Capital Investment and Labor Demand: Evidence from 21st Century Stimulus Policy*

E. Mark Curtis
Wake Forest University

Daniel G. Garrett
University of Pennsylvania

Eric Ohrn
Grinnell College

Kevin A. Roberts
Stanford GSB

Juan Carlos Suárez Serrato
Stanford GSB & NBER

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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 in industries that benefit the most from bonus to those in industries 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 measure the impact of capital adoption on workers, allowing plants ten years to adjust on multiple margins.

The combination of detailed plant-level data and cross-sectional variation in the generosity of tax incentives reveals a number of interesting facts. Difference-in-differences analyses show that plants respond to the tax policy by increasing their capital stock and employment, leading them to increase their overall output. In contrast, capital investment did not increase average worker earnings or plant productivity. 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 nearly 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 in industries that benefit the most from this incentive—those that invest more in equipment that is deducted slowly according to IRS rules—to plants in industries 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 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, the effects of 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, 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. 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. Because we find similar employment and investment responses using the industry-level NBER-CES data, we also conclude that within-industry reallocation is not a major driver of our baseline reduced-form estimates. 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. In contrast, 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, female, Black, and Hispanic workers, as well as workers with fewer years of education. These composition shifts fully account for the observed decrease in average earnings; our estimates rule out earnings increases greater than 0.9% 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 close to 90% of the overall effect of the policy on the demand for production workers. In other words, plants reacted to the policy by increasing their scale rather than by replacing 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 increase in non-production employment. In contrast, because the increase in production employment is larger than the scale effect, the model yields an elasticity of substitution between capital and production labor of -0.44. This elasticity implies 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.

[1]Because 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 robust to alternative models that include structures and materials as inputs and that they 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. In a series of empirical tests presented in Appendix P.9, 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 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 elasticities of substitution. Second, we show that accounting for reallocation across plants and industries does not substantively change our findings. Specifically, we find similar elasticity estimates using moments based on industry-level data, which incorporate entry, exit, and reallocation across plants. We also find similar substitution elasticities when adjusting these industry-level estimates to account for cross-industry reallocation using methods developed by Oberfield and Raval (2021). Finally, we extend our model to allow for monopsony in the labor market and show that that capital and production labor continue to exhibit complementary responses in this setting (see Appendix O.5).

Our results build on classic studies that have estimated the effects of accelerated depreciation on business investment (Hall and Jorgenson, 1967; Cummins et al., 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 et al., 2019; 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 accumu-

[4] Zwick and Mahon (2017) estimate effects of bonus on payroll but not employment and Ohrn (2021) studies executive compensation. Garrett et al. (2020) estimate regional employment effects of bonus and find that, inclusive of local labor market spillover effects, the average fiscal cost of the jobs created by this stimulus policy was in the range of $20,000 to $50,000. Tuzel and Zhang (2021) study the effects of state accelerated depreciation policies on computer purchases and the mix of occupational employment.

[5] Criscuolo et al. (2019) and Siegloch et al. (2021) both explore joint capital and labor responses to place-based policies in the UK and Germany, respectively. Similarly, Lerche (2022) investigates firm responses to an investment tax credit in Germany and finds increases in employment and capital of similar magnitudes. LaPoint and Sakabe (2021) estimate responses to a geographically targeted Japanese version of bonus depreciation.

lation of capital stocks, plant sales, total factor productivity, labor earnings, overall employment, employment for production and non-production workers, and workforce demographics.

Because bonus was implemented during a period of employment decline, we assess 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, as well as on plants that are younger, smaller, and more likely to grow; plants in industries with high capital and skill intensities; plants that are more likely to adopt robots; and plants less exposed to Chinese import competition. We also use job flows data to show that the net employment effect of bonus depreciation is equally constituted by more job creation and less job destruction. Overall, we find that the effects of bonus depreciation are concentrated on the plants and industries most likely to thrive in the 21st century.

Our paper also contributes to the literature estimating elasticities of substitution between capital and different types of labor. 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 et al., 2000; Lewis, 2011). Our paper differs from prior work that relied on aggregate data (Krusell et al., 2000) or on cross-sectional variation in the cost of labor (Raval, 2019), because we use tax-driven, quasi-experimental variation in the cost of capital to estimate the production behavior of individual plants over a 15-year period. We then use 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

[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 et al., 2021). Appendix P.8 uses the methods of Oberfield and Raval (2021) to map our micro-level estimates to an aggregate elasticity of substitution.

[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.

increases labor demand (Acemoglu et al., 2020b; Dixon et al., 2021; Koch et al., 2021).[8,9] Hirvonen et al. (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 et al. (2022b) 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 robots.[10]

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 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. Despite declining in popularity during the later years of the 20th century, the use of these policies came back into vogue when the US introduced "Bonus Depreciation" in 2001. 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. In addition to bonus, firms could also benefit from an accelerated depreciation policy referred to as §179 ("Section 179"), which allows for full expensing of investment costs below a dollar limit.[11] Throughout the paper, we interpret our results as the combined effect of

[8] Acemoglu and Restrepo (2020) and Dauth et al. (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. See Aghion et al. (2022a) for a survey of research on the effects of automation on labor demand.

[9] Acemoglu et al. (2020a) 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 et al. (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.

[10] 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 et al., 1998, 2003; Akerman et al., 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.

[11] 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).

these policies.

To illustrate the mechanics of bonus, we consider the tax depreciation schedules of two different assets as determined by the IRS (IRS, 2002, see Table A.1 of Publication 946). Figure 1 shows examples of Modified Accelerated Cost Recovery System (MACRS) schedules for a tractor trailer (a three-year asset) in Panel A and a barge (a ten-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 Panels A and B, it is clear that, while both assets benefit from bonus depreciation, the asset that is depreciated more slowly according to IRS rules (i.e., the barge) benefits more.

While this realistic example is instructive, it is useful to have a measure of the benefit of bonus depreciation that applies to all assets. Let z_0 be the original PV of depreciation deductions per dollar of investment and let b be the bonus depreciation percent. Under bonus, the PV of depreciation deductions per dollar of investment, z, is given by $z = b + z_0 \times (1 - b)$. The fact that $\frac{\partial z}{\partial b} = 1 - z_0$ shows that bonus provides a larger subsidy to 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, z_0 is determined by the depreciation schedule assigned to each asset class. For equipment used in production, asset classes are defined by the activity for which a given piece of equipment is used. As a result, these classes align more closely with NAICS industry definitions than with the useful life of a specific asset.[12] Appendix B presents an overview of the historical context of these depreciation schedules. Importantly, Brazell et al. (1989) note that the asset lives from which MACRS evolved "were not intended to reflect actual useful lives, or even some percentage of the useful lives." 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

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

z_0 at the industry level.

Several real-world factors shape the application of accelerated depreciation policies. First, the generosity of bonus varied over time. However, 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, over the 2001 to 2011 period, when the average bonus rate was 45%.[13] Using this bonus rate and estimates from Zwick and Mahon (2017) based on IRS data, we calculate that by increasing the PV of depreciation deductions, bonus lowered investment costs by 2.5% on average.

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) used an ordered probit model to correctly predict the 2003 increase in bonus depreciation generosity before it happened. House and Shapiro (2008) similarly 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.

Additionally, 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 because 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. The total impact of bonus on the cost of capital is therefore likely to significantly exceed the value of depreciation deductions alone.[14]

From the perspective of policy analysis, our reduced-form estimates capture the ten-year

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

[14] In contrast, Kitchen and Knittel (2016) show some firms do not claim bonus, in particular those in tax loss positions. 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.

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 et al., 2019), China (Fan and Liu, 2020), Canada, and Poland (Guceri and Albinowski, 2021). Today, bonus and accelerated depreciation policies are being deployed to combat the world's largest economic crises, including global warming and the COVID-19 pandemic.[15] These trends highlight the importance of bonus depreciation and related policies in shaping investment and potentially labor demand in the 21st century.

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 considered the workhorse datasets of the US Census Bureau's Economic Census. These establishment-level datasets contain detailed information on manufacturing plants' inputs and outputs. 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

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

capital stock measures using the perpetual inventory method in non-CM years (as in Cunningham et al., 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 automated, particularly in response to policies that lower the cost of capital. Finally, we combine information on employment, capital stock, and material inputs to estimate plant-level measures of total factor productivity (TFP).[16] To avoid sensitivity to outliers, we winsorize all variables at the 1% level.

Our baseline regressions are performed on a balanced panel of establishments that are present in the ASM/CM between 1997 and 2011. A particular advantage of these data is that they allow us to track differences between treated and control plants for five years prior to policy implementation and to measure the effects of the policy over a ten-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.[17] 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).

[16]Following Criscuolo et al. (2019), we estimate residual TFP using industry-level cost shares. See Appendix A for details.

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

In a number of analyses, we rely on complementary data from the publicly-available Quarterly Workforce Indicators (QWI) (see, e.g., Abowd et al., 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. The state-industry QWI data that we use complement the ASM/CM data in three ways. First, they allow us to explore whether bonus had different employment effects on workers with different characteristics, including education, gender, age, race, and ethnicity. Accounting for the effects of bonus on the demographic composition of the workforce refines our understanding of the wage effects of the policy. Second, our state-industry analyses account for any potential effects of the policy on entry and exit. 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.[18] 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.

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.[19]

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

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

[19] We show this natural break in Panel A of Figure A1, which presents the 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. As we show below, we obtain similar results when we define treatment status using these different thresholds or when using the continuous variation in z_0.

[20] We also address this endogeneity concern empirically by investigating the stability of z_0 over time in Appendix C. 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.

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 differences in z_0 arise from 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 directly address this threat by including industry-by-year fixed effects. Instead, we rely on a number of 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.[21] These controls ensure that the effects of bonus are not confounded by trends arising from pre-treatment differences in plant size or productivity. Finally, in Section 5, we 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. DD estimates yield more precise estimates

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

and are suitable for outcomes that adjust rapidly to the policy. 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. We interpret LD estimates, which measure the cumulative effect of accelerated depreciation policies on plant outcomes over the ten-year period 2002–2011, as the medium-term effects of the policy.[22] One major benefit of measuring ten-year effects is that adjustment costs are unlikely to dramatically affect these 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 et al. (2004) and Cameron and Miller (2015).[23]

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 both 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

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

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

the manufacturing sector, confirming that the findings of House and Shapiro (2008) and Zwick and Mahon (2017) hold in our setting.[24]

Table 1 presents estimates of the effects of bonus on log investment. Column (1) reports DD estimates with only plant and year fixed effects and shows a relative investment increase of 17% ($p < 0.001$). Estimations that progressively include state-by-year fixed effects, plant size bins-by-year fixed effects, TFP bins-by-year fixed effects, and firm size bins-by-year fixed effects yield a narrow range of estimates between 15.1 and 15.8%.[25] Because investment data can include spells of non-investment, we consider alternative outcome variables that capture extensive margin responses in Table A3. Across all 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 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%. A crucial advantage of our setting is the ability to measure the effects of bonus over a ten-year period. However, some calibrated models of the economy may have longer convergence periods that imply that bonus may continue to stimulate capital growth in future years (Barro and Furman, 2018).

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 depreciation 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

[24]As we discussed above, Zwick and Mahon (2017) use the same threshold for bonus treatment in their event study analyses, which show that investment in treated firms increased by 11.8% relative to firms in the control group between 2002-04. Over that same period, our event study coefficients indicate that investment for the treatment plants increased by 10.2%. See Appendix E for a detailed comparison to earlier estimates.

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

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 underexplored question of whether plants used this increase in capital to replace workers, or if plants hired additional workers to interact with the new machinery.

Panel A of 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 they employ. This positive 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 different sets of controls, our 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 tax incentives for investment will incentivize firms to replace workers with machines.

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.[26] As we show in Panels B and C of Table 3, the point

[26] We follow Berman et al. (1994) in using the production/non-production task taxonomy in the ASM data when

estimate of the effect of bonus on production employment is larger than that on non-production employment across all our specifications.[27] Comparing the long-difference estimates in column (7), we find that the effect on production employment is more than 40% larger than the effect on the employment of workers specializing in non-production tasks.[28] Our results are therefore not consistent with the hypothesis that bonus induced a shift from production employment to automated technologies or to technologies that are more likely to be complementary to non-production employment.

As we discuss in Section 2, the results above focus on a balanced panel of plants. One possibility 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 accounting for the entry of new, more capital-intensive firms. To explore this possibility, we estimate the effects of bonus on employment using QWI data at the state-industry level. Importantly, these aggregated data capture extensive margins of response, such as plant exit or entry, that our balanced panel omits by construction. Figure A7 presents event study estimates of bonus depreciation on employment using quarterly QWI data and shows that these margins do not substantially alter our estimates of the effects of bonus depreciation on employment.

