta, \phi)$, which include the Allen elasticities. Third, as we show below, Allen elasticities allow us to isolate the effect of the policy on the cost of capital, ϕ, which we use to calculate demand elasticities for a given input J as follows: $\varepsilon^J_\phi = \frac{\beta^J}{\phi}$. Finally, by isolating ϕ and demand elasticities, Allen elasticities allow us to compute the Morishima elasticity (Blackorby and Russell, 1989). This alternative measure captures substitution between capital and production labor, relative to capital, and can be calculated as: $\sigma^M_{KL} = \varepsilon^L_\phi - \varepsilon^K_\phi$.

6.2 Separating Scale and Substitution using Reduced-Form Estimates

We first use the model to decompose the effects of bonus depreciation on labor demand into scale and substitution effects. To do so, 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}, the symmetry of Allen elasticities (i.e., that $\sigma_{KL} = \sigma_{LK}$) implies 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 3–6, $-s_K\eta\phi$. Intuitively, the scale

[54] 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, $s_J\sigma_{KJ} + s_L\sigma_{KL} > 0$.

effect captures the common increase in the use all inputs, absent substitution effects. Constant returns to scale implies that the increase in quantity sold also equals the scale effect.

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 using the ten-year effects of the policy.[55] Assuming that the input cost shares are $s_K = 0.2$, $s_L = 0.5$, 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 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.[56]

We now express elasticities of substitution as functions of our reduced-form moments and the elasticity of product demand, η. Taking the ratio of Equations 4 and 7 implies that

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

Input L is a substitute for capital ($\sigma_{KL} > 0$) when the effect of the policy on labor demand β^L is smaller than the scale effect $\bar{\beta}$. Conversely, L complements capital ($\sigma_{KL} < 0$) when $\beta^L > \bar{\beta}$.

Panel (B) of Table 7 reports estimates of substitution elasticities under different assumed values for the cost shares and demand elasticity. Column (1) shows that $\sigma_{KL} = -0.515$ when the elasticity of product demand $\eta = 3.5$.[57] Columns (2)–(5) report estimates that vary the capital cost share $s_K \in [0.10, 0.30]$ or the demand elasticity $\eta \in [2, 5]$. We consistently estimate that $\sigma_{KL} < 0$, implying that production labor complements capital. This result follows from the fact that bonus increased the use of production labor by 11.6%, which is greater than the 10% scale effect. In contrast, since the estimated increase in non-production labor is smaller than the scale effect, we estimate that non-production labor and capital are substitutes ($\sigma_{JK} > 0$). Therefore, our results are not compatible with the capital-skill complementarity hypothesis.[58]

[55] We use the following estimates in this calculation: β^K from column (1) in Table 2, and β^L and β^J from columns (6) of Panels (B) and (C), respectively, in Table 3.

[56] 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.

[57] 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.

[58] Griliches (1969) defines the capital-skill complementarity hypothesis using Allen elasticities of substitution as follows: $\sigma_{KL} > 0$, $\sigma_{KL} > \sigma_{KJ}$, and $\sigma_{KL} > \sigma_{LJ}$. Appendix K.1 shows that Allen elasticities of substitution can be used to estimate the parameters of a translog cost function (Christensen, Jorgenson and Lau, 1971, 1973). Our estimates are therefore consistent with models of production that allow for flexible patterns of substitution.

Panel (C) of Table 7 formally evaluates the hypothesis that capital complements labor. We reject the null hypothesis that $\sigma_{KL} \geq 0$ with p-values ranging from 0.047 to 0.099, depending on the values of s_K and η. Because the effect of bonus on non-production labor is close to $\bar{\beta}$, we do not reject the hypothesis that non-production workers complement capital, even though these effects are precisely estimated.

The discussion above clarifies that the 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 10% scale effect was responsible for close to 90% of the 11.6% total effect of the policy. The fact that the scale effect of the policy dominates the substitution effects we estimate allays concerns that bonus depreciation led plants to replace workers with machines.

Panel (D) of Table 7 presents estimates of the effect of bonus on the cost of capital, ϕ, and elasticities of capital and labor demand with respect to the cost of capital. Inverting Equation 7 implies that $\phi = -\frac{\bar{\beta}}{s_K \eta}$. Under our baseline parameterization, we estimate a semi-elasticity of the cost of capital with respect to bonus of $\hat{\phi} = -0.145$. This estimate reveals that—inclusive of interactions with financing and other frictions—bonus depreciation has a large effect on the cost of capital. Our estimate of ϕ then implies an investment elasticity of $\hat{\varepsilon}^I_\phi = \frac{\hat{\beta}^I}{\hat{\phi}} = -1.40$.[59]

An advantage of our setting is the ability to estimate demand elasticities for capital stocks and for different types of labor. We estimate an own-price capital demand elasticity of $\hat{\varepsilon}^K_\phi = -0.55$ and cross-price elasticities of production labor of $\hat{\varepsilon}^L_\phi = -0.80$ and non-production labor of $\hat{\varepsilon}^J_\phi = -0.62$.[60] These relatively modest elasticities reinforce the importance of estimating ϕ inclusive

[59] This estimate uses the long difference estimate on investment from Panel (A) of Figure 2. We relate this value to recent estimates from the literature in Appendix K.2 and show that it has a similar magnitude to estimates that account for interactions between tax policies and financing and other frictions.

[60] Appendix K.4 explores the dynamic patterns underlying these estimates. Panel (A) of Figure A14 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.

of financing and other frictions. Appendix K.2 discusses these elasticity estimates further.

Finally, these demand elasticities also allow us to estimate Morishima elasticities of substitution. Table A12 reports that $\hat{\sigma}^M_{KL} = \hat{\varepsilon}^L_\phi - \hat{\varepsilon}^K_\phi = -0.25$ (SE=0.14), which shows that the result that production labor complements capital is robust to using the Morishima elasticity. This estimate rejects the null hypothesis that $\sigma^M_{KL} \geq 0$ with a p-value=0.04. We also estimate a Morishima elasticity between non-production labor and capital of $\hat{\sigma}^M_{KJ} = \hat{\varepsilon}^J_\phi - \hat{\varepsilon}^K_\phi = -0.07$ (SE=0.19). To show that our results are consistent with a standard model of production, Appendix K.3 uses these elasticities to estimate the parameters of a nested CES production function that nests non-production labor separately from other inputs.

6.3 Structural Estimation of Capital-Labor Substitution

We now refine our estimation of capital-labor substitution elasticities in three ways. First, we jointly estimate the parameters of the model. Second, we incorporate the prediction of our model for the effect of the policy on plant revenue as an over-identifying moment. Finally, we ensure that the estimated parameters are consistent with axioms of cost-minimization. We incorporate these refinements by estimating our structural model via Classical Minimum Distance (CMD).

6.3.1 Identification and Estimation Approach

To identify η, first note that Equations 6 and 7 imply that $\beta^R = \frac{\eta-1}{\eta}\bar{\beta}$. Solving for η yields

$$\eta = -\frac{\bar{\beta}}{\beta^R - \bar{\beta}}. \tag{9}$$

The intuition for this expression is as follows. The effect of bonus on quantity sold is given by the scale effect since $\frac{\partial \log q}{\partial \text{Bonus}} = -\eta s_K \phi = \bar{\beta}$. The effect on prices can be decomposed from the revenue and quantity effects. Specifically, the plant lowers its price by $\frac{\partial \log p}{\partial \text{Bonus}} = s_K \phi = \beta^R - \bar{\beta}$. Equation 9 then shows that the elasticity of product demand η is the ratio of the percentage changes in quantity and prices.[61]

Equations 7 and 9 imply that $\phi = -\frac{(\bar{\beta}-\beta^R)}{s_K}$. To understand the identification of ϕ, note that the constant demand elasticity η implies that $\frac{\partial \log p}{\partial \text{Bonus}} = \frac{\partial \log \text{Unit Cost}}{\partial \text{Bonus}}$. Therefore, ϕ is identified by scaling-up the effects on prices (i.e., $\frac{\partial \log p}{\partial \text{Bonus}} = \beta^R - \bar{\beta}$) by the capital cost share, s_K.

[61]Combining Equations 8 and 9, we have that $\sigma_{KL} = \frac{\bar{\beta}-\beta^L}{\bar{\beta}-\beta^R}$. A similar expression identifies σ_{KJ}.

Having identified each of the model parameters with the reduced-form estimates, we now discuss how we estimate the model using CMD. 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.[62]

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).

6.3.2 Estimated Parameters

To highlight the intuition behind our model, we present structural estimates of σ_{KL} graphically in Panel (A) of Figure 8 as a function of different values of η. The dot-dashed blue line plots Equation 8, 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 $\eta = 3.076$ 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 plots Equation 8 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.

Panel (A) of Table 8 reports estimates of σ_{KL} as well as all other model parameters across a range of model specifications. Our baseline estimate of σ_{KL} in column (1) equals -0.44. While this point estimate indicates that capital and production labor are complements, the full model estimates imply that 89% of the effect of bonus on production labor is due to the scale effect. The complementarity between these inputs is responsible for the remaining 11%. Panel (B) of

[62] In practice, $\hat{W}$ equals 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 $[H(\hat{\theta})'\hat{V}^{-1}H(\hat{\theta})]^{-1}$, 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 $H(\hat{\theta})$.

Figure 8 plots the probability that $\hat{\sigma}_{KL}$ exceeds a given value. We reject values of σ_{KL} that are greater than 0.13 at the 95% confidence level.[63] Relative to prior estimates (e.g., Krusell, Ohanian, Ríos-Rull and Violante, 2000; Karabarbounis and Neiman, 2014), our findings allay the concern that bonus depreciation led plants to replace workers with machines. Columns (2)–(3) of Panel (A) of Table 8 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, $\sigma_{KJ} > 0$.

To gain intuition for these results, note that they follow directly from the fact that our estimates in Section 4 are such that $\hat{\beta}^{\text{L}} > \hat{\bar{\beta}} > \hat{\beta}^{\text{J}}$. 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 stock by 15.5%, which is twice as large as our estimated effect. 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.[64]

We briefly discuss additional robustness checks of our model; see Appendix K.5 for details. Column (2) of Table A14 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 types of labor. Columns (5)–(6) show that we estimate similar elasticities 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.[65]

[63] This figure also shows that we draw similar conclusions using models that only include capital and labor (orange line) or that separate capital into equipment and structures.

[64] Table A15 shows that we obtain qualitatively similar results when we do not impose this constraint.

[65] Our baseline results are based on our LD estimates and allow plants to adjust their production over a 10 year period. Figure A15 explores the dynamics of capital-labor substitution. This figure shows that capital and labor are initially very complementary ($\sigma_{KL} \ll 0$). Over time, σ_{KL} tends toward our 10 year elasticity of -0.44. 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.

6.4 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.[66] We test for heterogeneous responses by three proxies for lower labor costs: plant-level unionization, location in a right-to-work (RTW) state, and local labor market power. Our measure of "Union" is an indicator that equals 1 when more than 60% of workers at a plant are unionized.[67] RTW is an indicator equal to 1 for plants in RTW states (as of 2001), where employees have less bargaining power.[68] We measure labor market concentration using a NAICS 3-digit, commuting zone level Herfindahl-Hirschmann Index (HHI) based on 2001 market conditions.[69] In plants that operate in local labor markets that are highly concentrated, monopsony power may allow employers to set lower wages (see, e.g., Robinson, 1969; Manning, 2021).

Table 9 presents difference-in-differences estimates of the effects of bonus on investment, employment, and mean earnings that include interactions between bonus and each of these proxies for 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 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 the results from our empirical model of factor demands. Further, these analyses highlight how labor market institutions can impact capital investment.

[66]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).

[67]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.

[68]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.

[69]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).

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.

Overall, the model of factor demands estimated in this section delivers a number of economic insights. 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 full model estimates rule out values of σ_{KL} greater than 0.13. Fourth, our estimates are compatible with standard production models. Finally, the model delivers testable predictions, which validate the complementarity between capital and labor.

7 Robustness of Model Estimates

In this section we extend our model to also allow for potential cash flow effects of the policy to relax financing or capacity constraints. Allowing for cash flow effects to directly impact labor demand yields similar model estimates. We also explore whether bonus led to significant reallocation toward more capital intensive plants and industries. Incorporating these forces delivers quantitatively similar results to our baseline model estimates.

7.1 Incorporating Cash-Flow Effects

As we discuss in Section 1, a particular feature of bonus depreciation is that it creates cash flows for firms that purchase large amounts of physical capital. These additional cash flows may impact the demand for all inputs, especially labor or other inputs that are harder to finance.

In Appendix J.4, we extend our model to allow for bonus to both lower the cost of capital and to increase cash flows. In this extended model, σ_{KL} is now identified by:

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

where $\chi \geq 0$ captures the importance of the bonus depreciation cash flows relative to the decrease in overall input costs due to the policy. Just as in Equation 8, when we allow for cash-flow effects, the identification of σ_{KL} depends on the relative size of the increase in the use of production labor and the scale effect. The intuition for this result is that the scale effect is now governed by the extent to which the cash flows generated by the policy relax financing constraints.

Since we estimate that $\beta^L > \bar{\beta}$, Equation 10 shows that the cash flow adjusted model continues to produce estimates of $\sigma_{KL} < 0$. At the extreme, where $\chi = 0$ and there are no cash flow effects, we estimate that $\sigma_{KL} = -0.15$. As cash flow effects become more important, we find increasing degrees of complementarity between capital and production labor. Table A16 presents estimates of σ_{KL} using our baseline estimates of $\bar{\beta}$ and ϕ to calibrate χ. Across various parameterizations, we find estimates of σ_{KL} that are very similar to those presented in Table 7. This analysis shows that the result that capital and production labor are complements is robust to explicitly modelling the cash-flow effects of bonus.

7.2 Reallocation and Aggregation

Our estimates of elasticities of capital-labor substitution rely on plant-level data on employment and production. By relying on a balanced panel of plants, our estimates ensure that we compare how a stable group of plants combine capital and labor in response to changes in the cost of capital investment. While this is the right estimate for plant-level behavior, it does not account for reallocation across plants and industries or entry and exit. Intuitively, one may find larger aggregate elasticities of substitution if a reduction in the cost of capital leads new firms, or smaller firms that are underrepresented in our balanced sample, to adopt more capital-intensive forms of production. Similarly, a reduction in the cost of capital may lead to a reallocation of business activity toward plants and industries that are more capital intensive.[70] This section describes two ways in which we gauge the quantitative importance of these forces.

7.2.1 Industry-Level Estimates of Substitution Elasticities

First, to account for the roles of reallocation and entry and exit, we now estimate our structural model using the NBER-CES Manufacturing Industry Database. Table A17 shows the reduced-form effects of bonus on capital and production and non-production labor. As with our plant-level results, we find significant increases in the use of all inputs and that the effect on production employment is larger than the effect on capital. Appendix K.6 discusses how we use these results

[70] In a classic paper, Houthakker (1955) showed that when this reallocation effect is substantial, plants with Leontief production functions can aggregate to a Cobb-Douglas production function at economy level.

to estimate the industry-level counterparts of our plant-level models. Table A18 reports the implied scale effect of the policy and elasticities of capital-labor substitution using the industry-level data. Across all model specifications, we find very similar substitution elasticities and we estimate a capital-production labor elasticity of substitution $\sigma_{KL} = -0.59$ in our baseline specification. Because the data underlying these estimates account for entry and exit and for reallocation within industries, the fact that we estimate a similar value of σ_{KL} as when we use plant-level data indicates that reallocation and entry and exit within industries are quantitatively unimportant for our estimate of σ_{KL}.[71] These results are consistent with our results in Figure A5 showing that bonus stimulated employment growth in new and younger firms as well as with our results in Figure 4, which show that bonus had similar employment effects at the state-industry level of aggregation as at the plant level.

7.2.2 Aggregate Elasticities of Substitution

We now address the concern that the policy may lead to reallocation of business activity toward industries that are more capital intensive. If this were the case, our estimates of elasticities of substitution based on plant- or industry-level data could lead us to underestimate the degree of capital-labor substitution at the economy-wide level. Oberfield and Raval (2021) develop a method to account for this reallocation that relies on the dispersion in capital intensity across plants and industries and on output elasticities of substitution.

The method of Oberfield and Raval (2021) is based on nested CES production functions. We estimate the parameters of a nested CES production function in Appendix K.3. Our plant-level results yield an implied (Morishima) elasticity of substitution between capital and production labor from our plant-level estimation of -0.248 (SE=0.141) (see Table A13). To account for within-industry reallocation, we re-estimate this same implied elasticity using the model results that rely on NBER-CES industry-level data presented in Table A18. We estimate an equivalent elasticity at the industry-level of -0.264 (SE=0.213) (see Table A19). The similarity of the plant- and industry-level elasticity estimates reinforces the conclusion that within-industry reallocation is not a substantial margin of response to bonus depreciation.

We now implement the method of Oberfield and Raval (2021) to map our industry-level estimates to an aggregate elasticity that further accounts for cross-industry reallocation.[72] Table

[71] As with our plant-level results, we also find that the scale effect is the main driver of the effects of the policy.

[72] This method accounts for reallocation using an estimate of substitution between industries and a measure of

A20 presents our aggregate elasticity estimates. Across all parameterizations, our point estimates are consistent with complementarity between capital and production labor. Our baseline parameterization yields an estimate of this aggregate elasticity of substitution of -0.186 (SE=0.199), which rejects values greater than 0.14 at the 5% level.

Overall, this section shows that our main results are not sensitive to whether cash flow effects of the policy directly impact labor demand and that incorporating plant entry and exit and reallocation within and across industries does not have large quantitative effects on our estimates of how capital and production labor jointly respond to bonus depreciation.

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. This paper combines tax policy variation from bonus depreciation with confidential data to gain empirical leverage on this debate. We show that both capital and labor increased in response to the policy.

Our results document several previously unexplored 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. While bonus depreciation did not affect plant productivity, it did lead manufacturing plants to increase their scale.

We also find that bonus depreciation was less effective at stimulating manufacturing activity for industries that were more exposed to import competition from China. Bonus was also more effective at plants with high degrees of capital and skill intensity. Finally, we reject the hypothesis that bonus decreased employment in industries that were highly exposed to robotization; in fact, 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 grow in industries that are at a comparative disadvantage.

Using a structural model, we separate the scale and substitution effects induced by the policy. Because bonus lowered costs of production, the policy led to a large and statistically significant

the dispersion in capital intensity across industries. See Appendix K.7 for additional details.

scale effect. 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 capital investment stimulated by 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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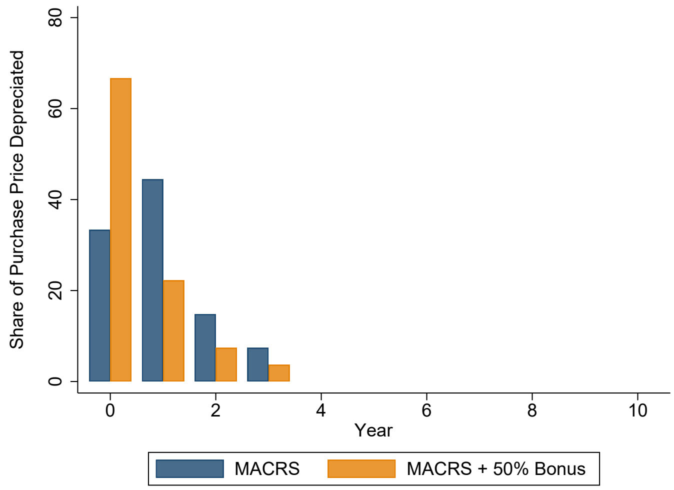
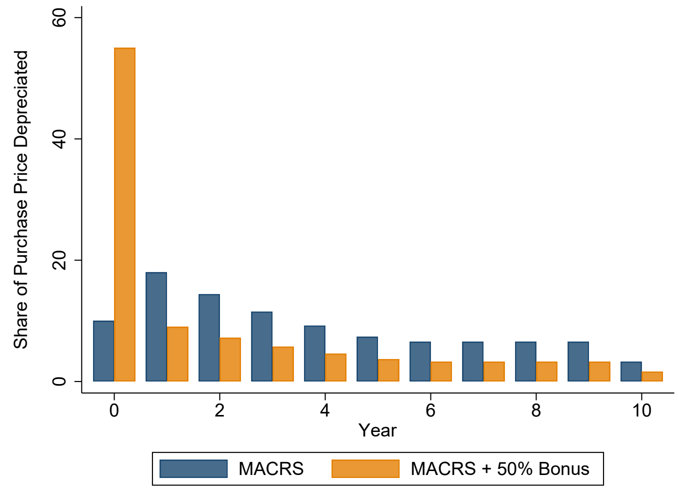
Figure 1: Bonus Depreciation Policy and Specific MACRS Assets

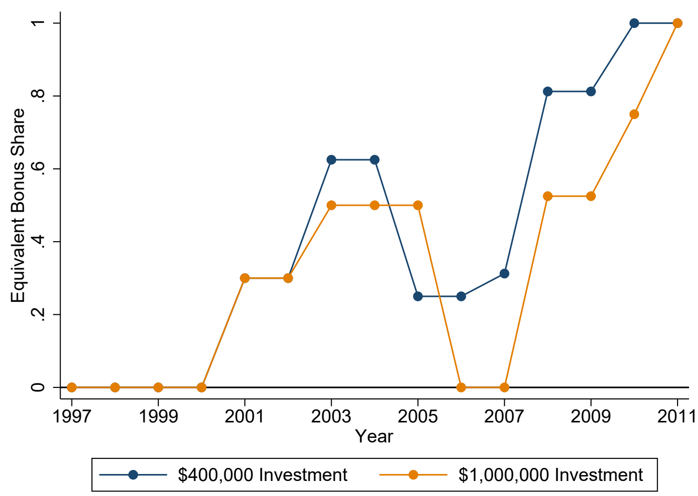
(A) 50% Bonus on 3-Year MACRS Assets



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



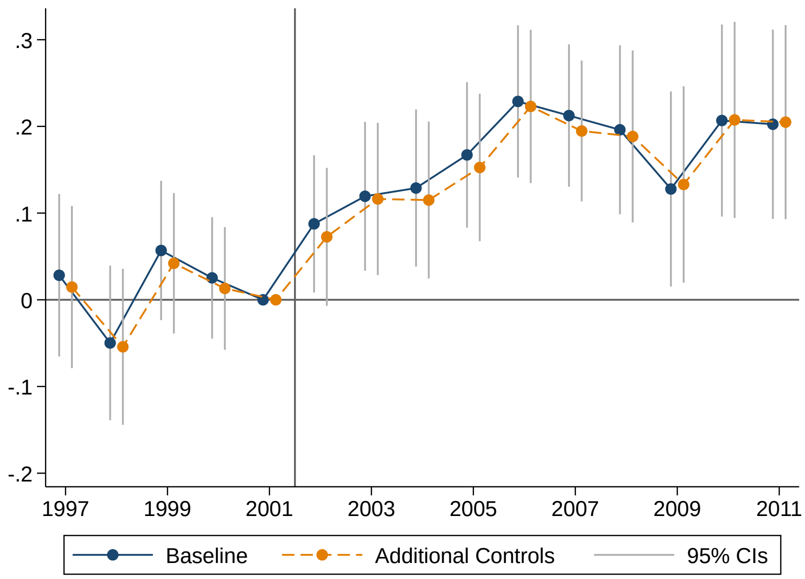
(C) Timing of Accelerated Depreciation Policies



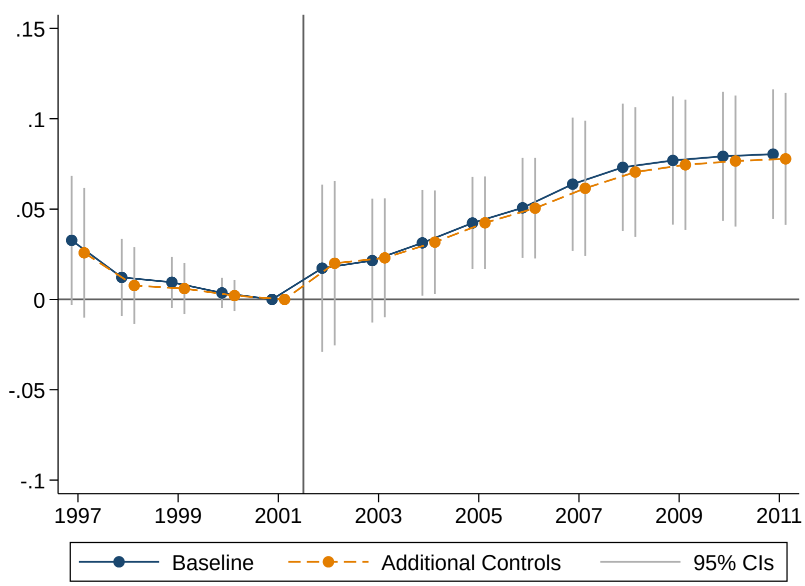
Notes: Panels (A) and (B) of Figure 1 show how 50% bonus changes the depreciation schedule for a 3-year asset and a 10-year asset, respectively. See Appendix B for further explanation of these calculations. The bonus depreciation provision has a larger effect on the deduction schedule for a firm that invests in more assets that are depreciated more slowly for tax purposes. Panel (C) 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 benefiting from §179 expensing starting in 2003. *Source:* Panels (A) and (B), authors' calculations based on IRS (2002) data. Panel (C), authors' calculations based on the statutory §179 and bonus rates explained in Kitchen and Knittel (2016).

Figure 2: Effects of Bonus Depreciation on Capital Investment

(A) Log Investment

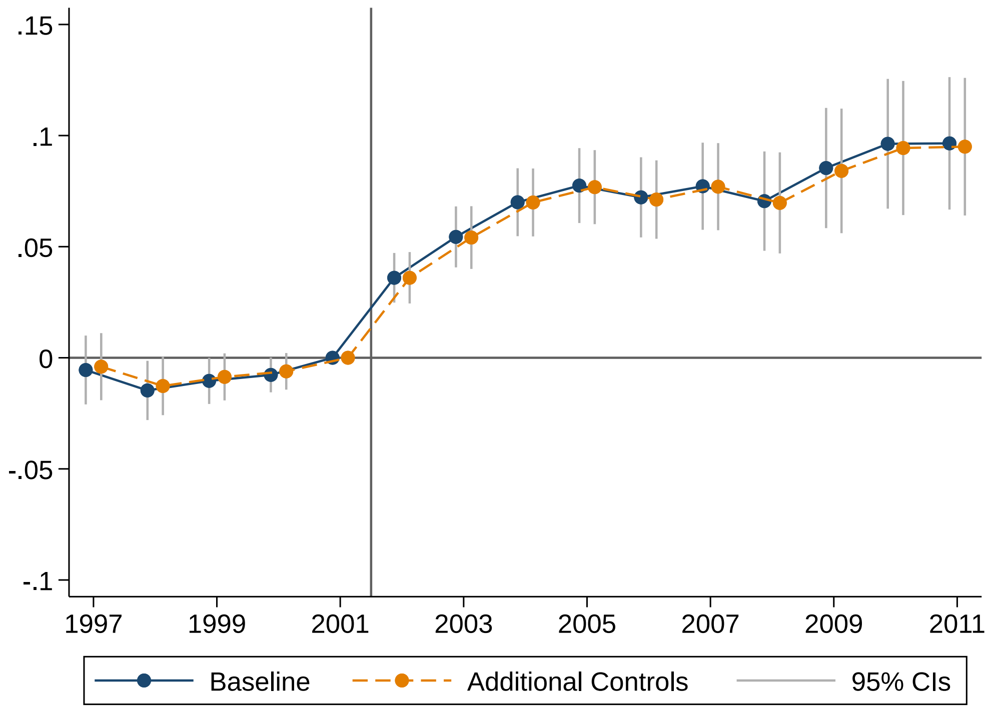


(B) Log Total Capital



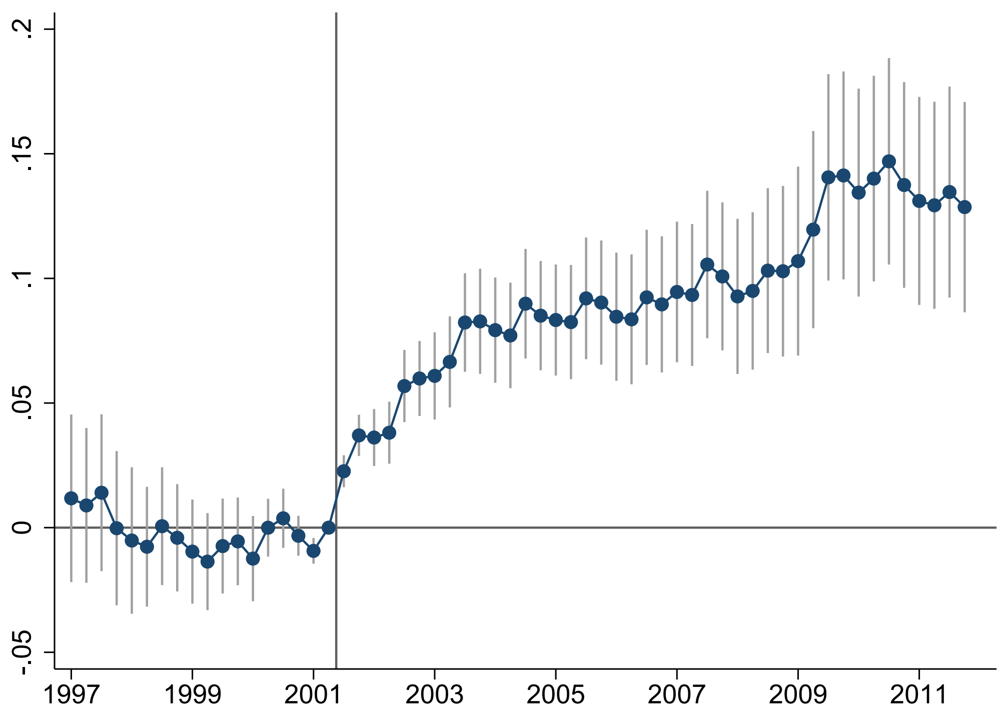
Notes: Figure 2 displays estimates describing the effect of bonus depreciation on log investment in Panel (A) and log total capital in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with bonus. The baseline specification in each panel 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, CM, 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, CM, and Zwick and Mahon (2017) data.

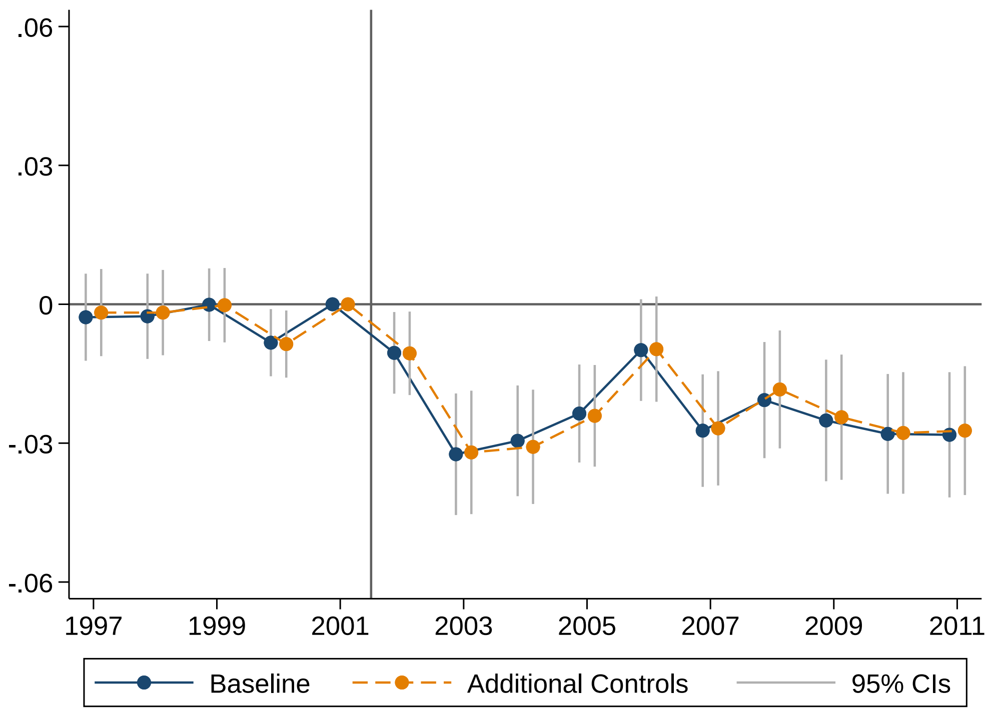
Figure 4: Effects of Bonus Depreciation on Log Employment; QWI Data



Notes: Figure 4 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 A4. 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.

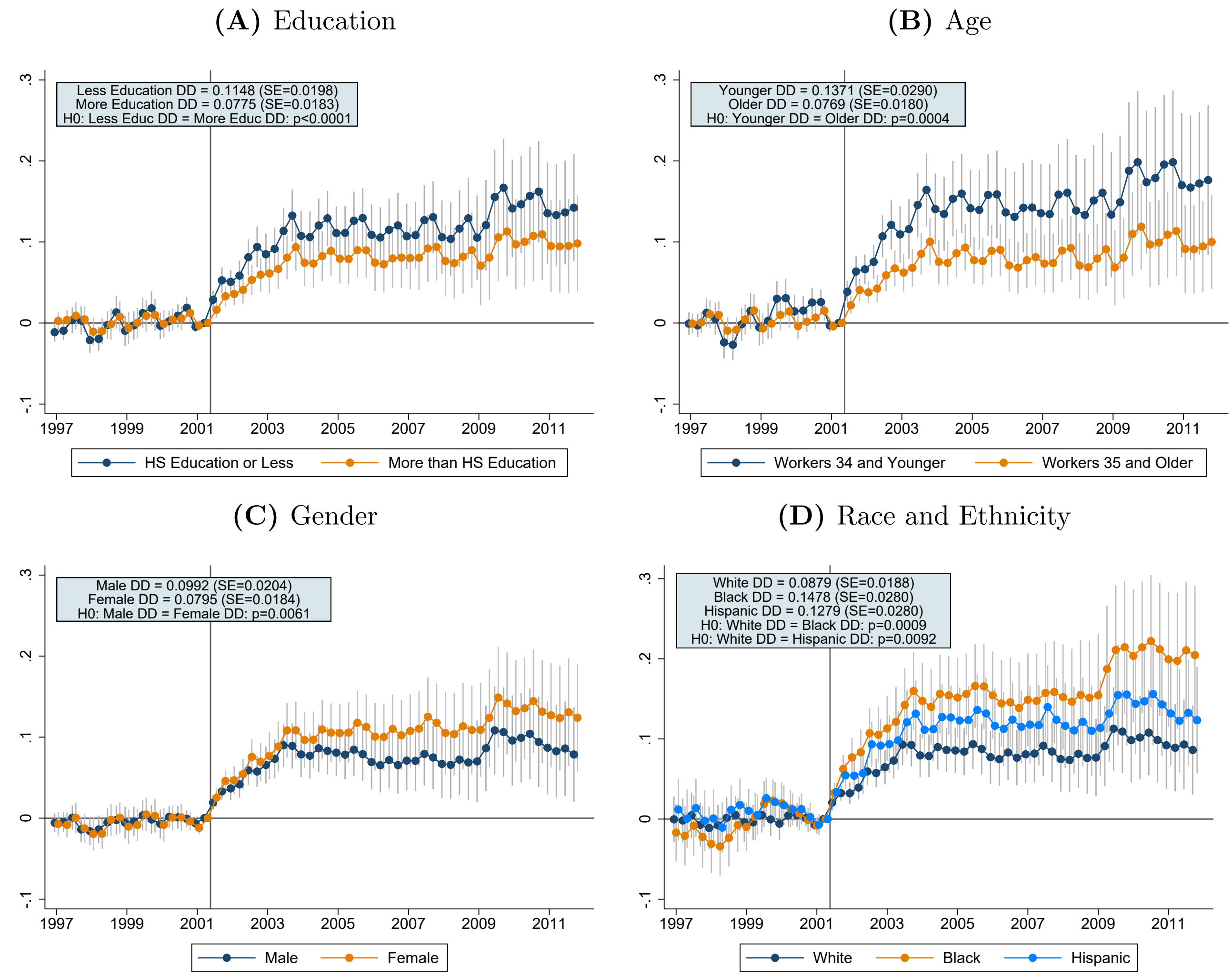
Figure 5: Effects of Bonus Depreciation on Earnings Per Worker

(A) Log Mean Earnings per Worker



Notes: Figure 5 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, CM, and Zwick and Mahon (2017) data.