We also use the QWI data to measure the effects on employment for smaller and younger firms, which are likely underrepresented in our balanced ASM/CM panel. Panel A of Figure A9 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 results for small and young plants also suggest that the effect of bonus on employment is generalizable to the full US manufacturing sector.[29]

estimating labor demand. Appendix H demonstrates that we obtain consistent results when we estimate the effect of bonus depreciation on more granular employment categories using US Census and American Community Survey data and occupation definitions based on tasks, as in Acemoglu and Autor (2011).

[27] 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).

[28] Panels A and B of Figure A8 present event study graphs of the effects of bonus on production and non-production employment. As we show in Table A4, the result that the effect of bonus on production employment is larger than on 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.

[29] The effect for young firms is consistent with Isphording et al. (2021), who suggest that young firms are more

We further validate our employment results in several ways, described fully in Appendix F. Specifically, we show that our reduced-form results are robust to a continuous treatment definition, alternative discrete cutoffs in the z_0 distribution, the inclusion of controls for the cost of capital and financial risk, and controlling for industry-level Information and Communication Technology (ICT) usage. We also show that our pre-trend tests are not confounded by differential business cycle exposure going back to the 1991 recession, and that reallocation within firms or local labor markets does not drive our results. 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 of 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. Panel B of Figure 3 presents event study plots of the effects of bonus on average worker earnings. Relative to control plants, 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.[30] 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 the policy changes the composition of the workforce. We use QWI data to show that this is the case.[31] Figure 4 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

likely to be financially constrained than small firms. In Appendix P.7, we directly quantify the roles that entry and exit play in shaping the employment response to bonus.

[30] We find a similar negative effect when we estimate the impact of bonus on average earnings using QWI data; see column (2) of Table A7.

[31] 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.

larger by 3.9 percentage points ($p<0.001$). These differential effects alter the composition of the workforce, increasing the share of lower education workers by 0.9%.[32] Panel B of Figure 4 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 9.3 percentage points ($p<0.001$), which increases the share of younger workers by 4.3%. 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 3.8%, the share of Hispanic or Latino workers by 16%, and the share of Black workers by 1.2%. Overall, we find that bonus had larger employment effects for workers that are paid, on average, relatively less. These results support the hypothesis that the decrease in average earnings per worker is likely due to changes in workforce demographics induced by the tax policy.[33]

We follow a two-step procedure to quantify how these demographic changes affect average earnings. First, using pre-treatment data, we regress earnings per worker on demographic shares (young, female, possessing fewer years of education, non-White). Using these estimates and observed demographic shares, we predict state-industry earnings during the full sample period. These predicted counterfactual earnings capture only the changes in earnings due to demographic shifts and hold earnings per worker constant within each demographic group. We then estimate the response of these counterfactual earnings to bonus depreciation. If the average earnings response we find is caused exclusively by demographic shifts due to the policy then we would expect our counterfactual event study estimates to look very similar to those presented in Panel B of Figure 3.

Figure A16 compares the counterfactual event study estimates with the earnings event study based on ASM data (Panel B of Figure 3). The counterfactual estimates closely track the ASM findings throughout the sample period. The similarity of the two series indicates that, indeed, the negative earnings response to bonus depreciation is due primarily to the policy-induced

[32] Table A7 presents estimates of bonus on different demographic shares. For instance, column (3) of Table A7 shows that the fraction of workers with fewer years of education increased by 0.00395. We calculate the 0.9% increase by dividing this estimate by the 46% base fraction of these workers.

[33] Bonus depreciation may induce these types of composition effects because plants resort to low-wage workers when they have exhausted preferred, high-wage labor pools. If this is the case, we would expect the earnings response to be more negative in tighter labor markets. In Appendix L, we explore this hypothesis by estimating heterogeneous effects by county-level unemployment rates. In contrast to this hypothesis, we do not find evidence of heterogeneity on this margin.

demographic shifts in the workforce we document above.

In Appendix K, we provide further details on this procedure as well as present two other complementary analyses to explore connections between the earnings response and the demographic composition of the workforce. First, we estimate the effect of bonus depreciation on earnings while directly controlling for changes in workforce demographics. Second, we perform a modified Kitagawa-Oaxaca-Blinder decomposition to attribute the earnings response to either changes in composition or changes in average earnings for demographic groups. Findings from both analyses reinforce the conclusion that policy-induced shifts in workforce composition are responsible for the negative earnings response to bonus depreciation.

Overall, our results show that bonus depreciation did not increase average earnings per worker.[34] However, our employment results also show that bonus depreciation disproportionately helped disadvantaged workers at a time when their employment prospects in the manufacturing sector were dwindling (Gould, 2018).[35]

4.4 Productivity and Production Responses

The unique nature of the ASM data also allows us to explore the effect of bonus depreciation on measures of productivity and total production. Panel A of Figure 5 presents results from an event study of the effects of bonus on our measure of plant-level TFP. We do not find evidence that capital investment led to increases in plant productivity. This result does not suggest bonus depreciation increases productivity, nor does it show that adjustment costs due to incorporating new capital lead to any measurable decrease in TFP. Panel B of Table 4 reports statistically insignificant estimates for both difference-in-differences and long-difference analyses. Column (5) of this panel implies a 95% confidence interval of the effect of bonus on productivity between -1.4% and 0.9%.[36]

[34] This result is consistent with Fuest et al. (2018), who find that local tax cuts across German municipalities did not increase average earnings.

[35] Appendix H 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).

[36] As we show in the previous section, bonus impacts the composition of the workforce. One concern is that our TFP estimates are biased downwards because 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 suggests no positive effect of the policy on TFP.

Motivated by the earnings responses and compositional shifts that we document in Section 4.3, in Appendix M, we also estimate the effect of bonus depreciation on plant-level labor productivity (total output per hours worked) and labor share (total payroll per total revenue). We find no effect on labor productivity, suggesting that plant-level average productivity is not meaningfully affected by the modest shift toward lower-wage workers. Results in Appendix M also show no significant effect on the labor share. This result suggests that any negative effects due to the shift towards lower-wage workers are offset by the increase in total employment relative to the capital stock.

While bonus did not increase plant-level TFP or labor productivity, the fact that bonus decreased overall costs of production may have allowed plants to expand their operations. The event study in Panel B of Figure 5 shows this to be true. Panel C, column (5) 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. Because Panel B of Figure 5 shows that the effect of bonus on production grew over time, we also report long-difference 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

The US manufacturing sector saw significant employment declines during the period we study. It is crucial to interpret our findings given this context. In this section, we first show that our results are driven by the effects of the tax policy and not by sector-level trends. We then discuss possible interpretations of our results given this context.

Charles et al. (2019) identify four main factors that led to the 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 was paired with an increase in "capital intensity," i.e., an increase in the share of output attributable to capital. The last two factors are the dramatic increase in import competition from China (e.g., Autor et al., 2013; Acemoglu et al., 2016; Autor et al., 2016; Pierce and Schott, 2016) and the increased adoption of automated production processes (e.g., Acemoglu and Restrepo, 2020).

We first show that controlling for increases in skill and capital intensities, import competition from China, and automation does not meaningfully impact our empirical results. To do so, we use 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 insofar as they were determined before bonus. As in Charles et al. (2019), we measure skill intensity at the industry 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 industry-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 et al. (2016) interacted with year fixed effects.[37] 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 A17 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.[38] As this table shows, the effect of bonus on investment is essentially unchanged when including these more fine-grained controls. Employment responses to bonus depreciation are slightly attenuated, decreasing from 7.9 to 6.9%. We also continue to find that bonus depreciation does not lead to significant gains in average earnings for the workers of more affected plants.[39] 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.

[37] Figure A17 shows that we obtain similar results when we use QWI data to jointly estimate the employment effects of both bonus depreciation and the "NTR gap," an alternative measure of import competition studied by Pierce and Schott (2016).

[38] Our measures of skill and capital intensity flexibly control for underlying transformational factors to the extent that they were defined by an industry's initial conditions in 2001. Appendix N discusses additional analyses that show robustness to this assumption (see Table A19). The appendix also shows that the results of Table A17 are robust to using finer measures of industry exposure to drivers of transformation in the manufacturing sector (see Table A18).

[39] Intuitively, controlling for skill intensity works in the same way as controlling for employment demographics. For this reason, we find similar null effects on average earnings as we do in Section 4.3.

A related question is whether bonus had larger effects on plants and industries that were least likely to thrive during this period of employment decline. We implement this analysis by including interactions between the difference-in-differences term and the cross-sectional continuous components of each control described above. For comparability in interpretation, we normalize each interactor to have mean zero and divide it by its interquartile range. As such, the interaction terms are interpreted as differences in the effect of bonus depreciation between units in the 25th and 75th percentiles of each factor. Table 5 presents results from these analyses for log investment and log total employment.[40] Column (1) shows that investment responses to bonus depreciation are larger for plants in industries 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 for plants in industries with high levels of capital intensity. These results imply that bonus depreciation did not encourage plants to invest in technologies characterized by low levels of capital and skill intensity.

Column (3) of Table 5 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. 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. Overall, the results of Table 5 show that bonus depreciation did not simply prop up non-competitive industries during a period of general employment decline.

While our estimated effects of bonus depreciation are not generated by the major drivers of transformation in the US manufacturing sector, it is important to recognize that the sector lost 5.5 million jobs from 2000–2017 (Charles et al., 2019). Figure 6 places our estimates in this context by comparing the magnitude of the effects of bonus depreciation to aggregate trends in

[40] Table A20 presents estimates from models in which all interaction terms are included together. Signs are the same and magnitudes are similar for all coefficients.

log capital stock and log employment during the period we study (see Appendix J for details). The aggregate trends presented in this figure motivate us to interrogate the hypothesis that the strong employment response that we document is specific to this time period of significant employment decline in the US manufacturing sector. An important question motivated by this historical context is whether the employment responses we document are primarily due to plants maintaining workers rather than adding new jobs.

We now present several pieces of evidence suggesting our results are not driven by studying a sector during a period of employment decline. First, there is a growing body of literature that now documents results similar to ours. Specifically, Criscuolo et al. (2019), Siegloch et al. (2021), Lerche (2022), and Hirvonen et al. (2022) all find large employment responses to investment incentives in other settings. The fact that these papers all find positive employment effects during varied time periods and in other countries suggests our findings are not specific to the US or to the 1997–2011 period. Second, as we show in Section 4.2, new and young firms—which are more likely to be growing—also respond to bonus depreciation by increasing employment. Third, our baseline results rely on a balanced sample of plants that survive through our analysis period; therefore, by construction our baseline estimates cannot be driven by plant death or by the prevention of plant death. Moreover, recall that we find similar estimates when using plant-level data (Panel A of Figure 3), state-by-industry data (Figure A7), or industry-level data (Panel B of Figure A15), suggesting that the prevention of plant deaths is not the central factor behind the employment responses we observe. Fourth, as we just discussed above, bonus depreciation had larger effects for plants in industries that were most likely to thrive during this period of structural transformation (Table 5).

Finally, we directly explore whether the effects of bonus are primarily driven by reducing firm exit or limiting job destruction. To do so, we use data from the Census Business Dynamics Statistics (BDS) program to decompose the effect of bonus into industry-level employment flows. Panel A of Figure A10 presents estimates of the effects of bonus on four types of job flows: (1) job creation by incumbent establishments, (2) job creation by new establishments, (3) job destruction by incumbent establishments, and (4) job destruction by exiting establishments. This figure shows that bonus increased net employment flows on all four margins. Panel B decomposes the net employment effect of bonus into its component flows. By 2011, the effects on job creation and job destruction have equal contributions to total employment growth, allaying the concern that our results are primarily driven by preventing job destruction rather than creating new jobs.

While it is important to recognize that our results are based on our empirical context, the evidence presented here suggests that the employment decline experienced by US manufacturing during this period is not the sole driver of our finding that investment stimulus also led to substantial increases in employment. Moreover, lawmakers rely on fiscal policy to stimulate investment and employment in times of economic turmoil, which highlights the policy relevance of our findings.