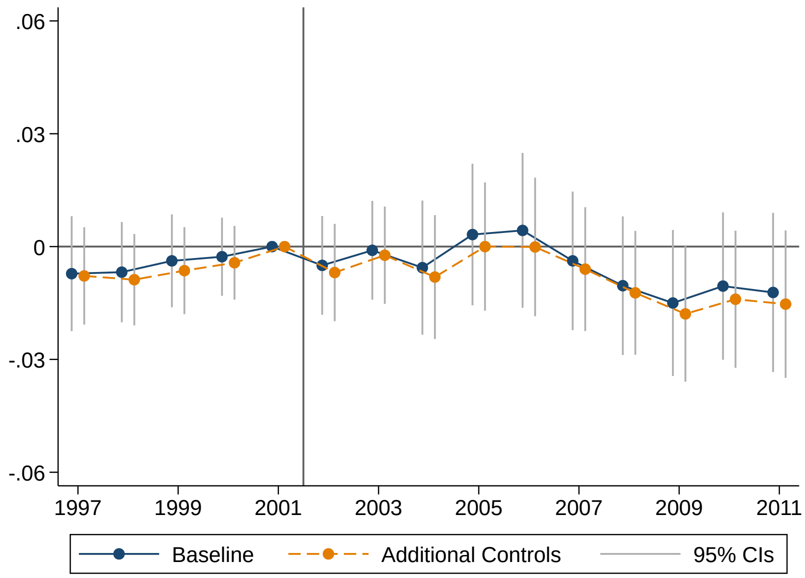
Figure 6: Effects of Bonus Depreciation on Employment by Demographic Group



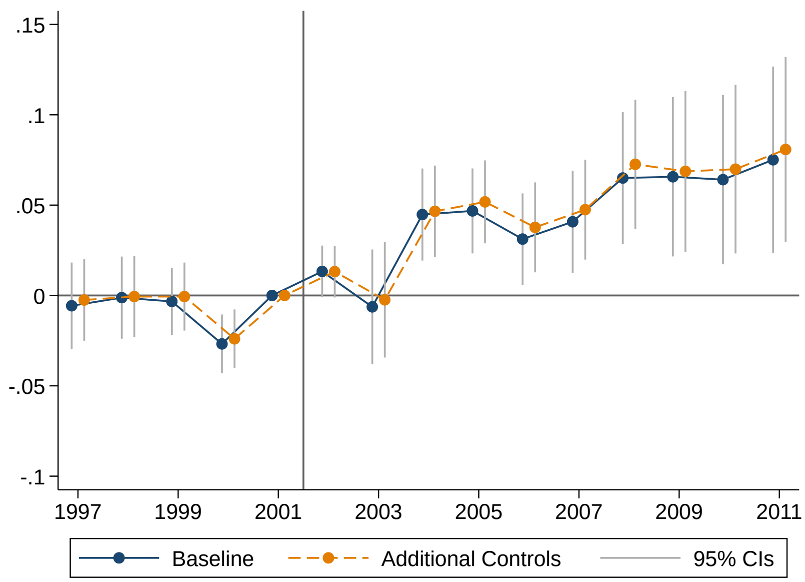
Notes: Figure 6 displays estimates describing the effects of bonus depreciation on log employment for a number of demographic subgroups using QWI data. Panel (A) shows effects separately for workers with high school education or less and for workers with more than high school education. Panel (B) shows effects separately for workers 35 years of age and younger and 36 and older. Panel (C) shows effects separately for men and women. Panel (D) presents separate effects for white, Black, and Hispanic workers. All specifications used for each panel include 4-digit NAICS-by-state fixed effects, state-by-quarter fixed effects and controls for industry-level pre-period trends in employment for the focal group. 95% confidence intervals are included for each annual point estimate with standard errors clustered by the 4-digit NAICS-by-state level. The text box in each panel reports the associated DD estimates for each subgroup as well as the p-values from hypothesis tests comparing DD estimates for different subgroups. *Source:* Authors' calculations based on QWI and Zwick and Mahon (2017) data.

Figure 7: Effects of Bonus Depreciation on Productivity and Production

(A) Total Factor Productivity



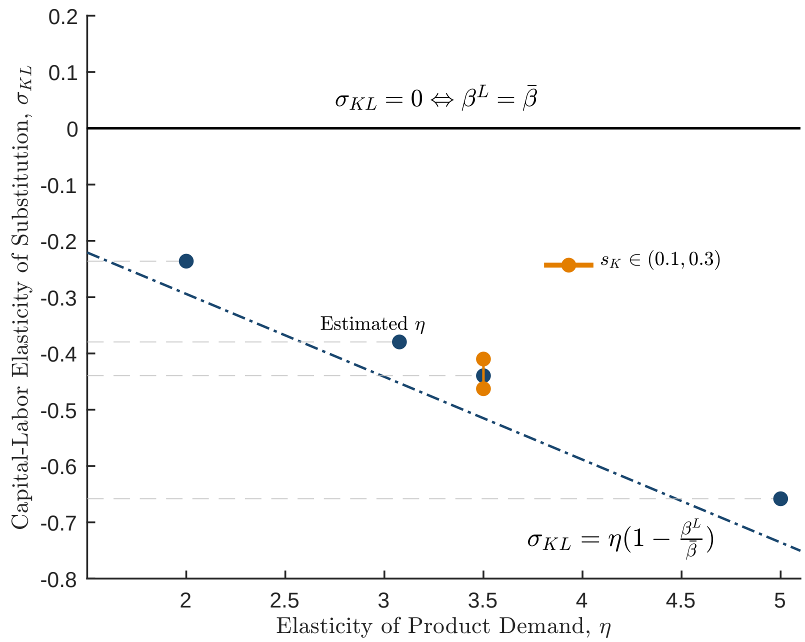
(B) Log Total Value of Shipments



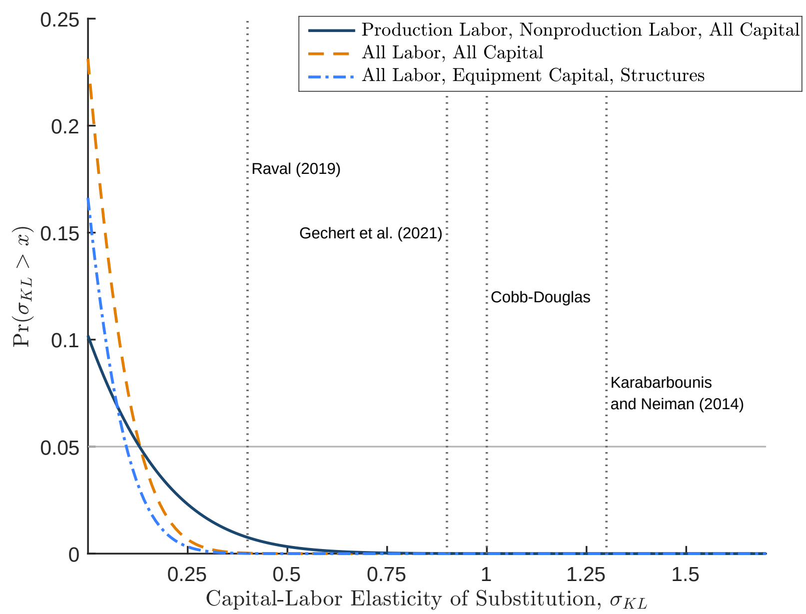
Notes: Figure 7 displays estimates describing the effects of bonus depreciation on total factor productivity in Panel (A) and log total value of shipments in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with bonus. The baseline specification 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, CM, and Zwick and Mahon (2017) data.

Figure 8: 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 8 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 8 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 A14) 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 A14). 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, CM, 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, CM, 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	✓	✓	✓	✓	✓	✓
$\text{PlantSize}_{2001}\times$Year FE		✓		✓		✓
$\text{TFP}_{2001}\times$Year FE		✓		✓		✓
$\text{FirmSize}_{2001}\times$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, CM, 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, CM, 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		✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE			✓	✓	✓		✓
TFP_{2001}×Year FE				✓	✓		✓
FirmSize_{2001}×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, CM, 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, CM, 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, CM, 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: Allen Elasticities of Substitution				
Production labor-capital, σ_{KL}	-0.515	-0.426	-0.608*	-0.294	-0.736
	(0.336)	(0.330)	(0.362)	(0.192)	(0.481)
Nonproduction labor-capital, σ_{KJ}	0.376	0.445	0.303	0.215	0.537
	(0.587)	(0.545)	(0.637)	(0.335)	(0.838)
	Panel C: p-values for Substitutability Tests				
Substitutability of production labor	0.063	0.099	0.047	0.063	0.063
$H_0 : \sigma_{KL} \geq 0$					
Complementarity of non-production labor	0.739	0.793	0.683	0.739	0.739
$H_0 : \sigma_{KJ} \leq 0$					
	Panel D: 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_ϕ^K	-0.555***	-0.271***	-0.852***	-0.317***	-0.793***
	(0.109)	(0.058)	(0.149)	(0.062)	(0.155)
Investment, ε_ϕ^I	-1.398***	-0.684***	-2.146***	-0.799***	-1.997***
	(0.357)	(0.180)	(0.532)	(0.204)	(0.509)
Production Labor, ε_ϕ^L	-0.803***	-0.393***	-1.232***	-0.459***	-1.147***
	(0.067)	(0.033)	(0.109)	(0.038)	(0.096)
Non-production Labor, ε_ϕ^J	-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) presents estimates of the Allen elasticities of substitution between capital and production labor and capital and non-production labor using equations (4) and (5), respectively. Panel (C) conducts hypothesis tests of the substitutability and complementarity of production and non-production labor, respectively. Panel (D) 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. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations based on ASM, CM, 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	3.076
						(2.123)
Production labor-capital, σ_{KL}	-0.440	-0.463	-0.410	-0.236	-0.658	-0.380
	(0.346)	(0.356)	(0.353)	(0.208)	(0.489)	(0.435)
Nonproduction labor-capital, σ_{KJ}	0.733	0.727	0.738	0.393	1.097	0.633
	(0.639)	(0.608)	(0.671)	(0.381)	(0.907)	(0.710)
	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	0.069	0.069	0.069	0.046	0.078	0.065
Production labor	0.109	0.109	0.108	0.103	0.110	0.108
Nonproduction labor	0.076	0.076	0.076	0.074	0.076	0.076
Capital	0.096	0.096	0.097	0.092	0.097	0.096
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	-0.27	-0.09	-0.23	-0.10	-0.16

Notes: Table 8 presents estimates of the structural parameters of the three input model of production labor, non-production labor, and capital in Section 6. 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. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, 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, CM, 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 shows employment results by the task content of occupations using Census and ACS data. Appendix G provides additional employment results using QWI data. Appendix H places our results in the context of aggregate and long-run trends in the manufacturing industry. Appendix I decomposes the wage changes into compositional changes and other factors. Appendix J derives the complete model and presents extensions that add financing constraints and cash flow effects and cash flow effects. Finally, Appendix K discusses additional 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/CM.
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 CM years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CM.
IHS Investment	Inverse hyperbolic sine function of investment, as defined above, by plant i in year t. *Source:* ASM/CM.
$\Delta PPENT_t / PPENT_{1997-2001}$	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/CM.

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Table A.1 – *Continued from previous page*

Variable	Description
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 CM years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CM and Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2020).
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 CM years 1997, 2002, 2007, and 2012. Interim years imputed using investment variable defined above. *Source:* ASM/CM 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/CM.
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/CM.
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/CM.
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/CM.
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/CM.
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/CM 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).

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Table A.1 – *Continued from previous page*

Variable	**Description**
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.
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/CM.
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/CM.
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/CM.
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/CM.
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/CM.
Log Employment, QWI	Natural logarithm of total employment in each four-digit NAICS industry × state × year. *Source:* QWI.
Log Mean Earnings, QWI	Natural logarithm of mean earnings in each four-digit NAICS industry × state × year. *Source:* QWI.

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Table A.1 – *Continued from previous page*

Variable	**Description**
Fraction of Employees with High School Education or Less	Fraction of employees in each four-digit NAICS industry × state × 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 × state × year that are 35 years old or younger. *Source:* QWI.
Fraction of Female Employees	Fraction of employees in each four-digit NAICS industry × state × year that are female. *Source:* QWI.
Fraction of Non-White Employees	Fraction of employees in each four-digit NAICS industry × state × 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 × state × year whose reported ethnicity is Hispanic or Latino. *Source:* QWI.
Fraction of Black Employees	Fraction of employment in each four-digit NAICS industry × state × year whose reported race is Black. *Source:* QWI.
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 Share	Share of output in 2001 that was used as investment in equipment capital from BEA Commodities by Industries - Summary, data item F02E divided by item T019. *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.

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Table A.1 – *Continued from previous page*

Variable	**Description**
Log Employment, Decennial Census and American Community Survey	Natural logarithm of total employment in each four-digit NAICS industry × state × year. *Source:* 1990/2000 Censuses and 2005/2010 ACS.
Occupation-Task Definitions	Occupations are classified into four broad categories: (1) professional, (2) administrative, (3) production, and (4) services occupations. Professional occupations specialize in non-routine, cognitive tasks. Administrative occupations specialize in routine, non-cognitive tasks. Production occupations specialize in routine manual tasks. Services occupations specialize in non-routine manual tasks. *Source:* Acemoglu and Autor (2011)
Tech Industries	Industries with more than 25% of employment in technology oriented occupations. These include Aerospace Products and Parts (NAICS 3364), Other Chemicals (3259), Basic chemicals (3251), Pharmaceuticals (3254), Electrical Equipment and Components (3359), Audio and Video Equipment (3343), Navigational and Control Instruments (3345), Semiconductor and Compoent Manufacturing (3344), Communications Equipment Manufacturing (3342), Computer and Peripheral Equipment (3341). *Source:* Heckler (2005)
ICT z score	Normalized share of workers engaging in tasks involving ICT during the period 2002–2016. *Source:* Gallipoli and Makridis (2018).

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 are phased out dollar for dollar starting 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 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 schedule 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 1, 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.[73] 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

[73] 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.

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 3, 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 4. 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 interpretation 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.

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 Effects by Task Content of Jobs

This section discusses the effects of bonus depreciation on employment for workers in various occupations defined as routine/non-routine and cognitive/non-cognitive as in Acemoglu and Autor (2011). We also show how these results change for workers in different demographic groups.

To perform this analysis, we map occupation data from the U.S. Census and American Community Survey (ACS) to the broad task classifications of Acemoglu and Autor (2011). They classify Census occupations into four broad categories: (1) professional, (2) administrative, (3) production, and (4) services occupations. Professional occupations are defined as managerial, professional, and technical occupations that specialize in non-routine, cognitive tasks. Administrative occupations are defined as sales, clerical and administrative support that specialize in routine, non-cognitive tasks. Production occupations are defined as production, craft, repair and operative occupations that specialize in routine, manual tasks. Services occupations specialize in non-routine manual tasks.

We construct counts of employment in each of these four categories at the state-by-industry level using microdata from the IPUMS samples of the 1990 and 2000 Censuses, the 2005 ACS, and the 2010 ACS 5-year estimates. Our sample comprises adults between the ages of 18 and 64 that are not institutionalized and are employed in manufacturing industries. We drop imputed values for employment status. We define industries by their 1990 Census industry codes in order to maintain a consistent sample over time. Because exposure to bonus is defined at the 4-digit NAICS industry code, we utilize NAICS-Census code industry crosswalks to assign treatment status to Census industry codes. We exclude Census industries that cannot be mapped to a unique treatment status based on this crosswalk.

Figure A9 presents estimates from event study regressions that show the effect of bonus depreciation on workers in production occupations and routine occupations (production plus administrative) using data from the years 1990, 2000, 2005, and 2010. Estimates are weighted by employment in 2000 and standard errors are clustered at the industry-state level. The event study shows that bonus depreciation has large effects on production labor and on routine labor. The effects on production labor reinforce the conclusion that the effects of bonus depreciation are concentrated among those workers directly interacting with production machinery. The similar time pattern for routine work also suggests bonus depreciation increases demand for administrative labor.

Table A5 presents coefficients describing the effect of bonus depreciation on employment from 2000 to 2010 for groups of workers classified by the routine/non-routine, cognitive/non-cognitive, and across a number of different demographic groups. Each coefficient is taken from a different regression where the observation unit is a state-industry. All regressions include industry and state-year fixed effects, are weighted using 2000 employment, and use standard errors clustered at the state-industry-level.

The top line estimate in column (1) shows that bonus depreciation increased employment in most treated industries by 8.56% from 2000 to 2010. This estimate is close to our long-difference estimate presented in Panel A, column (6) from Table 3. Moving across the estimates presented in the table, we see large positive effects for routine work and smaller statistically insignificant effects on non-routine work.[74] Columns (4) through (7) show that the effect of bonus depreciation is largest for production workers, who perform manual routine tasks. The effect of bonus depreciation is also large and positive for administrative workers who perform cognitive routine tasks. Effects on professional and service workers are smaller and not statistically significant.

While bonus depreciation affects demand for all workers, column (1) also shows that the policy has outsized effects on young workers, workers with fewer years of education, female workers, Black workers, and Hispanic workers. These results reinforce the demographic analyses using QWI data presented in Section 4.3. Comparing the demographic subgroups results between column (1) and columns (2) and (6) suggests that the pattern of relatively larger effects of bonus depreciation on employment for traditionally disadvantaged groups is even stronger for routine and production workers.

In sum, this task-based analysis reinforces the conclusion that the effect of bonus depreciation on employment is largest for workers interacting with production machinery and engaging in manual-routine tasks. Among workers performing these types of tasks, the effect of bonus depreciation is larger for young workers, workers with fewer years of education, female workers, Black workers, and Hispanic workers.

G Additional Employment Results using QWI Data

This Appendix extends the employment results discussed in Section 4. 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 A5. This sample restricts on plants being very small and aggregates up to the state level, so

[74] In 2000, production occupations accounted for approximately 80% of all routine employment in manufacturing.

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 find that employment in plants treated by bonus is increasing relative to untreated plants. Quarterly coefficients are shown in Panel (B) of Figure A5.

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.

Evidence presented in Panel (A) of Figure A7 suggests a similar conclusion. In Panel (A), we show how the QWI employment event study differs when we use 25th percentile and 40th percentile cutoffs to define bonus depreciation treatment. All three treatment definitions suggest large, positive effects of bonus depreciation on employment which suggest our baseline employment effects are largely unaffected by the choice of z_0 cutoff we use to define treatment.

Figure A7 presents a number of additional robustness checks. In Panel (B), we address the concern that our findings are driven by increased employment due to additional demand for capital goods rather than changes in the cost of capital due to the policy. To do so, we use the 2001 BEA Input-Output tables to identify industries that sell capital goods to other industries. These data, available as the Use of Commodities by Industries - Summary through the BEA Interactive Tables tool, describe the share of output in a given industry that is used in nonresidential private fixed investment in equipment at the 3-4 digit NAICS levels (data item F02E divided by item T019). For example, NAICS 333 covers many firms that manufacture machinery and this industry has 44.7% of output used as private fixed investment in equipment in 2001. On the other side of the spectrum, NAICS 326 businesses, those involved in manufacturing plastics and rubbers, have 0.1% of output used in fixed investment in equipment. We control for the share of output in each industry that is used in fixed investment in capital equipment and interact this control with year fixed effects. Our results in Panel (B) of A7 show the same pattern of increasing employment by 12.7% by 2011 for state-industries with the most benefit from depreciation incentives. We also test whether the final coefficient in 2011 is different with the capital good producer controls and fail to reject the null that the coefficient is the same as the baseline QWI analysis (12.9%) with a p-value of 0.89.

Next, we address the concern 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 then include quintile bins of this external cost measure interacted with year fixed effects in Panel (C). Again, our results are very similar to baseline suggesting differences in the cost of external financing are not driving our results.

In Figure A8, we show that our results are not driven by growth in the use of information and communications technologies (ICT). We take two approaches. First, in Panel (A), we present additional estimates of the effect bonus depreciation on log employment controlling for two measures of ICT growth. For each control, we include tercile indicators interacted with year fixed effects. The first measure is ICT capital intensity measured as a share of capital stock in ICT goods using BEA Detailed Data for Fixed Assets and Consumer Durable Goods from 1997 to 2001. The second measure is the Gallipoli and Makridis (2018) Z-score, the normalized share of workers engaging in tasks involving ICT during the period 2002–2016. Both sets of estimates with these additional ICT controls are very similar to baseline suggesting growth in ICT usage is not biasing the results.

The second approach is account for ICT growth is simpler. In Panel (B), we present estimates after dropping "tech" industries from our regressions. We define "tech" industries as those with more than 25% of employment in technology oriented occupations following Heckler (2005). These industries include Aerospace Products and Parts (NAICS 3364), Other Chemicals (3259), Basic chemicals (3251), Pharmaceuticals (3254), Electrical Equipment and Components (3359), Audio and Video Equipment (3343), Navigational and Control Instruments (3345), Semiconductor and Compoent Manufacturing (3344), Communications Equipment Manufacturing (3342), Computer and Peripheral Equipment (3341). These industries represent represent 21.4% manufacturing employment in 2001. Despite the smaller sample, we continue to find bonus depreciation has large and significant effects on employment.

H Aggregate and Long-Run Manufacturing Trends

This section provides additional context to the employment and capital investment results presented in Section 4. Figure A11 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 4 to these series to illustrate the aggregate effects implied by our results. We weight these regressions using 2001 employment counts at the industry level. 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 A11 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.

I 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 Table A7. This table begins with the original log earnings regression coefficient indicating that bonus decreases earnings-per-worker at most-treated plants by 3.1%. 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.[75] In the final column with all controls, we find that bonus leads to a statistically insignificant 0.7% increase in earnings. This indicates that the change in workforce composition explains the decrease in earnings.

Second, we apply a formal decomposition to measure the effect of each margin of workforce composition 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). 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 four equations, with each describing

[75]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.

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 employees that are female. All regressions include state-by-year and industry-by-state fixed effects. In expectation under the assumption that $\mathrm{E}(\varepsilon_{jst}|X_{jst}) = 0$, we can restate these equations as OLS estimates. Taking differences of the first two equations describes the effect of bonus on average wages 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 all other factors.

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

To find the relative wage effects for treated plants relative to control plants, we perform the same calculation for the control equations and then take a difference between the wage decomposition for treated and control plants. Estimates of the four regressions explaining log earnings are shown in columns (1)-(4) of 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, or close to 91% of the overall wage effect. Our analyses indicate that the change in the share of less educated workers and the share of female workers explain most of the decrease in earnings-per-worker, confirming our results from Table A7.

J Structural Model Derivation

Below we derive the model predictions presented in Section 6. The following exposition follows closely that in Harasztosi and Lindner (2019), which in turn follows Hamermesh (1996) to derive the output demand elasticity.

J.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

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

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

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 $P \equiv \left(\int_0^1 p(\omega_2)^{1-\kappa}d\omega_2\right)^{\frac{1}{1-\kappa}}$, 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

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

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

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

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

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

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

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

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

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

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

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

J.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:

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

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.

J.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.4 Cash Flow Effects of Bonus under Capacity Constraints

The previous subsection showed that in our baseline model the term ϕ captures the impacts of bonus on the cost of capital including a role for financing constraints. A potential concern is that our baseline model is miss-specified by ignoring how cash-flow effects of the policy may impact the choice of all inputs. A particular worry is that this miss-specification may be placing too large a role on the cost of capital effect of bonus (i.e., that ϕ is too large) and that ignoring cash flow effects may bias the estimate of σ_{KL}.

In this section, we explore the possibility that cash-flow benefits from bonus depreciation may allow plants to expand their production capacity. As in Section J, plants choose the optimal mix of inputs to minimize costs of production. In contrast to that section—where plants chose the quantity produced to maximize profits—we instead assume that plants are constrained in the total production costs they can expend. Formally, assume:

$$\max_{q(\omega)} \quad p(q(\omega))q(\omega) - c(w, R, p_j)q(\omega) \quad \text{subject to} \quad c(w, R, p_j)q(\omega) \leq \bar{c} + \tau b I(w, R, p_j),$$

where total costs must not exceed the combination of a capacity constraint $\bar{c}$ plus the cash flow the plant receives from bonus depreciation, $\tau b I(w, R, p_j)$. Assuming that the constraint binds, we have:

$$q(\omega) = \frac{\bar{c} + \tau b I(w, R, p_j)}{c(w, R, p_j)},$$

so that

$$\frac{\partial \ln q(\omega)}{\partial \text{Bonus}} = -s_K\phi + \underbrace{\frac{\tau b I(w, R, p_j)}{\bar{c} + \tau b I(w, R, p_j)}}_{s^b}(1 + \varepsilon_b^I)/b = -s_K\phi \left(1 + \underbrace{\frac{s^b(1 + \varepsilon_b^I)/b}{-s_K\phi}}_{\chi \geq 0}\right),$$

where s^b is the share of plant expenditures that comes from the cash-flow effect of bonus and where ε_b^I is the investment elasticity with respect to bonus. The last expression introduces the term χ as a measure of the relative importance of cash flow vis-a-vis cost of capital effects of bonus.

Following the derivations above, we obtain the effect of bonus on revenue as follows;

$$\frac{\partial \ln p(\omega)q(\omega)}{\partial \text{Bonus}} = \frac{\partial \ln p(\omega)}{\partial \ln q(\omega)}\frac{\partial q(\omega)}{\partial \text{Bonus}} + \frac{\partial q(\omega)}{\partial \text{Bonus}} = -s_K\phi(1+\chi)\left(1-\frac{1}{\eta}\right).$$

This expressions shows that, while the scale effect of the policy is now mechanical, the price and revenue effects depend on the elasticity of product demand, η.

Following the dichotomy of scale and substitution effects, note that since plants are still cost-minimizing, the substitution effects of bonus are the same as in our baseline model. In contrast, the scale effect of the policy is now given by the equation for $\frac{\partial \ln q(\omega)}{\partial \text{Bonus}}$ above. We thus obtain the following modified implications of the model:

$$\frac{\partial \log K(\omega)}{\partial \text{Bonus}} = (s_J\sigma_{KJ} - s_L\sigma_{KL} - s_K(1+\chi))\phi$$

$$\frac{\partial \log L(\omega)}{\partial \text{Bonus}} = s_K(\sigma_{KL} - (1+\chi))\phi$$

$$\frac{\partial \log J(\omega)}{\partial \text{Bonus}} = s_K(\sigma_{KJ} - (1+\chi))\phi$$

Note that these equations only differ from our baseline model in that $1+\chi$ has now replaced η. Intuitively, the scale effect in our baseline model is determined by profit maximization, which depends on the elasticity of product demand η. In contrast, in the capacity constrained model, the scale effect depends on the degree to which the cash flow effects of the policy allow plants to expand production.

As in our baseline model, the cost-weighted average of input effects continues to identify the scale effect:

$$\bar{\beta} = s_J\beta^J + s_K\beta^K + s_L\beta^L = -s_K\phi(1+\chi).$$

Similarly, we can identify η by comparing the scale effect to the implied price effect of the policy, so that $\eta = \frac{\bar{\beta}}{\bar{\beta}-\beta^R}$.

To identify σ_{KL}, note that

$$\frac{\bar{\beta}-\beta^L}{\bar{\beta}} = \frac{\sigma_{KL}}{(1+\chi)} \Longrightarrow \sigma_{KL} = (1+\chi)\left(1-\frac{\beta^L}{\bar{\beta}}\right).$$

Again, the only difference between our baseline model and the scale constrained case is that the term η is now replaced by $(1+\chi)$. A key implication of this expression is that, since $\chi \geq 0$ and $\beta^L > \bar{\beta}$, our estimates would also imply a negative value of σ_{KL} in this setting. That is, the conclusion that capital and production labor are complements in our setting is robust to allowing for cash flow effects to relax capacity constraints of manufacturing plants.

To obtain a plausible magnitude of χ, consider that we estimate that $\bar{\beta} = 0.10$ and that, in our baseline model, we estimate that $\phi = -0.14$. Together with the assumption that $s_K = 0.20$, the scale effect implies that $1 + \chi = \frac{\bar{\beta}}{-s_K \phi} = \frac{0.10}{0.2 * 0.14} = 3.57$. This value of $1 + \chi$ then implies a magnitude of σ_{KL} close to our baseline estimate of -0.54. To the extent that $1+\chi$ is greater than 3.57, we would obtain more negative estimates of σ_{KL}. The implied estimate of σ_{KL} is closer to zero when χ is small. At the extreme where $\chi = 0$, we have $\sigma_{KL} = -0.15$.[76] This value can be considered an upper bound for σ_{KL}, since the motivating assumption behind this analysis is that the cash-flow effect may play a significant role (i.e. $\chi \gg 0$).

To analyze this model more formally, we implement our estimate of the investment effects of bonus to estimate both σ_{KL} and s^b. We may identify σ_{KL} as follows:[77]

$$\sigma_{KL} = \frac{\bar{\beta} - \beta^L}{\bar{\beta} - s^b(1 + \varepsilon_b^I)/b}.$$

This expression differs from an analogous expression in our baseline model by replacing β^R with $s^b(1 + \varepsilon_b^I)/b$. Table A16 presents estimates of σ_{KL} utilizing this equation and estimates of $\bar{\beta}$ and ϕ. Across all columns, we find estimates of σ_{KL} that are very similar to those presented in Table 7. We can also use our long-difference estimate of the investment elasticity $\varepsilon_b^I = 0.20$ and $b = 0.45$—the average value across the sample period—to estimate s^b. Across all specifications, we estimate values no greater than 3.0%. That is, for plausible values of the model parameters we only require that at most 3% of plant expenditures are driven by the cash flow effects of the policy.

The alternative model in this section shows that allowing for the cash flow effects of bonus to help finance other plant costs—such as labor—does not alter the implication of our reduced-form estimates that $\sigma_{KL} < 0$—i.e., that capital and labor are complements in our setting. Indeed, for plausible values of the cash-flow effects of bonus, we find magnitudes of σ_{KL} that are similar to those in our baseline model.

[76] Note that when $\chi = 0$, the implied value of $\phi = -\frac{\bar{\beta}}{s_K} = -\frac{.10}{.20} = -0.50$. That is, low values of χ imply values of ϕ that are more negative than in our baseline model. Given the motivating concern that the baseline model puts too much weight on ϕ relative to cash flow effects, it is worth noting that for $\phi > -0.14$, it is necessary that $\chi > 2.57$, which then yields more negative estimates of σ_{KL}.

[77] From the scale effect, it follows that $-s_K\phi = \bar{\beta} - s^b(1 + \varepsilon_b^I)/b$. Note also that, since $-s_K\phi > 0$, we have that $\bar{\beta} > s^b(1 + \varepsilon_b^I)/b \geq 0$.

K Additional Model Results

This section presents various model results in greater detail. First, we present estimates of both translog cost functions and constant elasticity of substitution production functions. These estimated functions allow us to test several hypotheses of interest. These results demonstrate that our conclusion that capital and labor are complements in production holds up across several alternative models. We utilize our event study estimates over the 2002-2011 period to calculate several model parameters over time. Finally, we estimate the model using industry-level data and compute aggregate elastcities of substitution that account for within and across industry reallocation of production toward more capital intensive production units.

K.1 Translog Cost Function Estimation

We now show that our estimates of substitution elasticities are compatible with a canonical model of production. In his treatise on labor demand, Hamermesh (1996) recommends that empirical researchers specify models that allow for flexible cross-price elasticities between capital and different types of labor. One such model is the transcendental logarithmic cost function, or "translog" for short, which is a second-order approximation to an arbitrary functional form (Christensen, Jorgenson and Lau, 1971, 1973).

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:

$$\log C = \log Y + a_0 + \sum_i a_i \log w_i + 0.5 \sum_i \sum_j b_{ij} \log w_i \log w_j, \tag{15}$$

where

$$\sum_i a_i = 1; \quad b_{ij} = b_{ji}; \quad \sum_i b_{ij} = 0, \ \forall j, \tag{16}$$

and 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

$$\sigma_{ij} = [b_{ij} + s_i s_j]/s_i s_j, \quad i \neq j. \tag{17}$$

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 cost minimization implies 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:

$$\sigma_{ii} = [b_{ii} + s_i^2 - s_i]/s_i^2. \tag{18}$$

Equations (17) and (18) demonstrate that the partial elasticities of substitution we estimate are linear functions of the analogous translog parameters b_{ij}. Panels A of Tables A10 and A11 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 A10 and A11 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 Leontief production technology across all models. This result is consistent with our finding in Section 6 that the most of the effect of the policy on factor demands was driven by the scale effect. Importantly, these results show that the estimated complementarity between capital and production labor is compatible with a standard model of production.

K.2 Elasticities of Capital and Labor Demand

While separating scale and substitution effects clarifies the mechanisms that drive responses to bonus, the effects of policies that change the cost of capital—e.g., changes in interest rates or other tax provisions—depend on elasticities of capital and labor demand. We now estimate these elasticities using our model to recover the implied effect of the policy on the cost of capital.

As we discuss in Section 1, the effect of bonus on the cost of capital depends on a number of real world factors, including the roles of depreciation deductions, tax losses, and financing constraints. One advantage of our model is that it links the estimated effects on inputs of production to the effects of the policy on the cost of capital. Equation 7 implies that

$$\phi = -\frac{\bar{\beta}}{s_K \eta}. \tag{19}$$

Column (1) of Panel (D) of Table 7 shows that the semi-elasticity of the cost of capital with respect to bonus $\phi = -0.145$ when the elasticity of product demand $\eta = 3.5$. Columns (2)–(5) show that varying s_K and η delivers estimates of $\phi \in [-0.25, -0.10]$.

Following the prior literature, we first consider the elasticity of investment with respect to the cost of capital. Column (1) of Panel (D) of Table 7 shows that $\varepsilon^I_\phi = \frac{\beta^I}{\phi} = -1.40$.[78] This elasticity lies in the range $[-2.1, -0.84]$ across columns (1)–(5). Through the lens of a simple investment model without financing frictions, the results in Zwick and Mahon (2017) imply an elasticity of -7.2. Our smaller estimate of this elasticity is due to the fact that our estimate of ϕ includes financing and other constraints.[79]

An advantage of our setting is the ability to measure the effect of the cost of capital on the stock of capital used for production. Column (1) of Panel (D) of Table 7 reports our baseline estimate of $\varepsilon^K_\phi = \frac{\beta^K}{\phi} = \frac{0.080}{-0.145} = -0.55$.[80] For context, Equation 3 and our baseline values for s_K and η would imply that $\varepsilon^K_\phi = -1.5$ with Cobb-Douglas production. Thus, even though our estimated 8% increase in the capital stock is economically significant, we find a modest capital stock elasticity when we appropriately measure the effect of the policy on the cost of capital.

Our model-based estimate of ϕ also allows us to recover cross-price elasticities of labor demand with respect to the cost of capital. Column (1) of Panel (D) of Table 7 shows that we estimate an elasticity of $\varepsilon^L_\phi = \frac{\beta^L}{\phi} = \frac{0.116}{-0.145} = -0.80$ for production labor and $\varepsilon^J_\phi = \frac{\beta^J}{\phi} = \frac{0.090}{-0.145} = -0.62$ for non-production labor.[81] Both elasticities would equal -0.5 with Cobb-Douglas production. This comparison reinforces the dominance of the scale effect in our setting, since even a large degree of substitution would be overshadowed by the scale effect. In addition, since we estimate that $\varepsilon^L_\phi < \varepsilon^J_\phi$, our results are also not consistent with the hypothesis of capital-skill complementarity.

Our estimated elasticities of capital and labor demand highlight three policy-relevant insights.

[78] This estimate uses the long difference estimate on investment from Panel (A) of Figure 2.