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. We then compute elasticities of capital and labor demand with respect to this cost of capital, 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.[41] 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 et al., 2019). Bonus depreciation

[41] As we discuss in Appendix P.5, this assumption is consistent with a model in which capital and materials are combined in a Leontief fashion, which is empirically validated in the data. This appendix also shows that our estimate of the capital-labor elasticity of substitution is robust to allowing for capital and labor to be arbitrarily combined with materials and structures.

lowers the cost of capital, which we denote by $\phi \equiv \frac{\partial \ln(\text{Cost of Capital})}{\partial \text{Bonus}} < 0$.[42] ϕ includes both the increased present value of depreciation deductions and reductions in financing and other frictions.[43] Because our identification strategy relies on cross-industry variation, our estimates of substitution elasticities capture the average value across the manufacturing sector.[44] Appendix O provides a detailed derivation of the model.[45]

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 et al. (2019) interpret this equation as the production analogue of the Slutsky equation, because 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

[42] The model assumes that plants take input prices as constant. In Appendix G.3 we directly estimate the effect of bonus depreciation of input prices and find no effect on the pre-tax price of capital goods, reinforcing the findings in House and Shapiro (2008), Basu et al. (2021), and House et al. (2017). As we show above, we also do not find that bonus impacts the wages of workers conditional on composition. In Table A15, we also find similar estimates on employment and capital after we control for industry-level estimates of wage markdowns from Yeh et al. (2022). Appendix O.5 extends the model to allow for monopsony.

[43] Appendix O.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. In Appendix O.4, we show that our conclusions are robust to a model extension that allows for cash flow effects from bonus to affect labor demand directly.

[44] 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 because Table A17 and Figure A13 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 A18 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}.

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

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 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

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

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.[46] 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: $\varepsilon_\phi^J = \frac{\beta^J}{\phi}$. Finally, by isolating ϕ and demand elasticities, Allen elasticities allow us to compute Morishima elasticities (Blackorby and Russell, 1989). This alternative measure captures substitution between capital and production labor, relative to capital, and can be calculated as: $\sigma_{KL}^M = \varepsilon_\phi^L - \varepsilon_\phi^K$.

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

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 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 6 reports estimates of the scale effect using the ten-year effects of the policy.[47] 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 6 show that varying the cost shares has very small effects on our estimate of the scale effect. Because β^K, β^L, and β^J are positively correlated, the scale effect is estimated with a high degree of precision. $\bar{\beta}$ also 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.[48]

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 6 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 $\eta = 3.5$.[49] Columns (2)–(5) report estimates that vary the capital

[47] 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.

[48] 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.

[49] Ganapati et al. (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.

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, because 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.[50]

Panel C of Table 6 formally evaluates the hypothesis that capital complements labor. We reject the null hypothesis that $\sigma_{KL} \geq 0$ (i.e., that $\beta^L \leq \bar{\beta}$) with p-values ranging from 0.047 to 0.099, depending on the values of s_K and η. Even though β^L and $\bar{\beta}$ have overlapping confidence intervals, the data reject this hypothesis because β^L and $\bar{\beta}$ are positively correlated. 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. However, we find that 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 6 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 $\hat{\varepsilon}^I_{\phi} = \frac{\hat{\beta}^I}{\hat{\phi}} = -1.40$.[51]

[50] 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 P.1 shows that Allen elasticities of substitution can be used to estimate the parameters of a translog cost function (Christensen et al., 1971, 1973). Our estimates are therefore consistent with models of production that allow for flexible patterns of substitution.

[51] 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 P.2 and show that it has a similar magnitude to estimates

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 $\hat{\varepsilon}^K_\phi = -0.56$ and cross-price elasticities of production labor of $\hat{\varepsilon}^L_\phi = -0.80$ and non-production labor of $\hat{\varepsilon}^J_\phi = -0.63$.[52] These relatively modest elasticities reinforce the importance of estimating ϕ inclusive of financing and other frictions. Appendix P.2 discusses these elasticity estimates further.

Finally, these demand elasticities also allow us to estimate Morishima elasticities of substitution. Table A24 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 P.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 because $\frac{\partial \log q}{\partial \text{Bonus}} = -\eta s_K \phi = \bar{\beta}$. 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

that account for interactions between tax policies and financing and other frictions.

[52] Appendix P.4 explores the dynamic patterns underlying these estimates.

changes in quantity and prices.[53]

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.

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.[54]

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 7 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. Consistent with the fact that we estimate that $\hat{\beta}^L > \hat{\bar{\beta}}$, Equation 8 implies that any larger value of η will lead to a

[53]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}.

[54]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 $H(\hat{\theta})$.

more negative value of σ_{KL}, indicating a larger degree of complementarity.

Panel A of Table 7 reports estimates of σ_{KL} as well as all other 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 Figure 7 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.[55] Relative to prior estimates (e.g., Krusell et al., 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 7 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 $\hat{\beta}^{\mathrm{L}} > \hat{\bar{\beta}} > \hat{\beta}^{\mathrm{J}}$. In order to obtain an estimate of $\sigma_{KL} = 1$ (i.e., Cobb-Douglas), plants would have had to increase their capital use by 39%, 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 7 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.[56]

Our model estimates are robust across a number of specification and input choices. Column (2) of Table A21 shows that our results are robust to including the controls for factors of sectoral transformation discussed in Section 5. Column (3) shows that our results are robust to using difference-in-differences estimates of $\hat{\beta}$ instead of long-difference estimates. Column (4) reports similar parameter estimates when we measure labor using production hours instead of number

[55] Our model rejects small positive values of σ_{KL} because it optimally combines information from our reduced-form moments by using the covariance matrix between these estimates to increase the precision of the model parameters. 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.

[56] Table A27 shows that we obtain qualitatively similar results when we do not impose this constraint.

of workers. Column (5) shows that we also find a negative elasticity of substitution when we do not differentiate between different types of labor. Columns (6)–(7) show that we estimate similar elasticities of capital-labor substitution in models that have one type of labor and that take as inputs labor, capital, and either structures or materials. Across all of our models, we find that production workers complement capital in production.[57] Further details on these checks are presented in Appendix P.5.

We also show that our conclusions from this section are robust to several model extensions, including allowing for firm labor market power (i.e. monopsony; Appendix O.5) and allowing for cash flow effects to impact labor demand (Appendix O.4). We also show that plant entry and exit are not an important driver of our empirical estimates of the effect of bonus on labor demand (Appendix P.7). Consequently, we find qualitatively similar model estimates using industry-level data (Appendix P.6) and while accounting for reallocation across industries (Appendix P.8). The fact that we find similar plant-level, industry-level, and aggregate elasticity estimates suggests our results are not artifacts of entry and exit or particular reallocation responses across plants, locations, or industries.

The result that capital and labor are complements in production also carries interesting testable hypotheses. Specifically, we would expect to see larger investment responses when plants face lower wages. In Appendix P.9, 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. We find larger investment responses in all three cases.[58]

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 are empirically supported and validate the

[57]Our baseline results are based on our LD estimates and allow plants to adjust their production over a ten-year period. Figure A21 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 ten-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.

[58]Once again, the similarity of our plant- and industry-level estimates implies that complementarity is not a byproduct of these potential reallocation margins.

complementarity between capital and labor.

7 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 at affected plants actually decrease, despite increases in employment. This change in earnings is explained by increases in the shares of workers that are younger, female, more racially diverse, and that have fewer years of education. While bonus depreciation did not affect plant productivity, it did lead manufacturing plants to increase their scale.

We also find that bonus depreciation was more effective at stimulating manufacturing activity for plants in industries that were more capital- and skill-intensive, that were more insulated from Chinese import competition, and that were more likely to adopt the use of industrial robots. Overall, bonus does not seem to encourage plants to double down on outdated modes of production and instead most benefits plants that are likely to thrive in the 21st century.

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 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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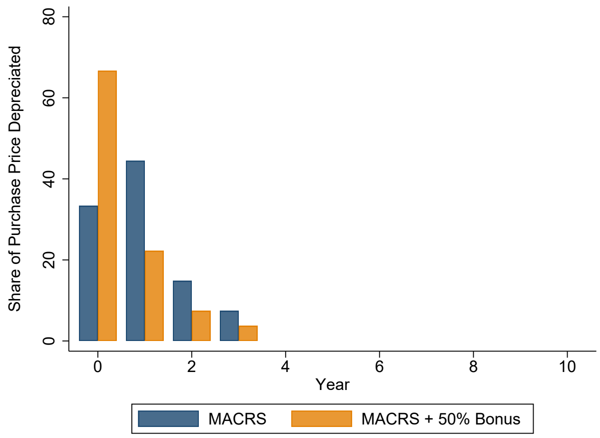
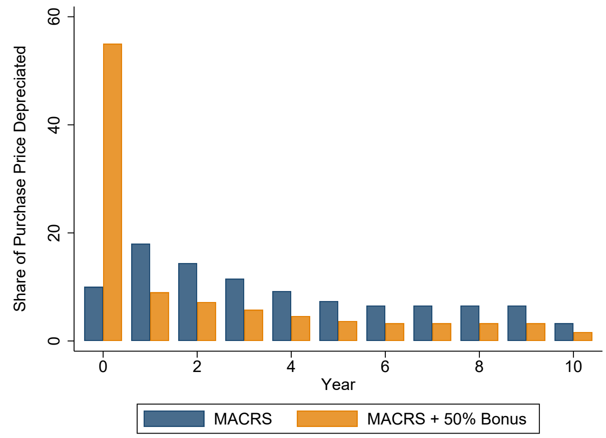
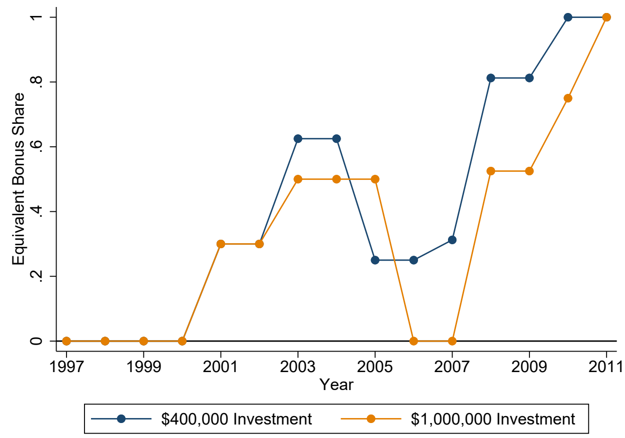


Panel A: Three-Year MACRS Assets



Panel B: Ten-Year MACRS Assets

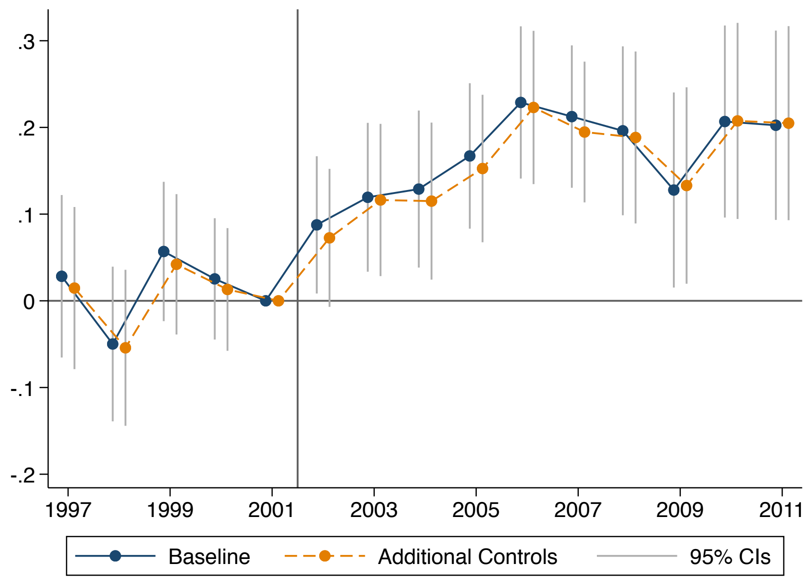


Panel C: Timing of Accelerated Depreciation Policies

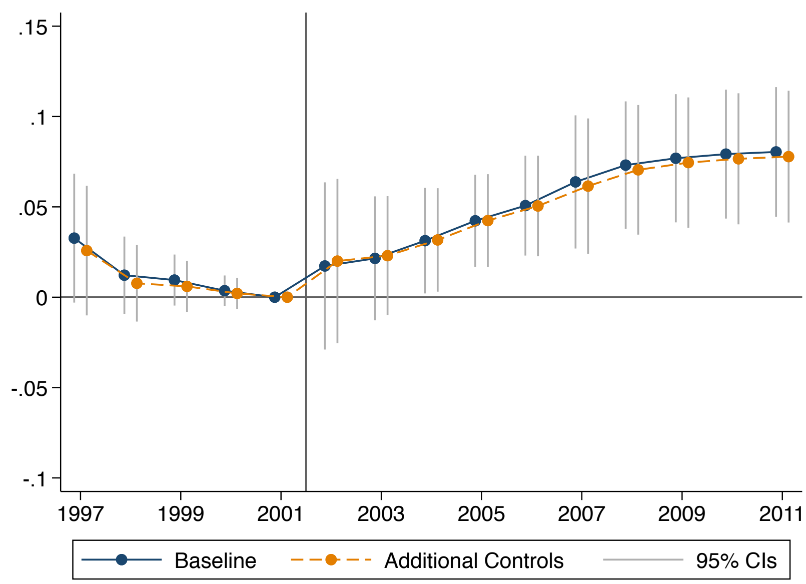
Figure 1: Bonus Depreciation Policy and Specific MACRS Assets

Note: Panels A and B of Figure 1 show how 50% bonus changes the depreciation schedule for a three-year asset and a ten-year asset, respectively. See Appendix C for further explanation of these calculations. The bonus depreciation provision has a larger effect on the deduction schedule for a firm that invests in assets that, on average, 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 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).



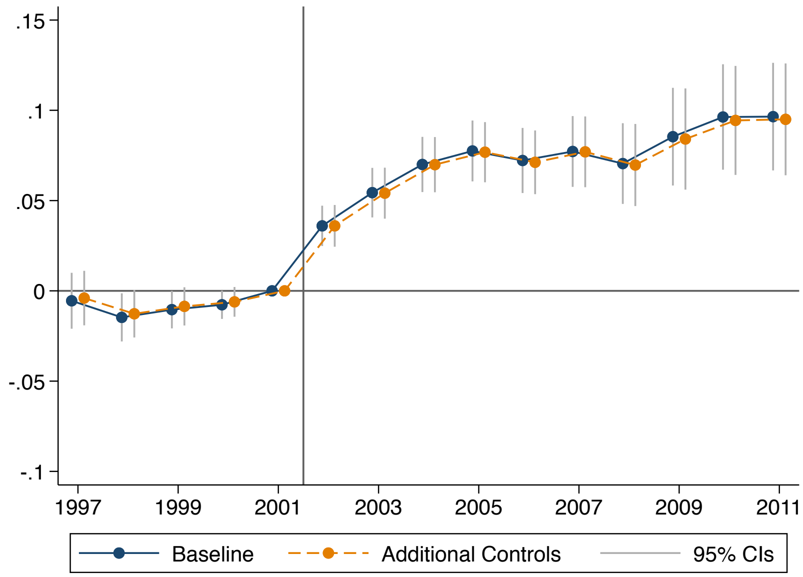
Panel A: Log Investment



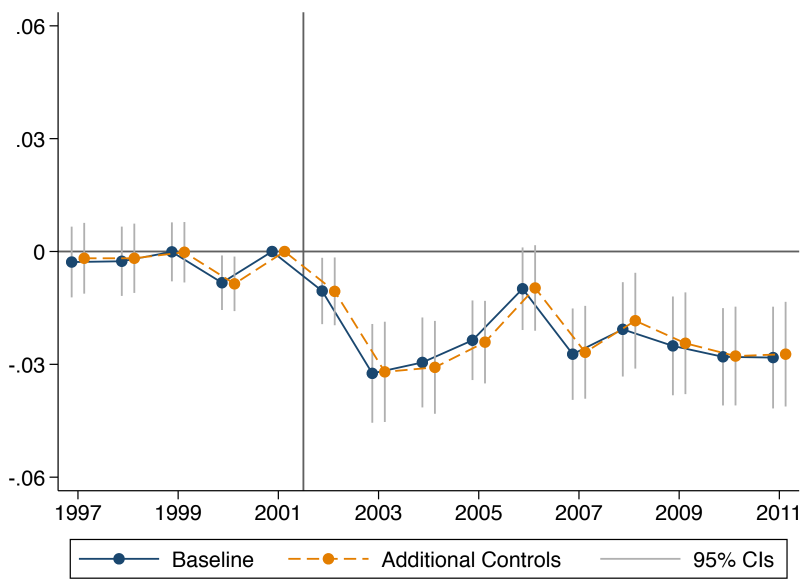
Panel B: Log Total Capital

Figure 2: Effects of Bonus Depreciation on Capital Investment

Note: 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. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.



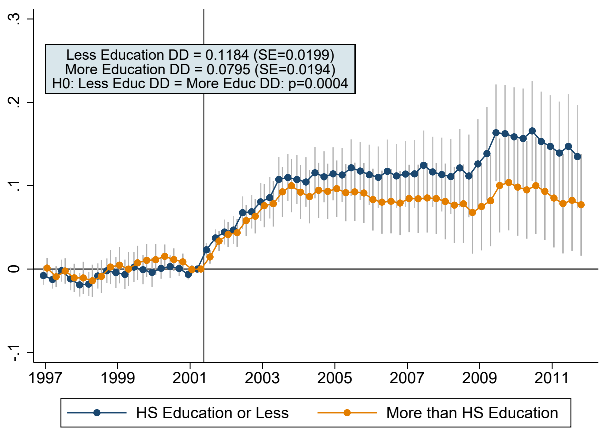
Panel A: Log Employment



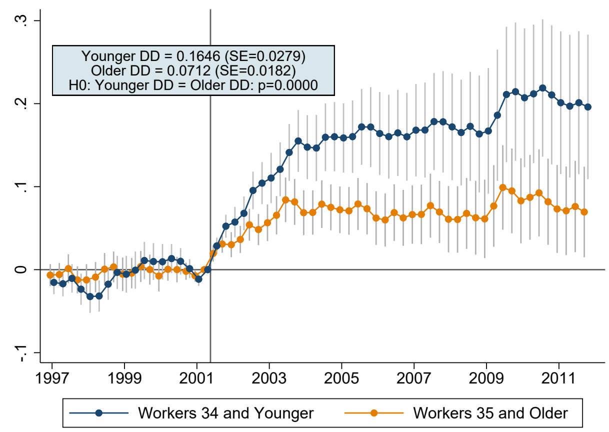
Panel B: Log Mean Earnings per Worker

Figure 3: Effects of Bonus Depreciation on Labor Demand

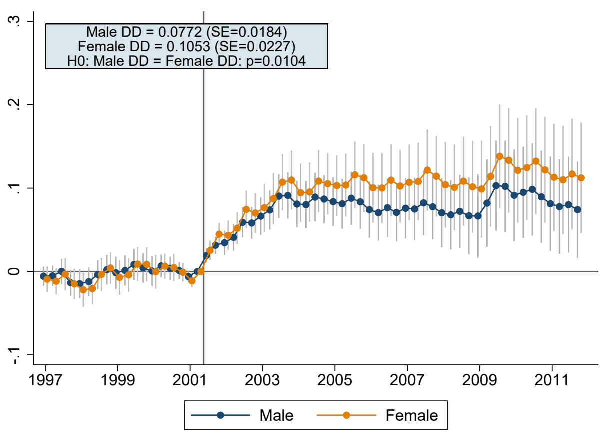
Note: Figure 3 displays estimates describing the effect of bonus depreciation on log employment and log mean earnings per worker. Plotted coefficients are estimates of β_y from Equation 1, which are the annual coefficients associated with bonus. The baseline specification includes state-by-year and plant 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 Panel A, columns (6) and (7) of Tables 3 and 4. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.



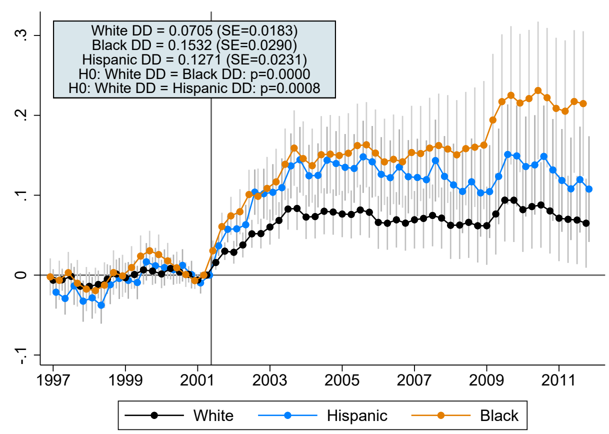
Panel A: Education



Panel B: Age



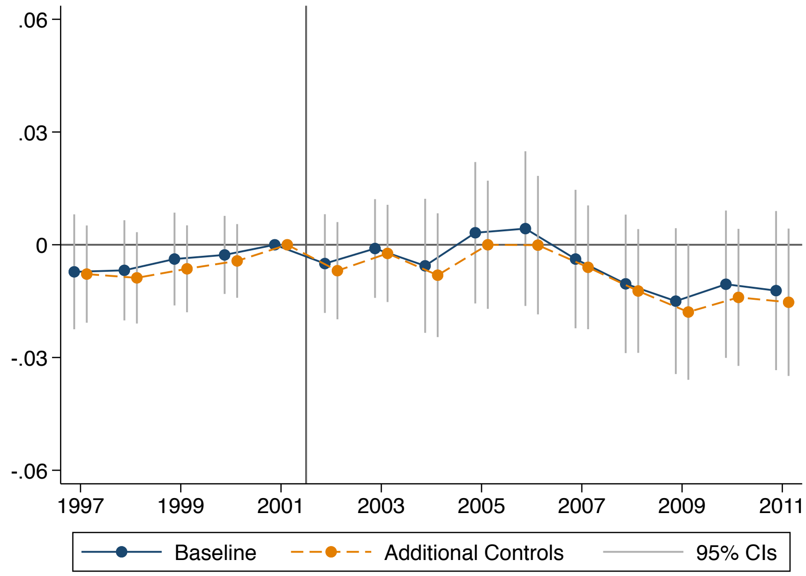
Panel C: Gender



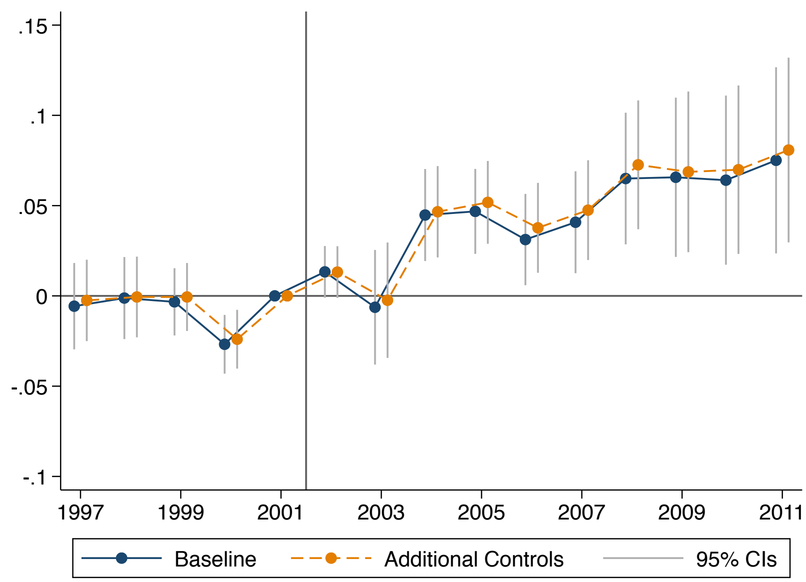
Panel D: Race and Ethnicity

Figure 4: Effects of Bonus Depreciation on Employment by Demographic Group

Note: Figure 4 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 34 years of age and younger and 35 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 each respective group. 95% confidence intervals are included for each annual point estimate with standard errors clustered at 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.