[79] In Appendix J.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 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. 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.

[80] This elasticity lies in the range $[-0.80, -0.32]$ across columns (1)–(5).

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

First, understanding how fiscal policies relax financing and other constraints is critical for forecasting the effects of fiscal policies on capital and labor demand. Second, the scale effect is the biggest driver of the effects of changes in the cost of capital. Finally, this result alleviates the concern that lowering the cost of capital would reduce labor demand.

K.3 Constant Elasticity of Substitution Parameter Estimates

We now demonstrate that the elasticities in Panel (D) of Table 7 can be used to estimate key parameters from a nested constant elasticity of substitution (CES) production function. We consider a CES production function in which production labor and capital are nested separately from non-production labor:

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

where J represents non-production labor, L represents production labor, K represents capital, and ρ_1 and ρ_2 are our CES parameters of interest.[82]

The first-order conditions associated with cost minimization yield the following expression that relates the ratio of optimal L and K to the price ratio:

$$\frac{L}{K} = \left(\frac{(1-\mu_2)}{\mu_2}\frac{R}{w}\right)^{\frac{1}{1-\rho_2}}. \tag{20}$$

Taking logs and differentiating this expression with respect to the cost of capital ϕ leads directly to our identification result for ρ_2:

$$\varepsilon_\phi^L - \varepsilon_\phi^K = \frac{1}{1-\rho_2}, \tag{21}$$

which can be rearranged to yield an expression for ρ_2.[83]

In order to derive an expression for ρ_1, we first note that cost minimization implies the following result that relates CES parameters to input cost shares:

$$\frac{RK}{RK+wL} = \frac{\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}}{\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}} + (1-\mu_2)\left(\frac{w}{1-\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}} = \frac{s^K}{s^K+s^L}. \tag{22}$$

[82] An alternative approach nests non-production labor and capital separately from production labor (e.g., as in Krusell, Ohanian, Ríos-Rull and Violante, 2000). This approach is not compatible with our findings. To see this, recall that we estimate $\sigma_{KL} < 0$. Because this approach assumes that $\sigma_{LJ} = \sigma_{KL}$, the production function would have two (out of three) negative elasticities of substitution and would therefore violate second-order sufficiency conditions of cost minimization (see, e.g., Allen, 1938, p. 505).

[83] Note that the left-hand-side expression in this equation and in Equation (25) below are also Morishima elasticities of substitution.

As with Equation (20), we may also derive the following expression for the optimal quantity ratio of J and K using first-order conditions:

$$\frac{J}{K} = \left(\frac{R}{\mu_2}\right)^{\frac{1}{1-\rho_2}} \left(\frac{p_j}{\mu_1}\right)^{\frac{-1}{1-\rho_1}} \left[\frac{1}{(1-\mu_1)}\left[\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}} + (1-\mu_2)\left(\frac{w}{1-\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}\right]^{\frac{\rho_1-\rho_2}{-\rho_2}}\right]^{\frac{1}{1-\rho_1}} \tag{23}$$

Unlike Equation (20), taking logs of this expression and differentiating does not isolate ρ_1. Instead, we utilize expressions for the optimal quantities of J and K implied by cost minimization. Taking logs and differentiating these expressions with respect to R allows us to link ρ_1 to Morishima elasticities. Equation (22) and the definition of Morishima elasticities at the end of Section 6.2 yield the following result that relates ε_ϕ^J and ε_ϕ^K to an approximate expression around initial cost shares:

$$\varepsilon_\phi^J - \varepsilon_\phi^K \approx \frac{1}{1-\rho_2}\left[1 + \frac{\rho_1-\rho_2}{1-\rho_1}\frac{s^K}{s^L+s^K}\right]. \tag{24}$$

The expression holds locally since we use numerical values of s^K and s^L to approximate capital and labor cost shares, which are otherwise functions of prices and production parameters. Rearranging this expression, combined with Equation (21), shows that ρ_1 is given by:

$$\varepsilon_\phi^J - \varepsilon_\phi^K \approx (\varepsilon_\phi^L - \varepsilon_\phi^K)\frac{s^L}{s^L+s^K} + \frac{1}{1-\rho_1}\frac{s^K}{s^L+s^K}. \tag{25}$$

According to Table 7, $\varepsilon_\phi^L - \varepsilon_\phi^K < 0$ and $\varepsilon_\phi^J - \varepsilon_\phi^K \approx 0$, implying that $\rho_2 > 1$ and $\rho_1 < 1$.[84] Panel (A) of Table A13 uses Equations (21) and (25) to show that we estimate $\rho_1 = -1.67$ and $\rho_2 = 5.03$. Panel (B) of Table A13 shows that our estimates imply that $\frac{1}{1-\rho_2} = -0.25 < 0.37 = \frac{1}{1-\rho_1}$. Thus, our results are not consistent with the capital-skill complementarity hypothesis. Panel (C) tests whether our results match the degree of capital-skill complementarity found in Krusell, Ohanian, Ríos-Rull and Violante (2000). Our estimates reject the null of this high degree of capital-skill complementarity with a high degree of precision. This result is driven by the fact that bonus depreciation led to a substantial increase in the employment of production workers.

K.4 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

[84] Table A12 reports that $\varepsilon_\phi^L - \varepsilon_\phi^K = -0.248$ (SE=0.141) and that $\varepsilon_\phi^J - \varepsilon_\phi^K = -0.070$ (SE=0.188). 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 for a three-input production function to be consistent with cost minimization.

to changes in the cost of capital, and capital-labor substitution elasticities. Alternatively, we may utilize the event study estimates from Section 4 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 A14 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 4 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 $\varepsilon_\phi^I = \beta^I/\phi$ and $\varepsilon_\phi^L = \beta^L/\phi$, 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 A15 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.

K.5 Additional Model Estimates

To motivate the three input model presented in the main text, we consider a two input model with capital and labor. The two-input version of Equation 8 is:

$$\sigma_{KL} = \eta\left(1 - \frac{\beta^L}{s_L\beta^L + s_K\beta^K}\right). \tag{26}$$

To implement this equation, we set input cost shares so that $1 - s_K = s_L = 0.8$. Panel A of Figure A13 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., $\sigma_{KL} < 0$.[85] Column (4) of Table A14 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.[86] A second interpretation is that plants in our data are not well approximated by a two input model.

We also consider several alternative models in which different inputs are used in production. Table A14 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 A14 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 A14 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.

Finally, we estimate a five input model that combines production labor, non-production labor, materials, capital structures, and capital equipment. Panel B of Figure A13 reports values of σ_{KL} implied by a five-input analogue of Equation 26 across values of η. Once again, our estimates imply negative values of σ_{KL}.

[85] To be consistent with a Cobb-Douglas production function, Equation 26 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 $\eta = 2$.

[86] 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}.

K.6 Capital-Labor Elasticity of Substitution in Industry-Level Data

The model estimates so far are based on reduced-form estimates of capital and labor responses at the plant level from the ASM/CM data. Our baseline analyses focus on within-plant adjustments by relying on a balanced panel of plants. We now address whether entry and exit or reallocation to more capital intensive plants generate different substitution patterns at the industry level. To explore whether these margins impact our structural estimates, we estimate our model of factor demands using long difference estimates of the impact of bonus using the NBER-CES industry-level data. We follow our main specifications as closely as possible, although we cannot control for geographic or plant-specific characteristics or trends. We weight these regressions using 2001 employment counts at the industry level.

We show estimates of the 2011 coefficient from Equation 1 in Table A17 for the outcomes log of production employment, log of non-production employment, and log of capital stock.[87] Our long difference estimates shows that bonus led to a relative increases in production employment of 17.9%, non-production employment increased of 13.2%, and capital stocks of 12.2% between 2001 and 2011. As with our plant-level results, we estimate larger effects on production employment than on non-production employment or capital.

Table A18 uses these industry-level results to estimate scale and substitution effects, and reports analogous statistics as those in Table 7. These tables show that our model has similar implications when we use industry or plant level data. In column (1), we estimate that σ_{KL} is equal to -0.59, and we reject the null hypothesis that $\sigma_{KL} \geq 0$ with a p-value of 0.072. For reference, Table 7 reports an estimate of -0.52 using plant-level estimates and the same parameterization. The similarity of the estimates of capital-labor substitution suggests that in our setting, entry, exit, and reallocation within industry are relatively minor factors.

K.7 Aggregate Capital-Labor Elasticity of Substitution

We now use the method developed in Oberfield and Raval (2021) to calculate the aggregate capital-labor elasticity of substitution. The method in Oberfield and Raval (2021) starts with a nested CES production function and generates an aggregate elasticity that accounts for reallocation toward more capital-intensive production units within and across industries.

[87] We directly observe production employment in the NBER-CES data. We define non-production employment as the difference between total and production employment. We obtain an industry price-adjusted capital stock by multiplying the capital stock by the investment price index.

To apply this method, we begin by using the industry-level elasticity estimates discussed in Appendix K.6 and presented in Panel (D) of Table A17. We use these estimates to compute the Morishima elasticities of substitution presented in Table A19. Because these elasticities are based on industry-level data, they already account for reallocation within industries. These estimates are very similar to their plant-level analogues presented in Table A12, suggesting that reallocation within industries is a not a substantial margin of response to bonus depreciation. As we discuss in Appendix K.3, these elasticites map to the parameters of a nested CES production function, as in the framework of Oberfield and Raval (2021).

Oberfield and Raval (2021) demonstrate that an aggregate capital-labor elasticity of substitution, σ_{KL}^{agg}, can be computed from our industry-level estimates of capital-labor elasticities of substitution, σ_{KL}^{N}. This aggregate elasticity of substitution is given by the following expression:

$$\sigma_{KL}^{agg} = (1-\chi^{agg})\sigma_{KL}^{N} + \chi^{agg}\big[(1-s_J)\varepsilon + s_J\sigma_{KJ}^{N}\big].$$

where σ_{KJ}^{N} denotes the mean industry-level elasticity of substitution between capital and non-production labor. The parameter χ^{agg} is a heterogeneity index that captures the dispersion of mean capital cost shares across industries. Letting $\alpha_n = \frac{rK_n}{rK+wL}$ be the cost share of capital in production inputs of industry n, α denote the economy-wide cost share, and $\theta_n = \frac{rK_n+wL_n}{rK+wL}$ denote industry n's share of economy-wide capital and production labor expenditures, the aggregate heterogeneity index is given by $\chi^{agg} = \sum \frac{(\alpha_n-\alpha)^2}{\alpha(1-\alpha)}\theta_n$. This quantity captures the degree to which aggregate capital-labor substitution will reflect within-industry substitution σ_{KL}^{N}; by substitution across industries of varying capital intensity, captured by the cross-industry demand elasticity ε; or by substitution toward non-production labor, captured by σ_{KJ}^{N}, which is in turn mediated by the cost share of non-production labor s_J. The relative importance of these forces thus depends on the degree of dispersion in capital intensities, with greater dispersion denoting greater degrees of cross-industry substitution.

Table A20 presents the results of this analysis for different calibrated values of η and s_{NL}.[88] The first row reports our industry-level elasticities of substitution, which account for within-industry reallocation. The second row calculates aggregate elasticities using Oberfield and Raval's (2021) estimated parameters: $\varepsilon = 1$ and $\chi^{agg} = 0.07$. Accounting for cross-industry reallocation yields aggregate substitution elasticities that are universally less negative. Across all specifica-

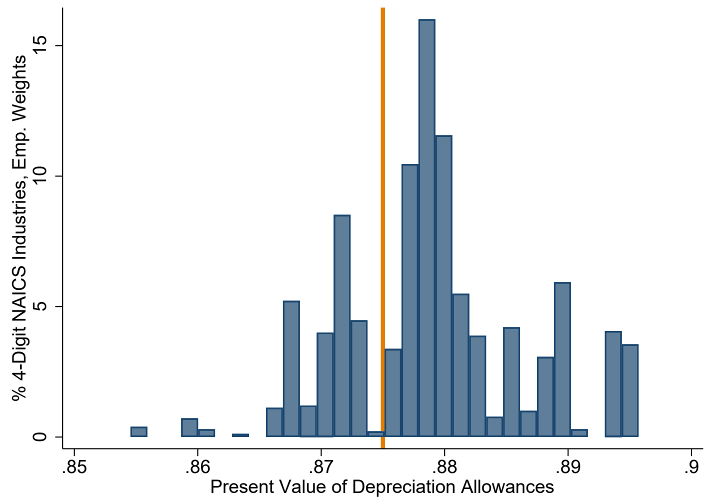
[88]Calibrations of the demand elasticity η affect estimates of industry-level and aggregate estimates through ϕ.

tions, we estimate aggregate elasticities consistent with complementarity between capital and production labor. Column (1) rejects values of σ_{KL}^{agg} greater than 0.14 at the 5% level; across all columns we reject values of σ_{KL}^{agg} greater than 0.21 at the same significance level.

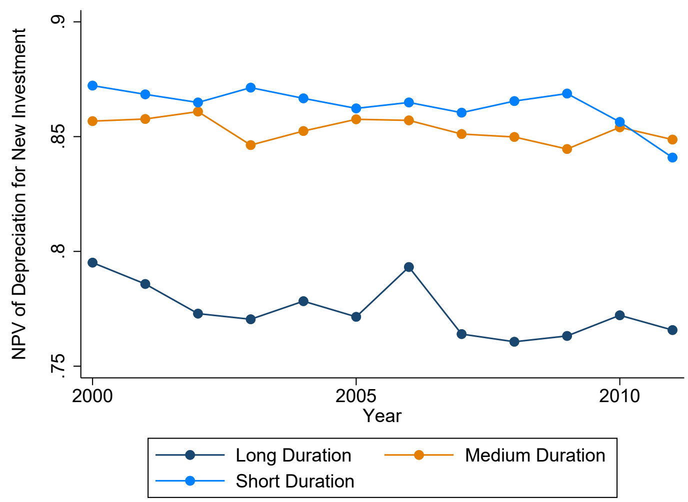
Appendix Figures

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

(A) Distribution of Depreciation NPV without Bonus

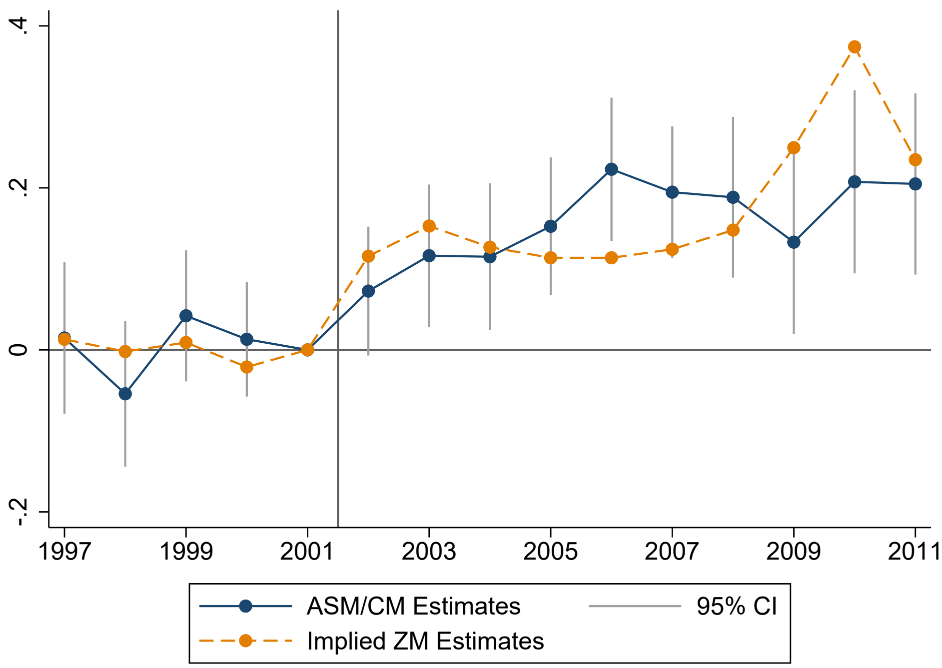


(B) Stability of Depreciation NPV Over Time



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 1. 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.

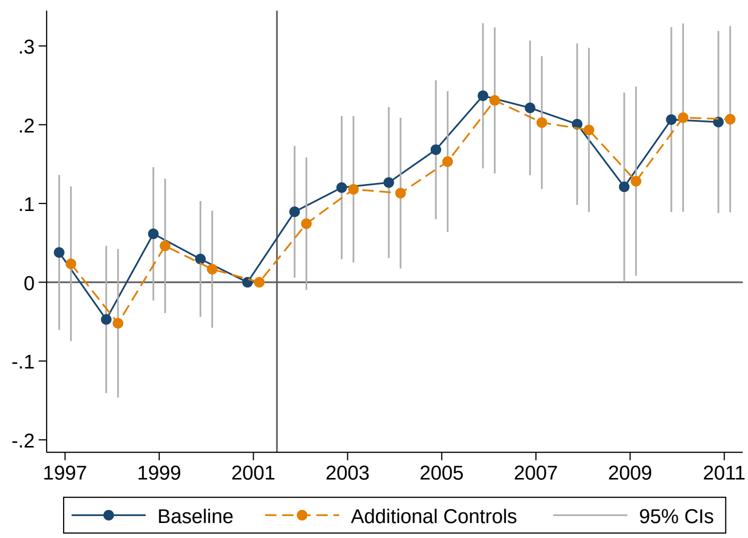
Figure A2: Comparison of Investment Event Study Results with Zwick and Mahon (2017)



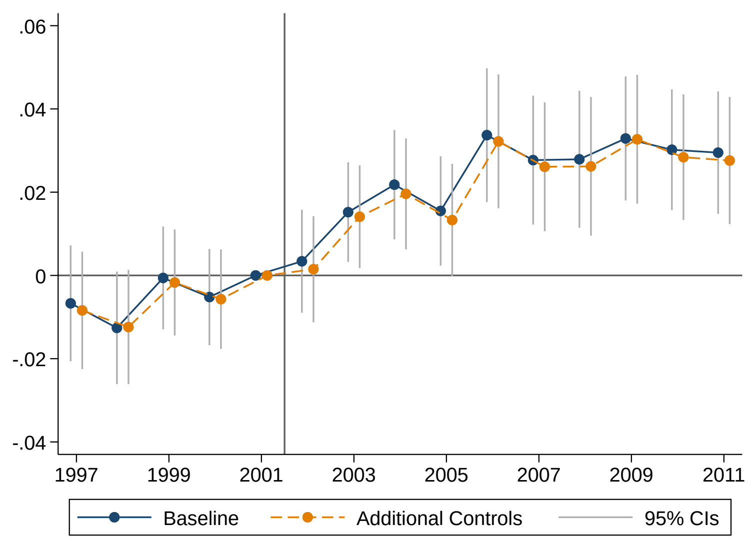
Notes: Figure A2 compares our investment results to those of Zwick and Mahon (2017). As we discuss in Section 3, we define exposure to treatment as a binary variable that takes the value of one when for firms with z_0 in the first three terciles of the distribution of z_0. Zwick and Mahon (2017) use 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, CM, and Zwick and Mahon (2017) data.