Panel A: Total Factor Productivity

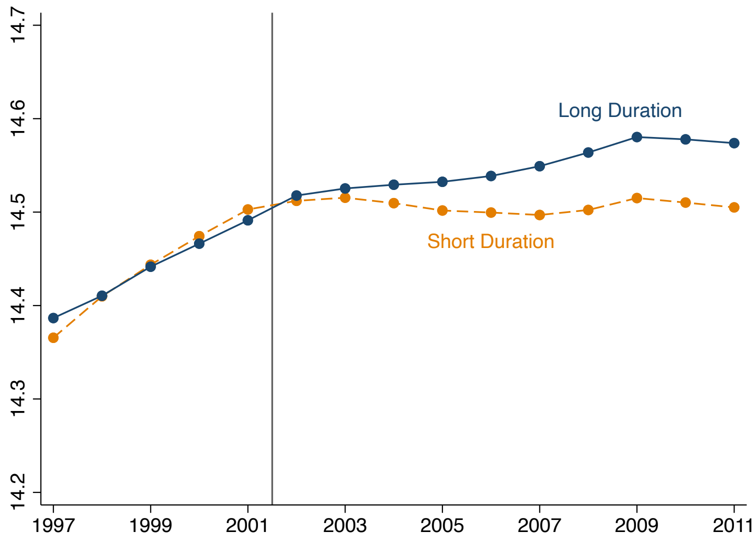


Panel B: Log Total Value of Shipments

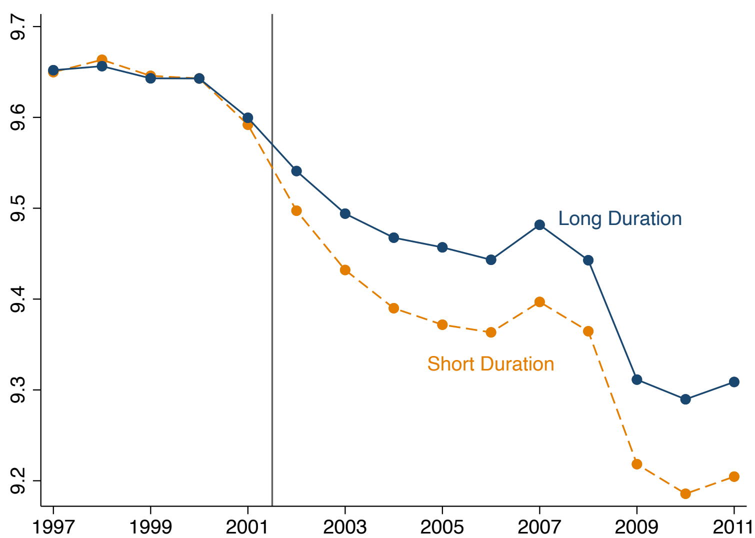
Figure 5: Effects of Bonus Depreciation on Productivity and Production

Note: Figure 5 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 Panels B and C, columns (6) and (7) of Table 4. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.



Panel A: Log Capital Stock

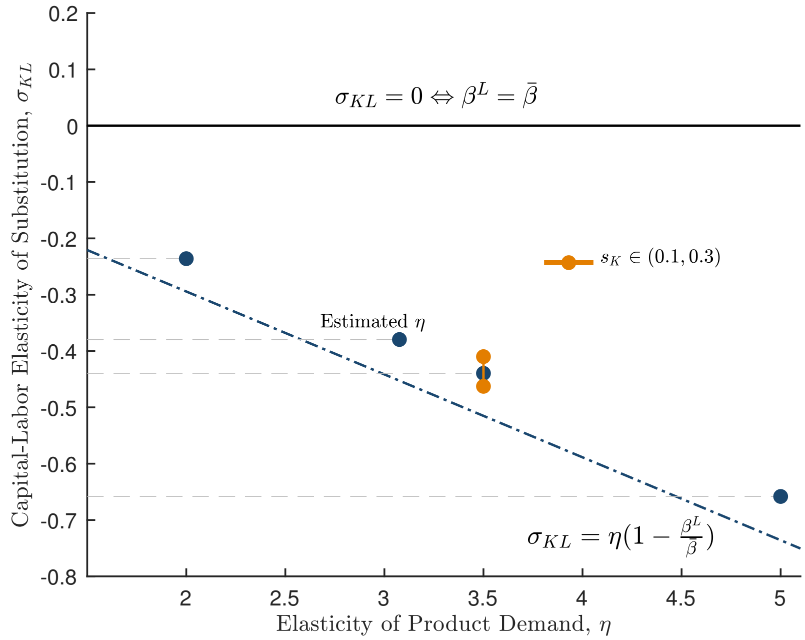


Panel B: Log Employment

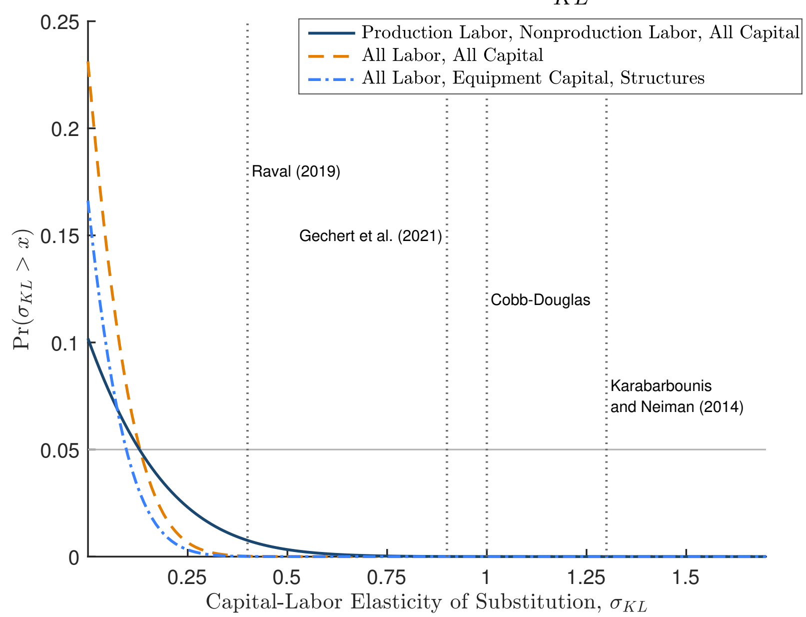
Figure 6: Effects of Bonus Depreciation Relative to Aggregate Trends

Note: Figure 6 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.



Panel A: Estimates of σ_{KL}



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

Figure 7: Model Estimates of Capital-Labor Elasticity of Substitution

Note: Panel A of Figure 7 graphically displays our estimates of σ_{KL} based on our long-difference 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 7 displays the probability that the estimated capital-labor substitution parameter σ_{KL} in our baseline model (column (1), Table 7) 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 (5), Table A21) and the light-blue dot-dashed line reports the case of a model with one type of labor alongside equipment and structures (column (6), Table A21). Vertical lines correspond to σ_{KL} values from Raval (2019), from Gechert et al. (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)
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]
Year FE	✓				
Plant FE	✓	✓	✓	✓	✓
State$\times$Year FE		✓	✓	✓	✓
$\text{PlantSize}_{2001}\times$Year FE			✓	✓	✓
$\text{TFP}_{2001}\times$Year FE				✓	✓
$\text{FirmSize}_{2001}\times$Year FE					✓

Note: Table 1 displays difference-in-differences estimates of Equation 2 describing the effects of bonus depreciation on log investment. Column (1) estimates include year and plant fixed effects. Column (2) estimates include state-by-year fixed effects and plant fixed effects. Columns (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.
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	✓	✓	✓	✓	✓	✓
PlantSize_{2001}×Year FE		✓		✓		✓
TFP_{2001}×Year FE		✓		✓		✓
FirmSize_{2001}×Year FE		✓		✓		✓

Note: Table 2 displays long-difference estimates of the impact 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.
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 Non-Production 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					✓		✓

Note: 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. Columns (1) and (6) include year and plant fixed effects. Column (2) estimates include state-by-year and plant fixed effects. Columns (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.
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					✓		✓

Note: 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-difference panel shows estimates of β_{2011} from specifications in the form of Equation 1. Column (1) includes year and plant fixed effects. Columns (2) and (6) include state-by-year and plant fixed effects. Columns (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.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table 5: 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	✓	✓	✓	✓

Note: Table 5 displays difference-in-differences 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 columns (1)–(4), the difference-in-differences coefficient is interacted with 6-digit NAICS industry-level 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.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), Acemoglu et al. (2016), and Acemoglu and Restrepo (2020) data.

Table 6: 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)
Non-production 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
Non-production 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

Note: Table 6 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.

Table 7: 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)
Non-production 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
Non-production 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
Non-production 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
Non-production 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

Note: Table 7 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.

Capital Investment and Labor Demand

E. Mark Curtis, Daniel G. Garrett, Eric Ohrn, Kevin A. Roberts, and Juan Carlos Suárez Serrato

Online Appendix

This appendix includes several sections of supplemental information. Appendix A contains definitions for all the variables used in the paper. Appendix B discusses the history of IRS depreciation schedules. Appendix C 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 D. We compare our results on investment with those of Zwick and Mahon (2017) in Appendix E, present empirical robustness tests in Appendix F, and present additional investment responses to bonus in Appendix G. Appendix H shows employment results by the task content of occupations using Census and ACS data. Appendix I provides additional employment results using QWI data. Appendix J places our results in the context of aggregate and long-run trends in the manufacturing industry. Appendix K decomposes the wage changes into compositional changes and other factors. Appendix L explores how labor market tightness influences our reduced-form results. Appendix M presents plant labor productivity and labor share results. Appendix N discusses the robustness checks presented in Section 5. Appendix O derives the complete model and presents extensions that add financing constraints, cash flow effects, and firm wage-setting power. Finally, Appendix P presents additional model results.

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.

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Table A.1 – *Continued from previous page*

Variable	**Description**
IHS Investment	Inverse hyperbolic sine function of investment, as defined above, by plant i in year t. *Source:* ASM/CM.
$\Delta\text{PPENT}_t/\text{PPENT}_{1997-2001}$	Investment as Share of Pre-Period Capital. Pre-period capital defined as the average total capital, as defined above, in the 1997–2001 period. Investment in machinery and equipment as defined above by plant i in year t. *Source:* ASM/CM.
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 et al. (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 et al. (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.

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Table A.1 – *Continued from previous page*

Variable	**Description**
TFP	Total Factor Productivity of plant i in year t. TFP calculated using a factor share approach following Criscuolo et al. (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 4-digit NAICS industry j. Finally, $\bar{\tau}_{jt}$ is the average value of τ_{it} in the 3-digit NAICS sector. *Source:* ASM/CM and Cunningham et al. (2020).
RTW	Indicator that plant i operated in a state with Right-to-Work laws in 2001. *Source:* Valletta and Freeman (1988).
Unionization	Indicator that for plant i, over 60% of total employment was unionized in 2005. *Source:* MOPS.
Log HHI	Natural logarithm of local labor market Herfindahl-Hirschmann Index (HHI) in 2001. Local labor market defined as the 3-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 at the 6-digit NAICS industry level in 2001. Skill intensity fixed effects defined as quartiles of skill intensity across 6-digit industries in estimating sample. *Source:* ASM/CM.
Capital Intensity	Capital intensity of plant i defined as total capital assets divided by employment at the 6-digit NAICS industry level in 2001. Capital intensity fixed effects defined as quartiles of capital intensity across 6-digit industries 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 6-digit NAICS industry level from 2000 to 2007. *Source:* Acemoglu et al. (2016).
AR Robotization	AR Robotization for plant i defined as the change in robotization at the 3-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.

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Table A.1 – *Continued from previous page*

Variable	Description
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 4-digit NAICS industry × state × year. *Source:* QWI.
Log Mean Earnings, QWI	Natural logarithm of mean earnings in each 4-digit NAICS industry × state × year. *Source:* QWI.
Fraction of Employees with High School Education or Less	Fraction of employees in each 4-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 34 Years Old or Younger	Fraction of employees in each 4-digit NAICS industry × state × year that are 34 years old or younger. *Source:* QWI.
Fraction of Female Employees	Fraction of employees in each 4-digit NAICS industry × state × year that are female. *Source:* QWI.
Fraction of Non-White Employees	Fraction of employees in each 4-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 4-digit NAICS industry × state × year whose reported ethnicity is Hispanic or Latino. *Source:* QWI.
Fraction of Black Employees	Fraction of employment in each 4-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 4-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 4-digit NAICS industry × state × year. *Source:* QWI.
Log Employment, NBER-CES	Natural logarithm of total employment in each 4-digit NAICS industry × year. *Source:* NBER and CES.
Log Investment, NBER-CES	Natural logarithm of total investment in each 4-digit NAICS industry × year. *Source:* NBER and CES.
Log Capital Stock, NBER-CES	Natural logarithm of total capital stock in each 4-digit NAICS industry × year. *Source:* NBER and CES.

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Table A.1 – *Continued from previous page*

Variable	**Description**
ICT Asset Shares	Share of fixed assets in information and communication technology at the three- and 4-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.
Input Price Indices	Industry-specific price indices based on BEA Underlying Detail Table 5.5.4U and 2002 Benchmark I-O accounts. *Source:* BEA.
Cost of External Capital	Average cost of borrowing, defined as interest divided by debt, for publicly traded firms for each 4-digit NAICS industry averaged over the 1997–2001 period. *Source:* Compustat.
Log Employment, Decennial Census and American Community Survey	Natural logarithm of total employment in each 4-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 Component 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).
Stayers: Creation	4-digit NAICS industry-level cumulative jobs created by firms that are at least one year old by year t relative to 2001. This is the sum of "job_creation_continuers" from the public Census file from 2001 to year t divided by total employment in 2001 *Source:* Census BDS .

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Table A.1 – *Continued from previous page*

Variable	**Description**
Births: Creation	4-digit NAICS industry-level cumulative jobs created by new firms by year t relative to 2001. This is the sum of "job_creation_births" from the public Census file from 2001 to year t divided by total employment in 2001 *Source:* Census BDS .
Stayers: Destruction	4-digit NAICS industry-level cumulative jobs destroyed by firms that continue operations by year t relative to 2001. This is the sum of "job_destruction_continuers" from the public Census file from 2001 to year t divided by total employment in 2001 *Source:* Census BDS .
Deaths: Destruction	4-digit NAICS industry-level cumulative jobs destroyed by firms exiting the market by year t relative to 2001. This is the sum of "job_destruction_deaths" from the public Census file from 2001 to year t divided by total employment in 2001 *Source:* Census BDS .

B A Brief History of Depreciation Schedules

This section presents a brief summary of the historical process that led to the adoption of modern depreciation schedules in the US. We base this description on the work of Brazell et al. (1989) and Brazell and Mackie III (2000).

Depreciation deductions were first discussed by the Treasury in 1920 in *Bulletin F: Depreciation and Obsolescence*. The bulletin encouraged taxpayers to base the tax lives of their assets on their own *facts and circumstances* but restricted the depreciation method to be straight-line, i.e., an equal proportion every year. By 1931, there was more discussion about how to raise revenue, as well as concerns that depreciation deductions were not being claimed fairly across taxpayers. In response, Treasury put out non-binding guidance for many different types of assets through Treasury Decision 4422. This new directive required taxpayers to file their own depreciation schedules and placed the burden of justifying the reasonableness of depreciation schedules on the taxpayer.

By 1960, there was a growing concern that the dispute process for adjudicating the reasonableness of depreciation schedules was inefficient and consumed inordinate departmental resources. This led Treasury to collect studies of depreciation rates that firms were choosing according to their own facts and circumstances. In 1962, Treasury published new guidelines built off of a series of such studies in Revenue Procedure 62-21 or *Depreciation Guidelines and Rules*. These guidelines provided ranges of the asset lives used under earlier rules. Procedure 62-21 also introduced the Reserve Ratio Test (RRT), which was intended to check that the new guidelines were being appropriately used by all taxpayers by comparing accumulated depreciation to the cost basis of assets within a class. In 1965, the IRS estimated that almost 90% of filers would fail the RRT, so it was placed on a moratorium and never applied. The survey information from the early 1960s was later used in the Asset Depreciation Range (ADR) system started in 1971, which ended the potential use of the RRT.

In 1981, the US moved to the Accelerated Cost Recovery System (ACRS), which was intended to dramatically simplify the administration of income taxes and management of depreciation schedules by putting all assets into a few loose categories that were also relatively generous. In the words of Brazell et al. (1989), "[ACRS] differed from previous changes, however, because the cost recovery periods were not intended to reflect actual useful lives, or even some percentage of the useful lives." The Modified Accelerated Cost Recovery System (MACRS), introduced in the Tax Reform Act of 1986, compiled a series of minor changes to ACRS and expanded the number of categories. These new categories were closer to the ADR categories, which had not been updated since 1965 and were based on the 1961–1962 Treasury studies. Finally, the Technical and Miscellaneous Corrections Act of 1988 revoked the authority of the Treasury to adjust class lives, requiring Congress to pass laws to adjust depreciation schedules. However, Congress has not adjusted class lives since then.

The identifying variation in this paper therefore relies on class life differences across industries that date to 1962 and that have not been modified since laws related to the Tax Reform Act of 1986.

C 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. The TCJA 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 C 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 was not 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 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 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 do not 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.

D Standard Error Clustering

Throughout the paper, we cluster standard errors at the level of treatment variation (e.g., Bertrand et al., 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 because

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

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).

E 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.[59] Similar to our results, ZM show that investment at

[59]Because tax data are retrospective for the following year, we normalize these estimates to the ASM survey year. This means we plot 2000 in ZM as equivalent to 2001 in the ASM data.

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 10.2%. This figure shows that we are not able to reject the hypothesis that the estimates in the orange line differ from those in the blue line for most years.

Overall, Figure A2 shows that our estimated effects of bonus on log investment are quite comparable with those reported by ZM. The similarity in these results is remarkable for several reasons. First, while we use Census and survey data, ZM rely on data from corporate tax returns. Second, while we focus on plants in the manufacturing sector, ZM study data on firms in the overall economy. Third, while our results focus on a balanced panel that includes mostly larger plants, ZM study a unbalanced 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.

F Reduced-Form Robustness Checks

This appendix discusses a number of robustness checks to our primary investment and employment results in Section 4.2. Specifically, we show that our reduced-form results are robust to (1) a continuous treatment definition and alternative discrete treatment cutoffs, (2) the inclusion of controls for the cost of capital and financial risk, and (3) controlling for or excluding Information and Communication Technology (ICT) intensive industries. We also show that our results are not driven by differential business cycle exposure going back to the 1991 recession, and that reallocation within firms or local labor markets does not drive our results. Due to disclosure limits related to the use of Census data, we rely on QWI data at the industry-state level to perform many of these robustness checks.

First, in Panel A of Figure A11, we show that we obtain similar results using the continuous variation in z_0. Additionally, Panel B of Figure A11 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. We also estimate the effects of bonus on employment using alternative treatment cutoffs. Panel A of Figure A12 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 A12, we show that we find almost identical effects of bonus on employment when we include interactions of this measure with year fixed effects. 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 A12 shows that our results are robust to controlling for industry-level quintiles of effective interest rates from Compustat interacted with year fixed effects.

In Figure A13, 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.[60] 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.

Because 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 A15, industries that benefit

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

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.

As shown in Garrett et al. (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 A11, we show that we obtain similar plant-level effects of bonus on employment and investment when we control for local exposure to bonus depreciation.[61]

Finally, we also find that our results are not driven by reallocation of productive resources from untreated to treated plants within the same firm. The results presented in Table A10 show that the plant-level investment and employment responses are largest at firms where all plants are treated and suggest that substitution between plants within the firm does not materially affect our estimates. These results complement our estimates in Table A11, which show that control plants in commuting zones with greater bonus exposure increase investment and employment relative to control plants with lower local bonus exposure. If local reallocation from untreated to treated plants were a major driver of our results, we would instead expect local bonus exposure to lead to relative declines in employment for control plants. While our difference-in-differences approach does not allow us to isolate all forms of reallocation, both of these sets of results suggest that our findings are not driven by within-firm or across-labor market reallocation.

G Additional Investment and Capital Results

G.1 Investment and Capital Robustness

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 as the natural log. The estimates are almost identical to the primary variable definition of log investment,

[61] As in Garrett et al. (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 et al., 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.

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 coefficients represent changes 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 Table A3.

As a final check to our investment and capital measures, we turn to the Quarterly Survey of Plant Capacity Utilization to test whether effective capital is changing in a way that may be different than reflected in the primary capital and investment measures. Capacity utilization (item 2, part C, also called "full production ratio" or FPR) is the share of revenue that was earned by a plant (item 2, part A) divided by counterfactual revenue as if operating at full capacity (item 2, part B). The QSPCU measures this in the fourth quarter of each year, so we omit the 2000 treatment variable for normalization. We use the capacity utilization published from 1997–2011 to test whether industries more treated by bonus use more or less of their capital after increasing their investment in response to bonus using our long-difference design. 2007 is imputed as the average of 2006 and 2008 because data are not available for that year. The results of this exercise are shown in Figure A5. Average capacity utilization is 67.6% with the 25th and 75th percentiles of 62.1% and 73.0% respectively. By 2011, we estimate plants in bonus-treated industries use 3.9pp less of their total capacity, although the point estimate is not statistically significant. If anything, we find that our measures of capital could slightly overstate how much capital equipment increases relative to labor as an input in production processes in the medium to long run.

G.2 Additional Controls for Capital Producers

This appendix presents additional specifications of the baseline results with controls for and interactions with capital producer share. We define capital producer share as the share of firm output that is used as physical capital in another firm's production process bonus depreciation may create additional demand for equipment capital assets, which in turn may result in an increase in demand for the types of firms that supply equipment capital assets to the market. The BEA keeps track of the amount of output used as "Nonresidential private fixed investment in equipment" from each industry defined at the 3- or 4-digit NAICS level depending on the industry, and there is large variation across industries. 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, businesses involved in manufacturing plastics and rubbers (NAICS 326) have 0.1% of output used in fixed investment in equipment. Most manufacturing industries, in fact, have no output used in fixed investment in equipment.

Bonus treatment is negatively correlated with capital producer share such that our bonus treated plants are more likely to not be capital producers ($1 - z_0$ and capital producer share have a correlation coefficient of -0.37). Nevertheless, we still think it is an important margin to explore given the large scale effects we estimate. We show that our baseline results are robust to including capital producer share interacted with year fixed effects, and also to the inclusion of the capital producer share as an interaction term with our bonus treatment indicator. We fail to find any statistically significant change or interaction when using this additional variable.

First, we re-estimate the dynamic difference-in-differences specifications for employment and capital previously displayed in Panel A of Figure 3 and Panel B of Figure 2, respectively. Focusing on the baseline specification, we add a control for each observation based on the capital producer share interacted with year fixed effects to allow the impact of producing more capital to vary over time. We display these new dynamic difference-in-differences estimates in Figure A6.

Panel A of Figure A6 shows the employment results with and without the additional capital producer share control interacted with year fixed effects. Both specifications have the same basic characteristics: there is no differential pretrend for bonus treated plants, employment begins increasing in 2002 immediately after bonus was originally implemented, and total employment has increased by about 10% by a decade later in 2011. Allowing plants to have flexible time trends that reflect how much of their output is used as capital equipment in another business does not change our employment results. In Panel B of Figure A6, we show the same specifications for the capital outcome. Again, with the baseline coefficients shown next to the coefficients that control for capital producer shares, we find that the impact on capital is more or less unchanged by adding capital producer share controls and that the treated capital response still reflects an 8% increase by 2011. The point estimates and standard errors for all of these specifications are included in Table A5.

Further, we also explore whether bonus may have had the largest impact in plants that were benefiting both from the bonus policy, directly, and from increased demand for their physical capital outputs. Table A6 reports estimates on investment, employment, and total value of shipments where we include the interaction of bonus and our capital producer share variable. For each of these outcomes the interaction term is close to zero and statistically insignificant, suggesting that capital producers did not see disproportionate growth in capital, employment, or total value of shipments relative to non-capital producers.

We show that the employment results using the QWI data show the same stability with respect to capital producer share controls of additional forms in Appendix I.

G.3 Effect of Bonus Depreciation on Input Prices

House et al. (2017) study the effect of bonus depreciation on both the production and purchase of capital assets. In the course of this study, they investigate how the policy affects the purchase price of capital assets. With regard to price effects, they conclude, "Overall, the results suggest that either there are no discernible impacts of investment tax subsidies on prices or that the true impact is difficult to measure accurately in the available data." Using a DSGE model, they show that a possible explanation for this null effect on prices is that purchases resulting from the stimulus are "are split roughly half between domestic and foreign production of equipment."

In this appendix, we use our reduced-form estimation strategy and data from the BEA to directly estimate the effect of bonus depreciation on input prices for industries in the manufacturing sector. As a first step, we construct industry-specific price indices by mapping annual price indices for aggregated equipment investment categories (NIPA Underlying Detail Tables: Table 5.5.4U) to NAICS 6-digit industries using BEA's benchmark 2002 I-O (Input-Output) accounts. These accounts detail the share of total investment spending that each industry spent on each equipment investment category. We construct separate price indices based on producer prices and purchaser prices. The producer price is the price paid for equipment to the producer. Purchaser price is the price paid by the purchaser which is primarily composed of the producer price, but also includes transportation costs, wholesale and retail markups, and taxes collected by wholesalers and retailers such as sales and excise taxes.

We estimate the effects of bonus on input prices using event study DD regressions of the form

$$Log(y_{jt}) = \alpha_j + \sum_{y=1997,\ y\neq 2001}^{2011} \beta_y \big[\text{Bonus}_j \times \mathbb{I}[y=t]\big] + \gamma_t + \varepsilon_{it},$$

where $Log(y_{jt})$ is the log of the 6-digit NAICS price index for industry j in year t. α_j and γ_t are industry- and year-fixed effects. Bonus_j is our binary bonus treatment variable, which varies at the NAICS 4-digit level. The coefficients β_{1997} through β_{2011} describe the percent difference in price levels between treated and control industries relative to the difference in 2001. Regressions are weighted by 2001 employment shares and standard errors are clustered at the 4-digit NAICS level.