Figure A3: Effects of Bonus Depreciation on Alternative Investment Outcomes

(A) IHS Investment



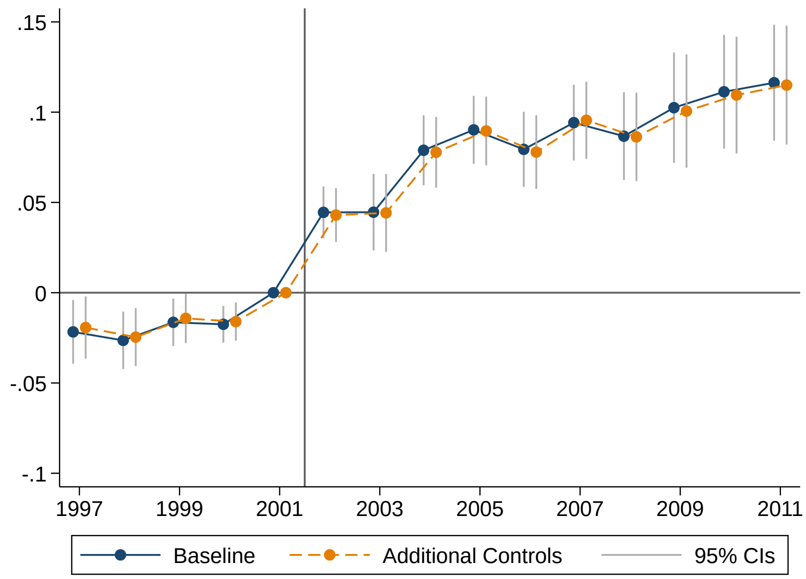
(B) ($\Delta\text{PPENT}_t/\text{PPENT}_{1997-2001}$)



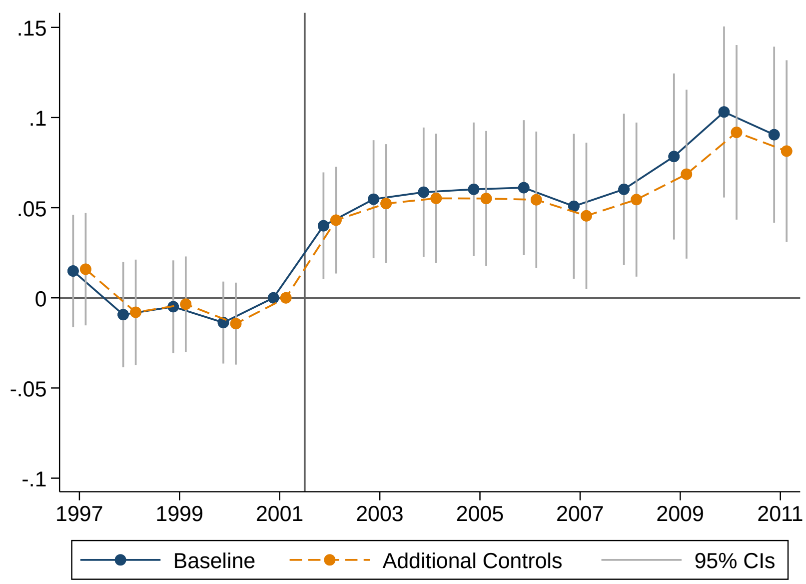
Notes: Figure A3 displays estimates describing the effect of bonus depreciation on the Inverse Hyperbolic Sine of Investment in Panel (A) and PPENT expenditures divided by previous PPENT stock in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients 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, CM, and Zwick and Mahon (2017) data.

Figure A4: Effects of Bonus Depreciation on Production and Non-production Employment

(A) Log Production Employment



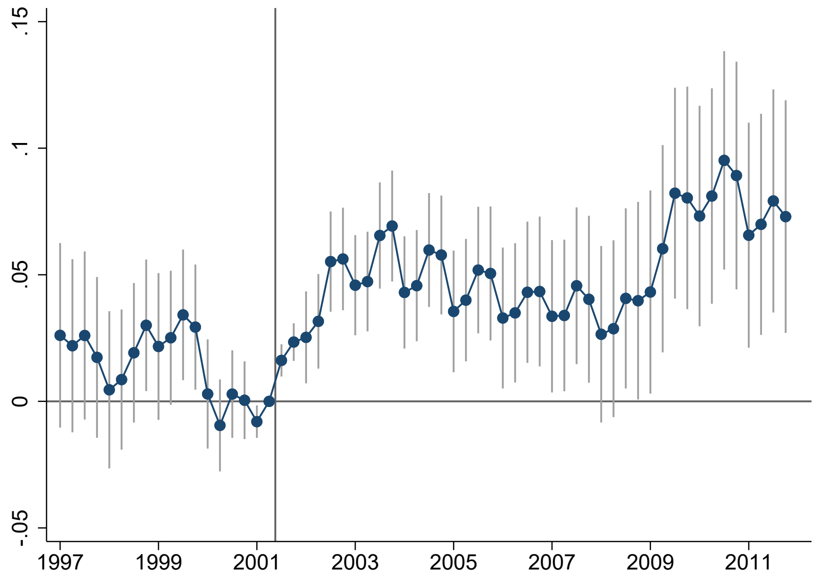
(B) Log Non-production Employment



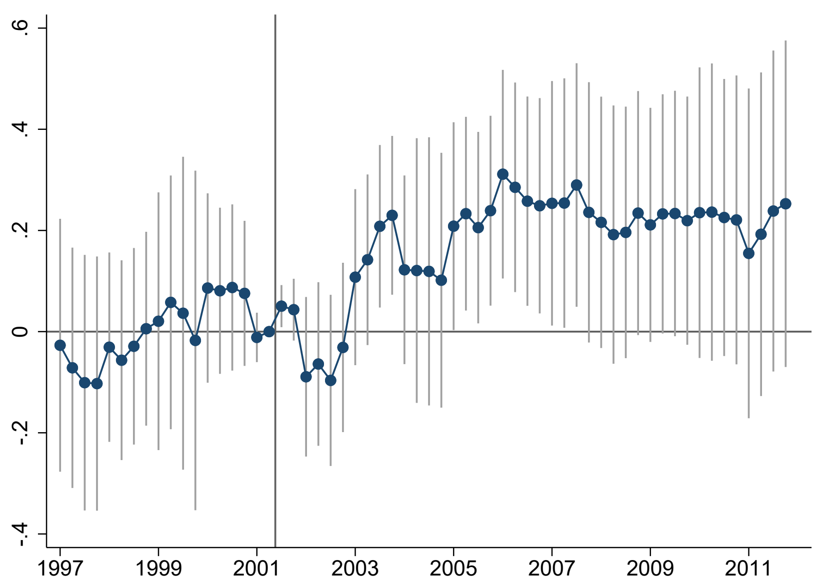
Notes: Figure A4 displays estimates describing the effect of bonus depreciation on log production employment in Panel (A) and log non-production employment in Panel (B). Plotted coefficients are estimates of β_y from Equation (1), which are the annual coefficients associated with bonus. The baseline 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, CM, and Zwick and Mahon (2017) data.

Figure A5: Effects of Bonus Depreciation on Smaller and Younger Firm Employment; QWI

(A) Firms with 1-50 Employees



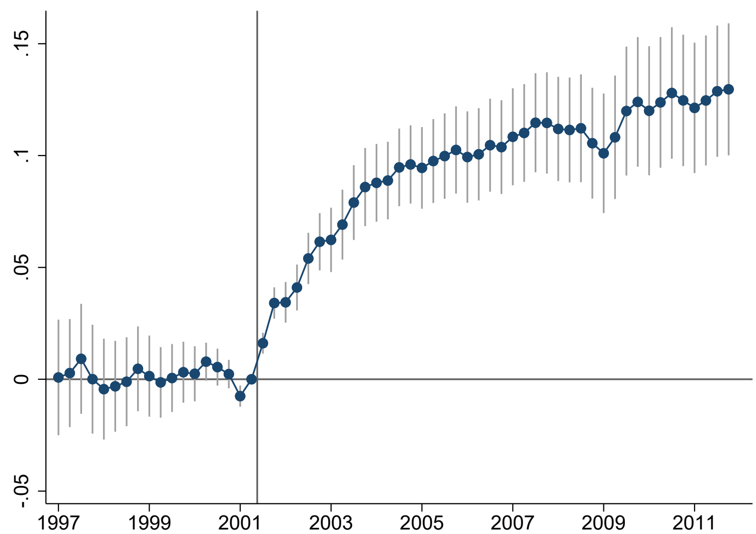
(B) Firms 0-5 Years Old



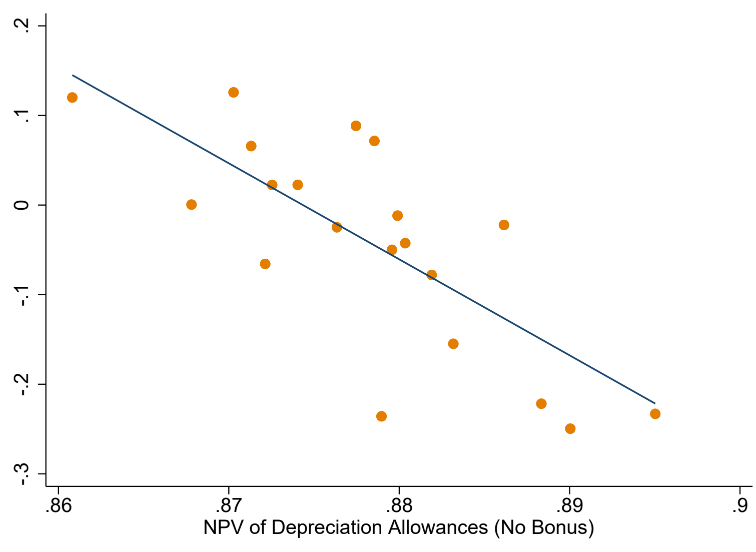
Notes: Figure A5 displays estimates describing the effect of bonus depreciation on Log Employment for small and young firms using state-by-industry QWI data. Panel (A) restricts the sample to firms with 50 or fewer employees. Panel (B) restricts the sample to firms that are five or fewer years old. The 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 A6: Effects of Bonus Depreciation on Employees, Continuous Treatment

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

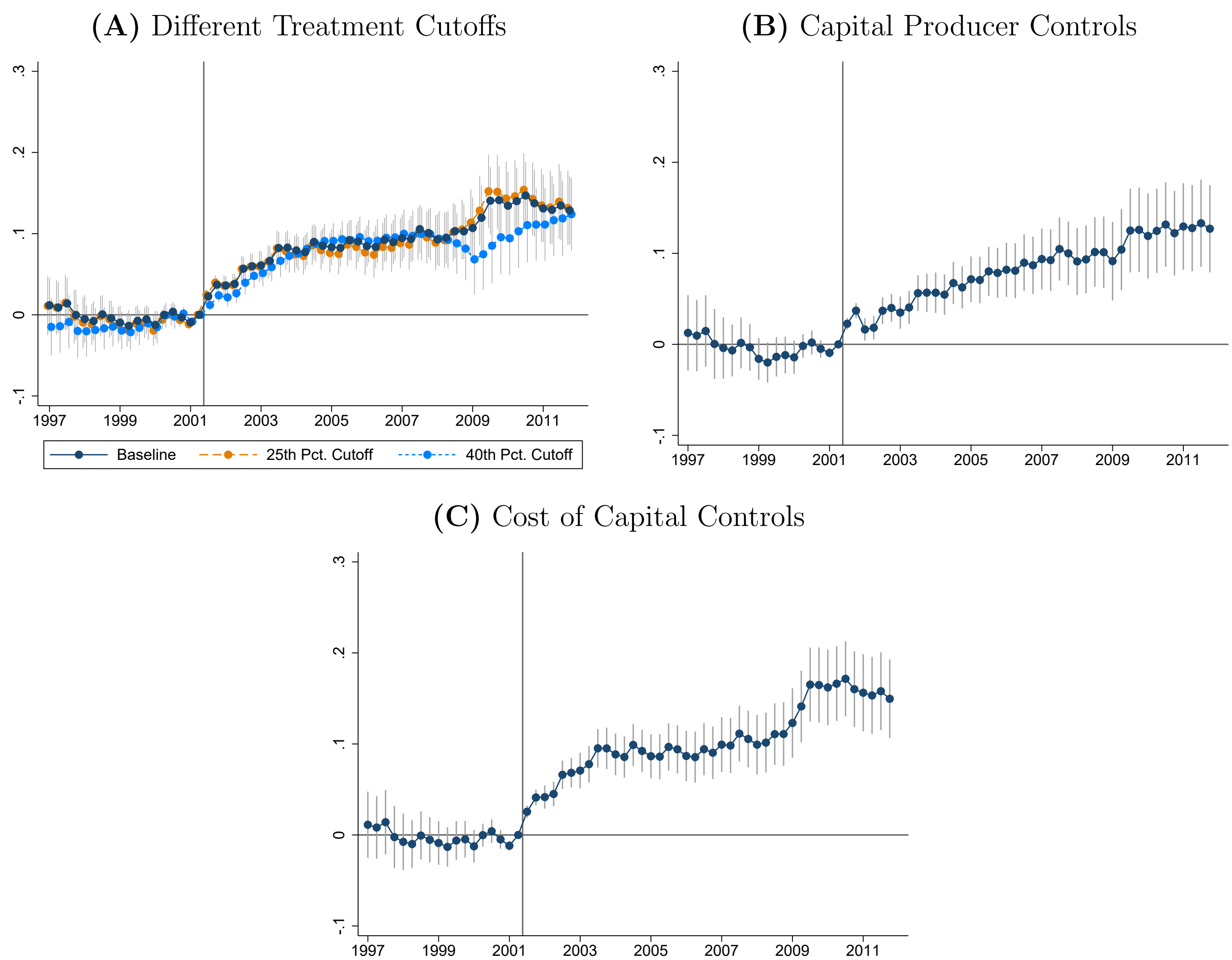


(B) Binscatter; Industry-Level Changes in Employment vs. z_0



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 4, but using the continuous $(1\text{-}z_0)\tau^{*}0.0375$ in place of the treatment indicator. Panel (B) presents a binned-scatter plot of industry-level changes between the pre- and post-periods 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.

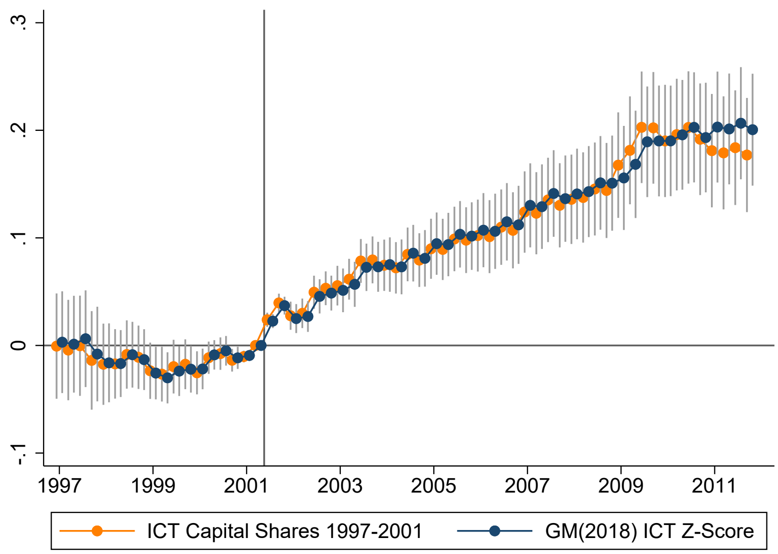
Figure A7: Effects of Bonus Depreciation, QWI Employment Robustness Checks



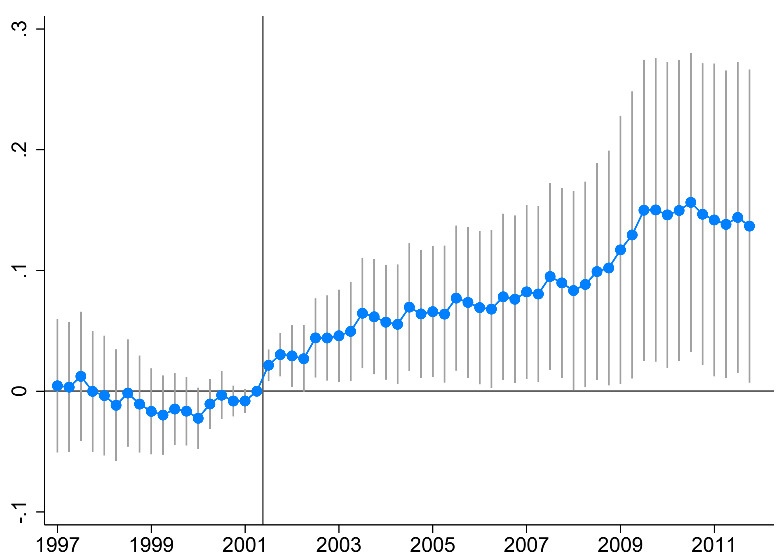
Notes: Figure A7 presents additional estimates of the effect of depreciation incentives on log employment in the state-by-industry QWI data as in Figure 4. Panel (A) shows the effects of bonus on employment using three different cutoffs in the z_0 distribution to determine treatment: 25^{th} percentile, 33^{rd} percentile, and 40^{th} percentile. Panel (B) includes a control for capital production as a share of output interacted with year fixed effects. Capital producing industries are identified using 2001 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 firms in 2001, defined as xint / (dltt + dlc). *Source:* Authors' calculations based on QWI, BEA, Compustat, and Zwick and Mahon (2017) data.