Figure A4 displays β_{1997} through β_{2011} for both producer and purchaser prices. Both series show no statistically significant price increase for treated industries relative to control industries after the policy was implemented. The producer price point estimate from a pooled DD regression is 0.0118, which suggests that bonus depreciation may have increased producer prices by just over 1% during our treatment period. The pooled DD estimate based on the purchaser price series is slightly larger at 0.0162. These estimates are economically small and statistically insignificant. The estimates are also small relative to our model-based estimate of the effect of bonus depreciation on the after-tax cost of capital, ϕ. In our baseline model, we estimate $\phi = -0.145$ (Table 6, column (1)), which suggests that bonus depreciation decreased the after-tax cost of capital by 14.5%. This change in the after-tax cost of capital is inclusive of any effect the policy had on the prices paid for capital equipment that we estimated in this appendix.

Overall, our findings reinforce House et al. (2017)'s conclusion that bonus depreciation did not have a statistically or economically significant effect on the pre-tax price of capital equipment.

H Additional Employment Effects by Job Task Content

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 US 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 five-year estimates. Our sample comprises adults employed in manufacturing industries between the ages of 18 and 64 that are not institutionalized. 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 A14 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 A8 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 6.84% from 2000 to 2010. 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.[62] Columns (4)–(7) show that the effect of bonus depreciation is largest for

[62] In 2000, production occupations accounted for approximately 80% of all routine employment in manufactur-

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.

I Additional Employment Results using QWI Data

This appendix extends the employment results discussed in Section 4.2. 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 balanced ASM/CM sample that is balanced. The ASM sample is 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.

Figure A7 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. All QWI regressions are weighted according to 2001 state-industry employment. 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 Panel A of Figure 3. Column (1) of Table A7 reports corresponding regression

ing.

coefficients.

We show QWI event study estimates for firms with 1-50 employees in Panel A of Figure A9. This sample is restricted to small plants and aggregated at the state level, so if a plant grows beyond 50 employees it will leave the sample and aggregate state employment in this category would decrease. This sample restriction shows that, even after selecting on small plants, long duration plants experienced more employment growth than short duration counterparts. We perform this analysis again for another group of plants undersampled by the ASM: those in the first five years of operation. We again find that employment in plants treated by bonus increased relative to untreated plants. Quarterly coefficients are shown in Panel B of Figure A9.

We also show that our results are robust 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 A11, 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 a smooth decrease in employment among industries that historically enjoyed shorter depreciation schedules (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 A12 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.

The rest of Figure A12 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 bonus depreciation policy. This test builds on the results in Appendix G.2 showing that capital producer share controls do not impact the results using ASM and CM data. Here, we highlight that the use of this control similarly does not impact QWI estimates. See Appendix G.2 for discussion on the definition of the capital producer share variable. Our results in Panel B of Figure A12 show the same pattern of increasing employment by 11.5% by 2011 for state-industries with the most benefit from depreciation incentives when controlling for the capital producer share interacted with time fixed effects. 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 (12.0%) with a p-value of 0.62.

We use the QWI data to create several additional difference-in-differences and long-difference specifications that that control differently for the capital producer share. Table A9 displays the estimated coefficients. First, in column (2), we show that controlling for the capital producer share interacted with year fixed effects does not materially impact our coefficient. Second, in column (3), we drop the top 10% of plants in terms of the capital producer share, which is most of NAICS 334 (computer and peripherals manufacturing) and 333 (machinery manufacturing). When dropping the plants where we expect most of their output to be equipment capital for other firms, we actually find larger employment responses. In column (4), we drop plants in industries with above 70th percentile capital production share, which means all plants with more than 10% of their output going toward equipment capital. We still continue to find a comparable effect on the increase in employment even among plants in industries that produce very little capital.

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 A13, 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 comes from the BEA Detailed Data for Fixed Assets and Consumer Durable Goods from 1997 to 2001 and measures ICT capital intensity as a share of capital stock in ICT goods. The second measure is the Gallipoli and Makridis (2018) Z-score, the normalized share of workers engaging in tasks involving ICT during the 2002–2016 period. Both sets of estimates with these additional ICT controls are very similar to baseline, which suggests that growth in ICT usage is not biasing the results.

The second approach is to 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 16.6% of manufacturing employment in 2001. Despite the smaller sample, we continue to find bonus depreciation has large and significant effects on employment.

J Aggregate and Long-Run Manufacturing Trends

This section provides additional context to the employment and capital investment results presented in Section 4. Figure 6 demonstrates that the positive effects of bonus depreciation on US 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 US manufacturing became more capital intensive over the 1997–2011 period (Charles et al., 2019).

Figure A15 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 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 and that we again find large positive effects in the post-2001 period.

K Worker Composition and Wage Decomposition

This section provides three 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 predict earnings per worker at the state-industry level based on average earnings for each demographic group in 1997–2001. Using pre-treatment data, we regress earnings per worker on demographic shares (young, female, possessing fewer years of education, non-White). Using these estimates and observed demographic shares, we predict state-industry earnings during the full sample period. Therefore, these counterfactual earnings capture only the changes due to demographic shifts and hold earnings per worker constant within each demographic group. We then estimate the response of these counterfactual earnings to bonus depreciation. If the average earnings response we find is caused exclusively by demographic shifts due to the policy then would expect our counterfactual event study estimates to look very similar to those presented in Panel B of Figure 3.

Figure A16 compares the counterfactual event study estimates with earnings event study using ASM/CM data (Panel B of Figure 3). The counterfactual estimates closely track the ASM/CM findings throughout the sample period. The similarity of the two series indicates that the negative earnings response to bonus depreciation is due primarily to the policy-induced demographic shifts in the workforce we document above.

Second, we replicate the log earnings regression with QWI data while controlling for the various measurements of workforce composition at the state-industry level. These are "bad controls" but we still think these results provide qualitative insight when viewed in conjunction the other methods. The results of these regressions are presented in Table A12. This table begins with the original log earnings regression coefficient estimates, which indicate 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 high school education or less, share of non-White workers, and share of female workers.[63] In the final column with all controls, we find that bonus leads to a statistically insignificant 0.1% increase in earnings. This suggests that the change in workforce composition explains the decrease in earnings.

Third, we apply a formal decomposition to measure the effect of each margin of workforce composition directly. The Kitagawa-Oaxaca-Blinder decomposition involves 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 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

[63] 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.

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.

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

Adding and subtracting the estimated value of $\hat{\beta}^{\text{bonus, pre}} \bar{X}^{\text{bonus, post}}$ 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.

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

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 A13. 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 workers with fewer years of education 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, which is close to 91% of the overall wage effect. Our analyses indicate that the change in the share of workers with fewer years of education and the share of female workers explains most of the decrease in earnings per worker, confirming our results from Table A12.

L Heterogeneity by Labor Market Tightness

In Section 4.3, we document that bonus depreciation caused plants to shift their worker composition towards a workforce that was younger, more female, more diverse, and had fewer of years of education. These compositional shifts entirely explain the negative earnings response we document. One potential explanation for this pattern of results is that plants were forced to hire low-wage workers in response to bonus depreciation because the supply of high-wage workers in their local labor markets was exhausted. If this were the case, our conclusions in Section 6 that new capital investments were more complementary with production than non-production labor could be due to the fact that the supply of the latter was limited. In this appendix, we test this potential mechanism by estimating the heterogeneous effects of bonus depreciation according to the county-level unemployment rates for each plant, which we calculate as the average during the 1997–2001 period. Table A14 presents these heterogeneity results for the DD effects on log investment, log employment, and log mean earnings per worker. If this mechanism were driving our results, we would expect to find more negative earnings responses in plants in counties with lower average unemployment rates. Instead, we find no statistically or economically significant heterogeneity on all three outcomes. These null heterogeneity results reinforce our conclusion that capital investments induced by bonus depreciation were more complementary with low-wage production workers than high-skill non-production workers.

M Plant Labor Productivity and Labor Share Estimates

In this appendix, we present plant-level estimates of the effects of bonus depreciation on labor productivity and labor share. We define labor productivity as total output divided by total hours worked, and we define the plant-level labor share as total payroll divided by total revenue. Table A16 presents long-difference estimates of these effects, where columns (1) and (3) include plant and state-by-year fixed effects. Columns (2) and (4) also include plant size-, TFP-, and firm size-by-year fixed effects. Across both sets of controls, we find no statistically significant effects of bonus depreciation on either outcome.

N Transforming Manufacturing Sector, Extended Results

In Section 5 we discuss how our results fit in the context of the transforming manufacturing sector over the sample. In doing so, we ensure that our results are not driven by other trends in manufacturing that may be correlated with our bonus measure. These trends include shifts towards more skilled labor, higher capital intensity, increased exposure to imports, and robotization.[64] Table A18 compares the difference-in-differences estimates of bonus depreciation on log investment and log employment with full controls for sectoral shocks as quartile and decile bins interacted with year fixed effects. Here, decile controls are shown side by side with results from the baseline quartile control specifications. Results are shown to be insensitive to using these finer bin categories.

Next, we show that our estimates from models with capital and skill intensity controls are not sensitive to the definition of these controls. Our baseline definition fixes skill and capital intensity to be a fixed characteristic of plants' 6-digit industry defined in the pre-treatment period. We generate quartile bins based on these measures and then interact these bins with years to allow them to flexibly evolve over time. By constructing bins according to the pre-treatment period, there is an implicit assumption that the transformation of the manufacturing sector as explored by Charles et al. (2019) is captured by the initial conditions that we measure. We present three sets of additional difference-in-differences results in Table A19 to show that our results are not driven by sorting plants according to initial conditions on these margins. Panel A shows estimates for log employment and Panel B shows estimates for log investment. Columns (1) and (4) show difference-in-differences estimates controlling for capital and skill intensity in 2001, respectively. Columns (2) and (5) use the changes in the intensity measures between 1997 and 2001 interacted with year fixed effects, and columns (3) and (6) use the change in intensity between 1997 and 2011 interacted with year fixed effects. Both of these measures potentially control for endogenous changes in either intensity measure. We find estimates between 0.075 and 0.089 for the log employment specifications and between 0.134 and 0.210 for the log investment specifications. These estimates are very similar to our baseline measure of skill and capital intensity.

In addition, Table A20 explores heterogeneous effects of bonus across the different manufac-

[64] Figure A17 shows that our estimated effects of bonus depreciation on employment are robust to the inclusion of controls for the import exposure measures of Pierce and Schott (2016).

turing trends documented by Charles et al. (2019). These specifications demean and standardize our measures of the interactions. We also scale the interactions so that the coefficients can be interpreted as the average effect of going from the 25th to 75th percentile. These results corroborate the findings in Section 5 that bonus depreciation did not prop up 20th century manufacturing.

O Structural Model Derivations and Extensions

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

O.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

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

$$\frac{\partial L}{\partial X} = \left(a \left(Q^{\frac{\kappa}{\kappa-1}} \right)^{\frac{\theta-1}{\theta}} + (1-a) X^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}-1} (1-a) X^{\frac{\theta-1}{\theta}-1} - \lambda = 0. \tag{O.2}$$

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

$$q(\omega_2) = I \frac{1}{1 + \left(\frac{1-a}{a}\right)^{\theta} P^{\theta-1}} P^{1-\kappa} p(\omega_2)^{-\kappa}. \tag{O.3}$$

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

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

O.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 markup 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 O.3 shows that $\eta = \kappa$. To the extent that bonus impacts the sector-level price index P, Equation O.3 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 Shephards' 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,

$$\frac{\partial \log K(\omega)}{\partial R} = \frac{c_{RR}}{c_R} + \frac{\partial \log q(\omega)}{\partial R}. \tag{O.4}$$

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 O.4 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.

O.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, because 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, because $G(\cdot)$ 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 $\phi = -0.276$.

O.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 misspecified because it ignores how cash-flow effects of the policy may impact the choice of all inputs. A particular worry is that this misspecification 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 our baseline model, plants choose the optimal mix of inputs to minimize costs of production. Whereas before 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 because 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, because $\chi \geq 0$ 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 $\phi = -0.145$. Together with the assumption that $s_K = 0.20$, the scale effect implies that $1+\chi = \frac{\bar{\beta}}{-s_K\phi} = \frac{0.10}{0.2*0.145} = 3.45$. This value of $1+\chi$ then implies a magnitude of σ_{KL} close to our baseline estimate of -0.52. To the extent that $1+\chi$ is greater than 3.45, 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 $\sigma_{KL} = -0.15$.[65] This value can be considered an upper bound for σ_{KL}, because 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 use our estimate of the investment effects of bonus to estimate both σ_{KL} and s^b. We identify σ_{KL} as follows:[66]

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

This expression differs from an analogous expression in our baseline model by replacing β^R with $s^b(1+\varepsilon_b^I)/b$. Table A28 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 6. 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.

[65] 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}.