Figure A8: Effects of Bonus Depreciation, Controlling for ICT Growth

(A) ICT Controls



(B) Dropping Tech Industries



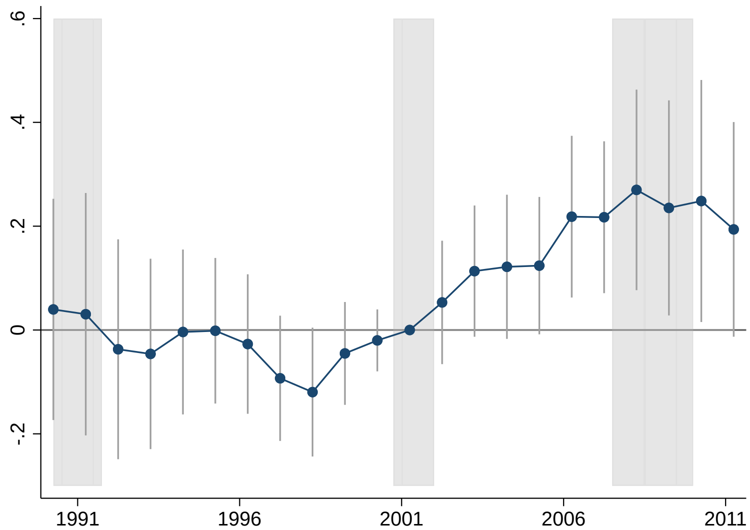
Notes: Figure A8 presents additional estimates of the effect of depreciation incentives on log employment in the state-by-industry QWI data as in Figure 4. Panel (A) includes tercile indicators for two measures of the use of information and communications technology (ICT) interacted with year fixed effects. The first is ICT capital intensity measured as a share of capital stock in ICT goods using BEA Detailed Data for Fixed Assets and Consumer Durable Goods from 1997 to 2001. The second is the Gallipoli and Makridis (2018) Z-score, which measures the normalized share of workers engaging in tasks involving ICT during the period 2002–2016. Panel (B) presents estimates that do not include tech industries. These include Aerospace Products and Parts (NAICS 3364), Other Chemicals (3259), Basic chemicals (3251), Pharmaceuticals (3254), Electrical Equipment and Components (3359), Audio and Video Equipment (3343), Navigational and Control Instruments (3345), Semiconductor and Compoent Manufacturing (3344), Communications Equipment Manufacturing (3342), Computer and Peripheral Equipment (3341). These industries represent 21.4% of 2001 manufacturing employment. *Source:* Authors' calculations based on QWI, BEA, Compustat, Gallipoli and Makridis (2018), and Zwick and Mahon (2017) data.

Figure A9: Effect of Bonus Depreciation on Employment by Task Content

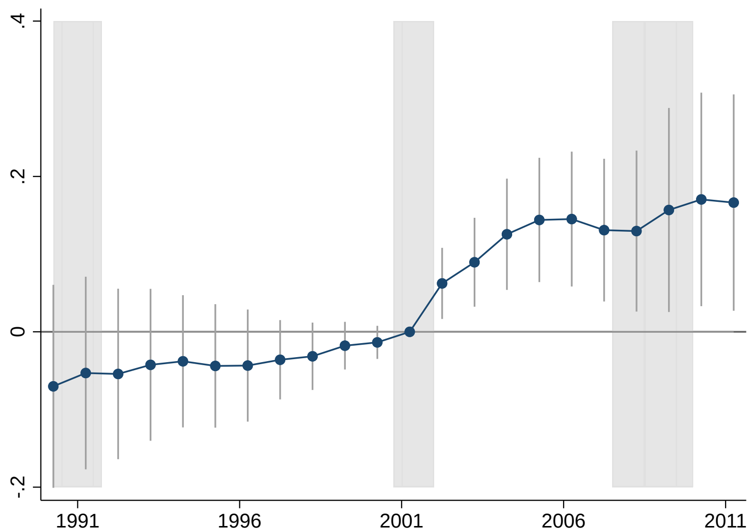
Notes: Figure A9 displays estimates describing the effect of bonus depreciation on employment in routine occupations and production occupations based on event study regressions. Plotted regression coefficients in years 1990, 2005, and 2010 represent the difference in employment by long- vs. short-duration industries relative to the same difference in 2000. Employment is categorized by matching occupation definitions from the Census and ACS to production and routine categories from Acemoglu and Autor (2011). Regressions are weighted by 2000 employment. Standard errors clustered at the state-industry level. *Source:* Authors' calculations based on Census, ACS, Zwick and Mahon (2017), and Acemoglu and Autor (2011) data.

Figure A10: U.S. Manufacturing Over the Business Cycle

(A) Log Investment



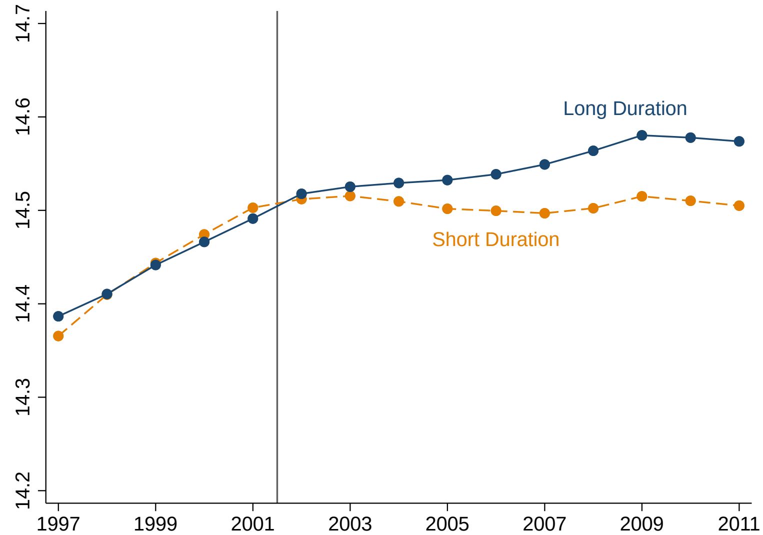
(B) Log Employment



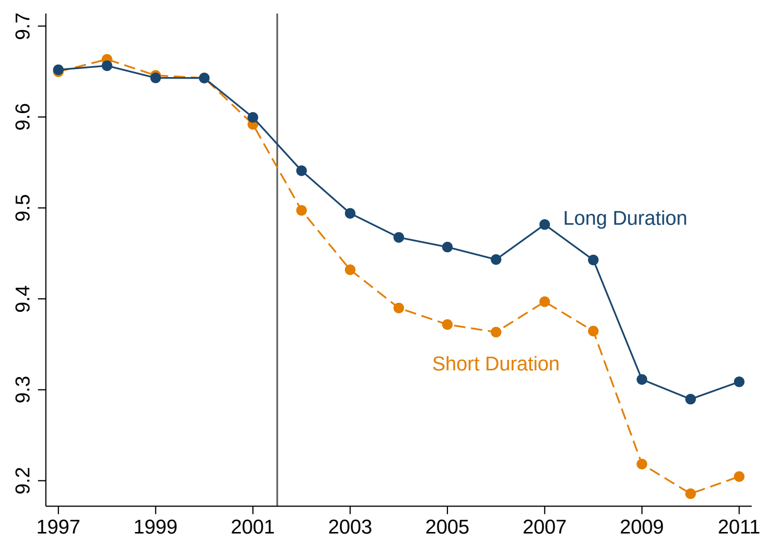
Notes: Figure A10 presents event study regression coefficients summarizing the effect of bonus depreciation on log employment and log investment in 4-digit NAICS industries over the 1990 to 2011 period. Coefficients obtained from industry-year level regressions akin to Equation (1) with observations 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 A11: Effects of Bonus Depreciation on Aggregate Trends

(A) Log Capital Stock



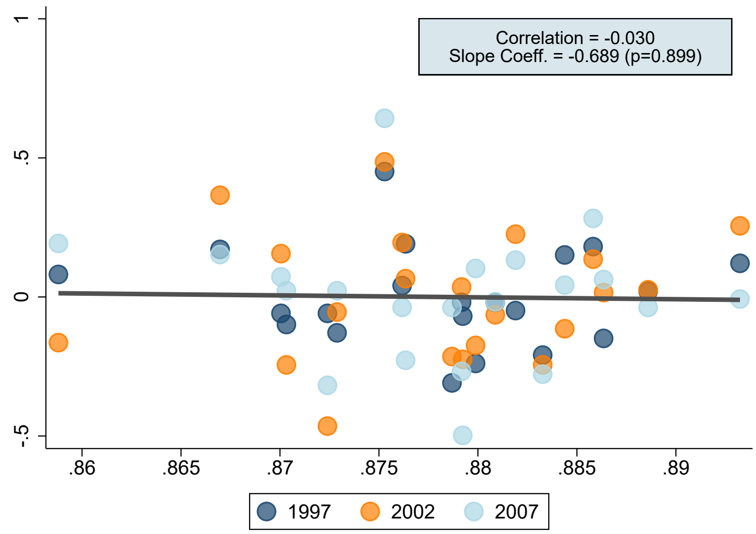
(B) Log Employment



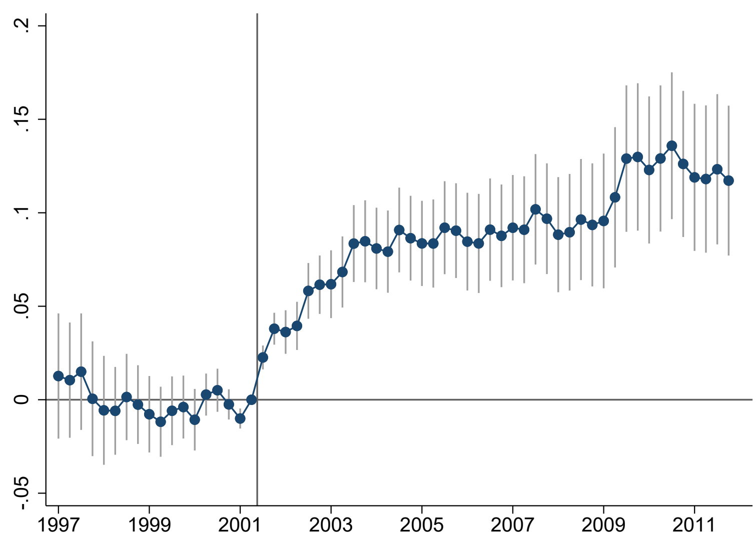
Notes: Figure A11 presents the effect of bonus depreciation on aggregate trends over log employment and log capital stock over the 1997-2011 implied by our reduced form estimates. We construct aggregate series across bonus treatment by calculating aggregate time series of log capital stock and log employment, respectively, for all manufacturing industries and adding or subtracting estimates of event study coefficients from Equation (1) to the resulting series. *Source:* Authors' calculations based on NBER-CES Manufacturing Industry Database, ASM, CM, and Zwick and Mahon (2017) data.

Figure A12: Bonus Depreciation Treatment and Differences in σ_{KL}

(A) Correlation Between Raval (2019) σ_{KL} and Zwick and Mahon (2017) z_0



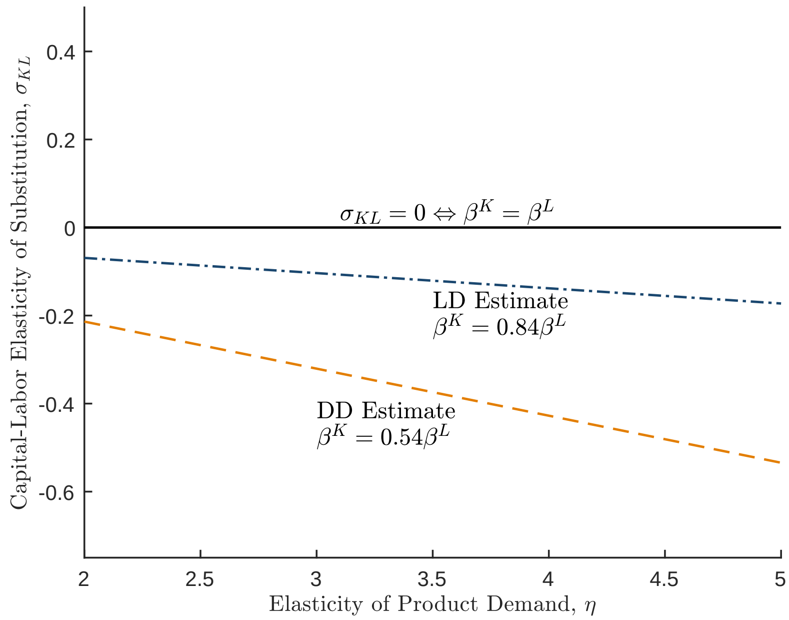
(B) Effect of Bonus Depreciation Employment Controlling for σ_{KL}



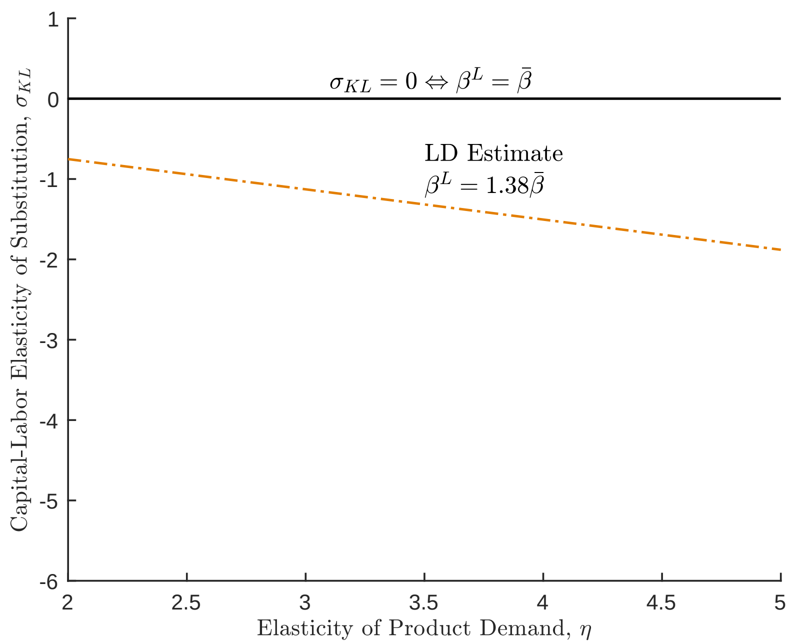
Notes: Panel (A) of Figure A12 shows how de-meaned σ_{KL} from Raval (2019) in years 1997, 2002, and 2007 vary across Zwick and Mahon (2017)'s z_0 measure averaged to the 3-digit NAICS level. The fitted linear relationship is based on year 2002 data. Panel (B) displays estimates describing the effect of bonus depreciation on log employment using state-by-industry QWI data as in Figure 4, controlling for tercile bins of 2002 σ_{KL} from Raval (2019) interacted with year fixed effects. *Source:* Authors' calculations based on data from the QWI, Zwick and Mahon (2017), and Raval (2019).

Figure A13: Additional Estimates of Capital-Labor Substitution

(A) σ_{KL} in a Two Input Model



(B) σ_{KL} in a Five Input Model

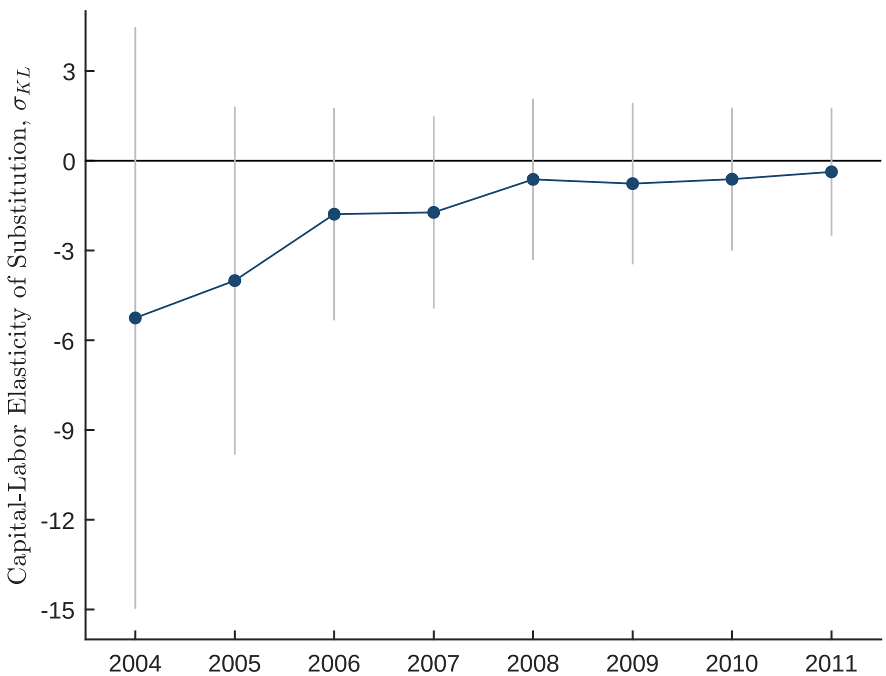


Notes: Figure A13 implements versions of Equation 26 across two- and five-input models and for a range of values of η. Panel (A) shows that both our long-differences and difference-in-differences reduced-form estimates are not consistent with large degrees of substitution between capital and labor in 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 26 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, CM, and Zwick and Mahon (2017) data.

Figure A14: Scale, Cost of Capital, and Elasticity Estimates over Time

Notes: Figure A14 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 $\bar{\beta}_t = s_J\beta_t^J + s_K\beta_t^K + s_L\beta_t^L$. 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 $\varepsilon_\phi^I = \beta^I/\phi$ and $\varepsilon_\phi^L = \beta^L/\phi$, respectively. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Figure A15: Capital-Production Labor Substitution over Time



Notes: Figure A15 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, CM, 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	✓	✓	✓	✓	✓	✓
$\text{PlantSize}_{2001}\times$Year FE	✓	✓	✓	✓	✓	✓
$\text{TFP}_{2001}\times$Year FE	✓	✓	✓	✓	✓	✓
$\text{FirmSize}_{2001}\times$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, CM, 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 worked 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, CM, and Zwick and Mahon (2017) data.

Table A4: Effects of Bonus Depreciation, QWI Sample

	(1) Log(Emp)	(2) Log(Earn)	(3) % < HS	(4) % < 35 years	(5) % Female	(6) % Black	(7) % Hispanic
	Difference-in-Differences						
Bonus	0.097***	-0.031***	0.00259***	0.01285***	0.00822***	0.0012	0.00536***
	(0.0156)	(0.00547)	(0.000605)	(0.00151)	(0.0024862)	(0.00074)	(0.000969)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.105]	[0.000]
	Long Differences						
Bonus	0.135***	-0.0314***	0.00394***	0.0306***	0.0118***	0.00409***	0.00589***
	(0.0216)	(0.0078)	(0.000724)	(0.0022)	(0.00679)	(0.00153)	(0.0017)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.008]	[0.001]
Share2001			0.25	0.3	0.25	0.07	0.06
State×NAICS FE	✓	✓	✓	✓	✓	✓	✓
State×Quarter FE	✓	✓	✓	✓	✓	✓	✓
Pre-Period Growth FE					✓	✓	✓

Notes: Table A4 shows the effect of bonus depreciation on outcomes 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 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. The outcomes across Specifications (5)–(8) are the fraction of female 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 A5: Effects of Bonus Depreciation on Employment by Task-Content and Demographics: 2000-2010 Changes

	(1) All	(2) Routine	(3) Nonroutine	(4) Professional Cognitive Nonroutine	(5) Admin. Cognitive Routine	(6) Production Manual Routine	(7) Services Manual Nonroutine
All Workers	0.0856***	0.126***	0.0264	0.0300	0.0876***	0.134***	0.0665
	(0.0201)	(0.0212)	(0.0217)	(0.0227)	(0.0235)	(0.0224)	(0.0467)
				Demographic Subgroups			
< HS Education	0.151***	0.159***	0.0906***	0.0806**	0.129***	0.159***	0.0873
	(0.0214)	(0.0220)	(0.0276)	(0.0335)	(0.0275)	(0.0228)	(0.0550)
Ages 18-35	0.143***	0.190***	0.0276	0.0262	0.113***	0.203***	0.0816
	(0.0272)	(0.0288)	(0.0349)	(0.0390)	(0.0400)	(0.0310)	(0.0942)
Female	0.126***	0.166***	0.0257	0.0545*	0.118***	0.143***	0.0406
	(0.0235)	(0.0251)	(0.0299)	(0.0317)	(0.0271)	(0.0316)	(0.0879)
Hispanic	0.154***	0.216***	-0.0398	0.0210	0.158	0.221***	-0.0197
	(0.0391)	(0.0427)	(0.0829)	(0.0971)	(0.106)	(0.0453)	(0.113)
Black	0.105**	0.158***	-0.0786	0.0977	-0.0134	0.162***	0.0408
	(0.0424)	(0.0448)	(0.0975)	(0.104)	(0.0952)	(0.0498)	(0.145)
Industry FE	✓	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: Table A5 displays coefficient estimates representing the effect of bonus depreciation on log employment at the state-industry level from 2000 to 2010. Specifications are estimated using subgroups of workers based on demographic categories and occupation task-content categories from Acemoglu and Autor (2011). All regressions include industry and state-year fixed effects. Standard errors are clustered at state-industry level and presented in parentheses. *Source:* Authors' calculations based on Census, ACS, Acemoglu and Autor (2011), and Zwick and Mahon (2017) data.

Table A6: 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 A6 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, CM, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) 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 displays difference-in-differences coefficients explaining the impact that bonus has on log earnings at the state-industry level. Column (1) does not include any controls for worker demographics and suggests bonus treatment lowered earnings by 3.1%. Columns (2)-(5) sequentially add controls for the share of young, less educated, non-white, and female workers in 2001, respectively, interacted with year fixed effects. Column (5) with controls for all demographic shares yields an estimate of 0.7, which is not statistically significant. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented below in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* QWI and Zwick and Mahon (2017) data.

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

	(1) Treat Pre	(2) Treat Post	(3) Control Pre	(4) 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 presents regression estimates and independent variable means needed to to perform the Kitagawa-Oaxaca-Blinder decomposition in Appendix I. Each column estimates a panel earnings regression describing the impact of demographic shares on average wages with two-way fixed effects for a different sample. Column (1) displays estimates from 1997-2000 for treated industries. Column (2) displays estimates from 2001-2011 for treated industries. Columns (3) and (4) replicate the analysis of the first two columns for untreated industries. 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, CM, Zwick and Mahon (2017), Acemoglu, Autor, Dorn, Hanson and Price (2016), and Acemoglu and Restrepo (2020) data.

Table A10: 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}	0.122	0.089	0.130	0.177	0.077	0.163	0.078
	(0.069)	(0.056)	(0.107)	(0.040)	(0.087)	(0.041)	(0.098)
b_{kk}	0.160	0.160	0.146	0.090	0.210	0.160	0.160
	(0.064)	(0.049)	(0.105)	(0.034)	(0.091)	(0.039)	(0.091)
b_{kl}	-0.144	-0.160	-0.133	-0.080	-0.190	-0.124	-0.166
	(0.035)	(0.030)	(0.050)	(0.020)	(0.048)	(0.021)	(0.049)
b_{kj}	-0.016	0.000	-0.013	-0.010	-0.020	-0.036	0.006
	(0.038)	(0.029)	(0.063)	(0.021)	(0.050)	(0.023)	(0.054)
b_{lj}	-0.106	-0.090	-0.117	-0.167	-0.057	-0.126	-0.084
	(0.035)	(0.030)	(0.050)	(0.020)	(0.048)	(0.021)	(0.049)
	Panel B: Production Function F-test p-values						
Cobb-Douglas	0.000	0.000	0.013	0.000	0.115	0.000	0.010
K Separability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J Separability	0.000	0.000	0.001	0.000	0.450	0.000	0.010
L Separability	0.000	0.000	0.007	0.000	0.000	0.000	0.001
Leontief	0.436	0.095	0.751	0.428	0.448	0.514	0.395
σ_{LJ}	0.29	0.40	0.22	0.13	0.49	0.16	0.44
	(0.15)	(0.14)	(0.22)	(0.03)	(0.51)	(0.09)	(0.22)
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	-0.12	-0.10	-0.27	-0.09	-0.23	-0.10

Notes: Table A10 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 $H_0 : b_{ij} = -s_i * s_j \forall i \neq j$ (Leontief). Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A11: 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}	0.184	0.159	0.165	0.133	0.220	0.215	0.151
	(0.071)	(0.055)	(0.119)	(0.099)	(0.061)	(0.042)	(0.101)
b_{jj}	0.056	-0.001	0.045	0.062	0.049	0.127	-0.020
	(0.134)	(0.103)	(0.219)	(0.138)	(0.126)	(0.080)	(0.191)
b_{kk}	0.160	0.160	0.146	0.090	0.210	0.160	0.160
	(0.064)	(0.049)	(0.105)	(0.034)	(0.091)	(0.039)	(0.091)
b_{kl}	-0.144	-0.160	-0.133	-0.080	-0.190	-0.124	-0.166
	(0.035)	(0.030)	(0.050)	(0.020)	(0.048)	(0.021)	(0.049)
b_{kj}	-0.016	0.000	-0.013	-0.010	-0.020	-0.036	0.006
	(0.038)	(0.029)	(0.063)	(0.021)	(0.050)	(0.023)	(0.054)
b_{lj}	-0.040	0.001	-0.032	-0.053	-0.029	-0.091	0.015
	(0.096)	(0.073)	(0.156)	(0.117)	(0.075)	(0.057)	(0.136)
	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	0.676	0.991	0.837	0.653	0.696	0.111	0.915
L Separability	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Leontief	0.436	0.095	0.751	0.428	0.448	0.514	0.395
σ_{LJ}	0.73	1.01	0.79	0.73	0.74	0.39	1.10
	(0.64)	(0.49)	(1.04)	(0.61)	(0.67)	(0.38)	(0.91)
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	-0.12	-0.10	-0.27	-0.09	-0.23	-0.10

Notes: Table A11 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 A14, $\hat{\sigma}_{LJ} = \hat{\sigma}_{KJ}$. 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 $H_0 : b_{ij} = -s_i * s_j \forall i \neq j$ (Leontief). Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A12: Morishima Elasticities of Substitution Parameter Estimates

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
	Panel A: Morishima Elasticities of Substitution				
Production labor-capital, σ^M_{KL}	-0.248*	-0.121*	-0.380*	-0.142*	-0.354*
	(0.141)	(0.067)	(0.223)	(0.081)	(0.202)
Nonproduction labor-capital, σ^M_{KJ}	-0.070	-0.034	-0.107	-0.040	-0.100
	(0.188)	(0.091)	(0.290)	(0.107)	(0.268)
	Panel B: p-values for Substitutability Tests				
Substitutability of production labor	0.040	0.036	0.044	0.040	0.040
$H_0 : \sigma^M_{KL} \geq 0$					
Complementarity of non-production labor	0.355	0.354	0.356	0.355	0.355
$H_0 : \sigma^M_{KJ} \leq 0$					
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: Panel (A) of Table A12 presents estimates of Morishima elasticities of substitution. Panel (B) presents p-values associated with tests of the substitutability and complementarity of the elasticities presented in Panel (A). Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A13: Constant Elasticity of Substitution Parameter Estimates

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
	Panel A: CES Parameter Estimates				
Nonproduction Labor, ρ_1	-1.662	-1.248	-2.299	-3.659	-0.864
	(4.158)	(2.753)	(6.933)	(7.277)	(2.911)
Production Labor, ρ_2	5.034**	9.251**	3.628**	8.060**	3.824**
	(2.300)	(4.575)	(1.543)	(4.026)	(1.610)
	Panel B: Implied CES Substitution Elasticities				
Nonproduction Labor, $\frac{1}{1-\rho_1}$	0.376	0.445	0.303	0.215	0.537
	(0.587)	(0.545)	(0.637)	(0.335)	(0.838)
Production Labor, $\frac{1}{1-\rho_2}$	-0.248*	-0.121*	-0.380*	-0.142*	-0.354*
	(0.141)	(0.067)	(0.223)	(0.081)	(0.202)
	Panel C: p-values for Skill Complementarity Test				
$H_0 : \frac{1}{1-\rho_2} - \frac{1}{1-\rho_1} - 1 > 0$	0.004	0.003	0.006	0.000	0.016
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: Panel (A) of Table A13 presents estimates of substitution parameters from a constant elasticity of substitution (CES) production function. Panel (B) presents the CES substitution elasticities implied by the results in Panel (A). Panel (C) tests the null hypothesis of $H_0 : \frac{1}{1-\rho_2} - \frac{1}{1-\rho_1} - 1 > 0$, consistent with the presence of skill complementarity of capital, across these models. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A14: Additional 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
Labor-capital, σ_{KL}	-0.440	-0.603	-0.332	-0.106	-0.138	-0.474
	(0.346)	(0.305)	(0.498)	(0.144)	(0.142)	(0.952)
Nonproduction labor-capital, σ_{KJ}	0.733	1.006	0.786			
	(0.639)	(0.489)	(1.043)			
Equipment-structures, σ_{KS}					1.908	
					(0.603)	
Materials-capital, σ_{KM}						0.182
						(0.507)
	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	0.069	0.060	0.052	0.065	0.064	0.057
Labor	0.109	0.098	0.080	0.094	0.094	0.091
Nonproduction labor	0.076	0.060	0.057			
Structures					0.041	
Materials						0.076
Capital	0.096	0.084	0.080		0.105	0.080
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	-0.12	-0.10	-0.13	-0.23	-0.23

Notes: Table A14 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. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A15: 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)
Production labor-capital, σ_{KL}	-0.509	-0.424	-0.594	-0.272	-0.759	-0.568
	(0.334)	(0.328)	(0.357)	(0.203)	(0.470)	(0.633)
Nonproduction labor-capital, σ_{KJ}	0.374	0.443	0.308	0.225	0.548	0.414
	(0.590)	(0.544)	(0.642)	(0.359)	(0.830)	(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	0.072	0.074	0.070	0.047	0.082	0.075
Production labor	0.115	0.116	0.115	0.108	0.118	0.116
Nonproduction labor	0.090	0.090	0.090	0.084	0.091	0.090
Capital	0.080	0.080	0.080	0.079	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	-0.14	-0.30	-0.09	-0.24	-0.10	-0.13

Notes: Table A15 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 $s_L\sigma_{KL} + s_J\sigma_{KJ} > 0$. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A16: Capital-Labor Elasticity of Substitution with Cash Flow Constraints

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
Production labor-capital, σ_{KL}	-0.515	-0.426	-0.608*	-0.294	-0.736
	(0.336)	(0.330)	(0.362)	(0.192)	(0.481)
Cash-flow expenditure share, s^b	0.027***	0.028***	0.026***	0.019***	0.030***
	(0.004)	(0.004)	(0.003)	(0.002)	(0.004)
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 A16 presents estimates of elasticities of substitution between capital and production labor under financing constraints as described in Appendix J.4. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A17: Effects of Bonus Depreciation; NBER-CES Industry-Level Data

	(1) Log Prod. Emp.	(2) Log Nonprod. Emp.	(3) Log Capital
Bonus	0.179**	0.132*	0.122***
	(0.0731)	(0.0703)	(0.0434)
	[0.016]	[0.065]	[0.006]
Year FE	✓	✓	✓
NAICS FE	✓	✓	✓

Notes: Table A17 presents coefficient estimates representing the effect of bonus depreciation on manufacturing inputs at the aggregate industry level using data from NBER-CES. All coefficients are for the long difference, or the impact of bonus on outcomes by 2011 relative to 2001. Column (1) shows the impact on log production employment, column (2) shows the impact on log non-production employment, and column (3) shows the impact on log capital. All specifications include year and industry fixed effects. Standard errors clustered at the state-industry level are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A18: Model-Based Implications of Reduced-Form Estimates: NBER-CES Aggregate Version

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
	Panel A: Scale Effect Estimates				
Scale Effect, $\bar{\beta}$	0.154**	0.157**	0.150**	0.154**	0.154**
	(0.064)	(0.068)	(0.060)	(0.064)	(0.064)
	Panel B: Allen Elasticities of Substitution				
Production labor-capital, σ_{KL}	-0.590	-0.501	-0.682	-0.337	-0.842
	(0.403)	(0.376)	(0.468)	(0.230)	(0.576)
Nonproduction labor-capital, σ_{KJ}	0.497	0.562	0.429	0.284	0.710
	(0.675)	(0.619)	(0.744)	(0.386)	(0.964)
	Panel C: p-values for Substitutability Tests				
Substitutability of production labor	0.072	0.091	0.072	0.072	0.072
$H_0 : \sigma_{KL} \geq 0$					
Complementarity of non-production labor	0.769	0.818	0.718	0.769	0.769
$H_0 : \sigma_{KJ} \leq 0$					
	Panel D: Cost of Capital Elasticity Estimates				
Effect on cost of capital, ϕ	-0.219**	-0.449**	-0.143**	-0.384**	-0.154**
	(0.091)	(0.193)	(0.057)	(0.159)	(0.064)
Capital, ε_{ϕ}^{K}	-0.554***	-0.271***	-0.850***	-0.317***	-0.792***
	(0.167)	(0.090)	(0.230)	(0.095)	(0.238)
Production Labor, ε_{ϕ}^{L}	-0.818***	-0.400***	-1.255***	-0.467***	-1.168***
	(0.081)	(0.038)	(0.140)	(0.046)	(0.115)
Non-production Labor, ε_{ϕ}^{J}	-0.601***	-0.294***	-0.921***	-0.343***	-0.858***
	(0.135)	(0.062)	(0.223)	(0.077)	(0.193)
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 A18 presents several results relating our reduced-form estimates to model outcomes across several alternative calibrations of cost shares and η using aggregate manufacturing data. Panel (A) displays estimates of the scale effect defined in Equation (7). Panel (B) presents estimates of the Allen elasticities of substitution between capital and production labor and capital and non-production labor using equations (4) and (5), respectively. Panel (C) conducts hypothesis tests of the substitutability and complementarity of production and non-production labor, respectively. Panel (D) 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. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A19: Industry-Level Estimates of Morishima Elasticities of Substitution

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
	Panel A: Morishima Elasticities of Substitution				
Production labor-capital, σ^M_{KL}	-0.264	-0.129	-0.405	-0.151	-0.377
	(0.213)	(0.101)	(0.338)	(0.122)	(0.304)
Nonproduction labor-capital, σ^M_{KJ}	-0.046	-0.023	-0.071	-0.027	-0.066
	(0.255)	(0.124)	(0.393)	(0.145)	(0.364)
	Panel B: p-values for Substitutability Tests				
Substitutability of production labor	0.108	0.100	0.115	0.108	0.108
$H_0 : \sigma^M_{KL} \geq 0$					
Complementarity of non-production labor	0.428	0.427	0.428	0.428	0.428
$H_0 : \sigma^M_{KJ} \leq 0$					
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: Panel (A) of Table A19 presents estimates of Morishima elasticities of substitution. Panel (B) presents p-values associated with tests of the substitutability and complementarity of the elasticities presented in Panel (A). Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Source:* Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A20: Industry and Aggregate Capital-Labor Elasticity of Substitution

	(1) Baseline	(2) Low s_K	(3) High s_K	(4) Low η	(5) High η
Industry Elasticity, σ_{KL}^{N}	-0.264	-0.129	-0.405	-0.151	-0.377
	(0.213)	(0.101)	(0.338)	(0.122)	(0.304)
Aggregate Elasticity, σ_{KL}^{agg}	-0.186	-0.061	-0.316	-0.085	-0.286
	(0.199)	(0.094)	(0.317)	(0.114)	(0.285)
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 A20 reproduces industry-level Morishima elasticities of substitution from Table A19 and presents estimates of the aggregate elasticities of substitution between capital and labor implied by these estimates. Standard errors are presented in parentheses. *Source:* Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.