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

O.5 Capital-Labor Elasticity of Substitution with Monopsony

We now consider how labor market power can impact our estimation of the model's parameters. This appendix first sets-up the model, then derives the main results, and concludes by discussing the empirical implementation and estimates of model parameters.

O.5.1 Model Setup

We assume capital and non-production are supplied in a competitive market and have prices R and p_j, while the wages of production workers are determined by $w = L^{\frac{1}{\zeta}}$, where ζ is the elasticity of labor supply to the plant. To add this additional force to the model, we consider the following nested CES production function:

$$\begin{aligned} q &= \left[\mu_1 J^{\rho_1} + (1-\mu_1)(\mu_2 L^{\rho_2} + (1-\mu_2)K^{\rho_2})^{\frac{\rho_1}{\rho_2}}\right]^{\frac{1}{\rho_1}} \\ &= \left[\mu_1 J^{\rho_1} + (1-\mu_1)M^{\rho_1}\right]^{\frac{1}{\rho_1}}, \end{aligned}$$

where J represents non-production labor, L represents production labor, K represents capital, ρ_1 and ρ_2 are our CES parameters of interest, and $M = (\mu_2 L^{\rho_2} + (1-\mu_2)K^{\rho_2})^{\frac{1}{\rho_2}}$.

O.5.2 Detailed Derivations

The plant solves the problem: $\max_{J,K,L} q^{1-\frac{1}{\eta}} - \left(RK + p_j J + L^{1+\frac{1}{\zeta}}\right)$. The first-order condition with respect to K is:

$$\begin{aligned} \left(1-\frac{1}{\eta}\right) q^{1-\rho_1-\frac{1}{\eta}} M^{\rho_1-\rho_2}(1-\mu_1)(1-\mu_2)K^{\rho_2-1} &= R \\ \left[\left(1-\frac{1}{\eta}\right)\frac{(1-\mu_1)(1-\mu_2)}{R}\right]^{\frac{1}{1-\rho_2}} q^{\frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2}} M^{\frac{\rho_1-\rho_2}{1-\rho_2}} &= K. \end{aligned}$$

Taking logs and derivatives yields:

$$\beta^K = \frac{\partial \ln K}{\partial \text{Bonus}} = -\frac{1}{1-\rho_2}\underbrace{\frac{\partial \ln R}{\partial \text{Bonus}}}_{=\phi} + \frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2}\frac{\partial \ln q}{\partial \text{Bonus}} + \frac{\rho_1-\rho_2}{1-\rho_2}\frac{\partial \ln M}{\partial \text{Bonus}}. \tag{O.5}$$

The first-order condition with respect to L is:

$$\begin{aligned} \left(1-\frac{1}{\eta}\right) q^{1-\rho_1-\frac{1}{\eta}} M^{\rho_1-\rho_2}(1-\mu_1)\mu_2 L^{\rho_2-1} &= \left(1+\frac{1}{\zeta}\right)L^{\frac{1}{\zeta}} \\ \left[\left(1-\frac{1}{\eta}\right)\left(1+\frac{1}{\zeta}\right)^{-1}(1-\mu_1)\mu_2\right]^{\frac{1}{1-\rho_2+\frac{1}{\zeta}}} q^{\frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2+\frac{1}{\zeta}}} M^{\frac{\rho_1-\rho_2}{1-\rho_2+\frac{1}{\zeta}}} &= L. \end{aligned}$$

Taking logs and derivatives yields:

$$\beta^L = \frac{\partial \ln L}{\partial \text{Bonus}} = \frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2+\frac{1}{\zeta}} \frac{\partial \ln q}{\partial \text{Bonus}} + \frac{\rho_1-\rho_2}{1-\rho_2+\frac{1}{\zeta}} \frac{\partial \ln M}{\partial \text{Bonus}}. \tag{O.6}$$

The first-order condition with respect to J is:

$$\begin{aligned} \left(1-\frac{1}{\eta}\right) q^{1-\frac{1}{\eta}} \frac{\mu_1 J^{\rho_1-1}}{q^{\rho_1}} &= p_j \\ \left[\left(1-\frac{1}{\eta}\right)\frac{\mu_1}{p_j}\right]^{1-\rho_1} q^{\frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_1}} &= J \end{aligned}$$

Taking logs and derivatives yields:

$$\beta^J = \frac{\partial \ln J}{\partial \text{Bonus}} = \frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_1} \frac{\partial \ln q}{\partial \text{Bonus}}. \tag{O.7}$$

Taking logs and derivatives of the definitions of M and q yields:

$$\frac{\partial \ln M}{\partial \text{Bonus}} = \frac{\mu_2 L^{\rho_2}}{\mu_2 L^{\rho_2} + (1-\mu_2)K^{\rho_2}} \beta^L + \frac{(1-\mu_2)K^{\rho_2}}{\mu_2 L^{\rho_2} + (1-\mu_2)K^{\rho_2}} \beta^K$$

and

$$\frac{\partial \ln q}{\partial \text{Bonus}} = \frac{\mu_1 J^{\rho_1}}{\mu_1 J^{\rho_1} + (1-\mu_1)M^{\rho_1}} \beta^J + \frac{(1-\mu_1)M^{\rho_1}}{\mu_1 J^{\rho_1} + (1-\mu_1)M^{\rho_1}} \frac{\partial \ln M}{\partial \text{Bonus}}.$$

We now use the first-order conditions for L and K to write:

$$\frac{s_L}{s_K} = \frac{L^{1+\frac{1}{\zeta}}}{RK} = \frac{\frac{\mu_2}{\left(1+\frac{1}{\zeta}\right)} L^{\rho_2}}{(1-\mu_2)K^{\rho_2}}.$$

This expression implies that $\frac{s_K}{s_K+\left(1+\frac{1}{\zeta}\right)s_L} = \frac{(1-\mu_2)K^{\rho_2}}{\mu_2 L^{\rho_2}+(1-\mu_2)K^{\rho_2}}$. Similarly, we can use the first-order conditions for J, K, and L to show that

$$\frac{s_J}{s_K+s_L} = \frac{\mu_1 J^{\rho_1}}{M^{\rho_1}(1-\mu_1)\left[\frac{s_K+s_L}{s_K+\left(1+\frac{1}{\zeta}\right)s_L}\right]}.$$

This expression implies that $\frac{s_J}{s_K+\left(1+\frac{1}{\zeta}\right)s_L+s_J} = \frac{\mu_1 J^{\rho_1}}{\mu_1 J^{\rho_1}+(1-\mu_1)M^{\rho_1}}$. Using these expressions, we now have that:

$$\begin{aligned} \frac{\partial \ln M}{\partial \text{Bonus}} &= \frac{\left(1+\frac{1}{\zeta}\right)s_L}{s_K+\left(1+\frac{1}{\zeta}\right)s_L}\beta^L + \frac{s_K}{s_K+\left(1+\frac{1}{\zeta}\right)s_L}\beta^K \\ \frac{\partial \ln q}{\partial \text{Bonus}} &= \underbrace{\frac{s_J}{s_K+\left(1+\frac{1}{\zeta}\right)s_L+s_J}}_{\equiv \tilde{s}_J}\beta^J + \underbrace{\frac{\left(1+\frac{1}{\zeta}\right)s_L}{s_K+\left(1+\frac{1}{\zeta}\right)s_L+s_J}}_{\equiv \tilde{s}_L}\beta^L + \underbrace{\frac{s_K}{s_K+\left(1+\frac{1}{\zeta}\right)s_L+s_J}}_{\equiv \tilde{s}_K}\beta^K \equiv \beta^q, \end{aligned}$$

where introduce a new definition of the modified scale term β^q and the modified cost shares $\tilde{s}_K, \tilde{s}_L$, and $\tilde{s}_J$.

Using the expression above and Equation O.7, we obtain:

$$\begin{aligned} \beta^J &= \frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_1}\beta^q \\ \eta\left(1-\frac{\beta^J}{\beta^q}\right) &= \frac{1}{1-\rho_1} \end{aligned} \tag{O.8}$$

Using Equation O.6, we can obtain:

$$\begin{aligned} \beta^L &= \frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2+\frac{1}{\zeta}}\beta^q + \frac{\rho_1-\rho_2}{1-\rho_2+\frac{1}{\zeta}}\beta^M \\ \frac{1}{\eta}\beta^q\frac{\beta^M-\beta^J}{\beta^q-\beta^J}+\frac{1}{\zeta}\beta^L &= (1-\rho_2)(\beta^M-\beta^L) \end{aligned}$$

To simplify this expression, we note that: $\beta^M-\beta^J = \frac{1}{\tilde{s}_K+\tilde{s}_L}(\beta^q-\beta^J)$. Similarly, we have that $\beta^M-\beta^L = \frac{\tilde{s}_K}{\tilde{s}_K+\tilde{s}_L}\left(\beta^K-\beta^L\right)$. We can then solve the equation above for $\frac{1}{1-\rho_2}$ and obtain:

$$\frac{1}{1-\rho_2} = \frac{\beta^K-\beta^L}{\frac{1}{\eta}\frac{\beta^q}{\tilde{s}_K}+\frac{1}{\zeta}\beta^L\left(\frac{\tilde{s}_K}{\tilde{s}_K+\tilde{s}_L}\right)^{-1}} \tag{O.9}$$

We now use the expression for β^K to solve for ϕ :

$$\begin{aligned} \beta^K &= -\frac{1}{1-\rho_2}\phi+\frac{1-\rho_1-\frac{1}{\eta}}{1-\rho_2}\beta^q+\frac{\rho_1-\rho_2}{1-\rho_2}\beta^M \\ \phi &= -\frac{1}{\eta}\beta^q+(1-\rho_1)(\beta^q-\beta^M)+(1-\rho_2)(\beta^M-\beta^K) \end{aligned}$$

As above, we can show that $\beta^M-\beta^K = \frac{\tilde{s}_L}{\tilde{s}_K+\tilde{s}_L}\left(\beta^L-\beta^K\right)$ and

$$\beta^q-\beta^M = \tilde{s}_J(\beta^J-\beta^M) = \frac{\tilde{s}_J}{\tilde{s}_K+\tilde{s}_L}(\beta^J-\beta^q).$$

Substituting in the expression above we can show that:

$$\phi = -\frac{1}{\eta}\beta^q\frac{1}{\tilde{s}_K}-\frac{1}{\zeta}\beta^L\frac{\tilde{s}_L}{\tilde{s}_K}. \tag{O.10}$$

O.5.3 Model Discussion and Empirical Implementation

This section discusses the model results, the empirical implementation, and the estimates of model parameters. Collecting the main results from the previous section (i.e., Equations O.8, O.9, and O.10), we have that:

$$\begin{aligned}\frac{1}{1-\rho_1} &= \eta\left(1-\frac{\beta^J}{\beta^q}\right)\\ \frac{1}{1-\rho_2} &= \frac{\beta^K-\beta^L}{\frac{1}{\eta}\frac{\beta^q}{\tilde{s}_K}+\frac{1}{\zeta}\beta^L\left(\frac{\tilde{s}_K}{\tilde{s}_K+\tilde{s}_L}\right)^{-1}}\\ \phi &= -\frac{1}{\eta}\beta^q\frac{1}{\tilde{s}_K}-\frac{1}{\zeta}\beta^L\frac{\tilde{s}_L}{\tilde{s}_K}.\end{aligned}$$

The expression for $\frac{1}{1-\rho_1}$ takes the same form as Equation 8. The only difference is that the term β^q relies on the modified cost shares $\tilde{s}_J$, which depend on the elasticity of labor supply ζ.

The expression for $\frac{1}{1-\rho_2}$ is reminiscent of Equation P.7, which shows that, in the absence of labor market power, the elasticity of substitution between K and L is given by the ratio of the percentage change in the capital-labor ratio to the percentage change in the cost of capital. In the presence of market power, the expression for $\frac{1}{1-\rho_2}$ shows that we must also account for changes in wages. The effects of the policy on the log capital-labor price ratio are given by:

$$\frac{\partial\ln\left(\frac{w}{R}\right)}{\partial\text{Bonus}}=\frac{\beta^L}{\zeta}-\phi=\frac{1}{\eta}\frac{\beta^q}{\tilde{s}_K}+\frac{1}{\zeta}\beta^L\left(\frac{\tilde{s}_K}{\tilde{s}_K+\tilde{s}_L}\right)^{-1},$$

where the change in the wage rate is given by: $\frac{\beta^L}{\zeta}$.[67] Note that this is the denominator in the expression for $\frac{1}{1-\rho_2}$. That is, we can interpret Equation O.9 as the ratio of the percentage change in the capital-labor ratio to the percentage change in the relative price of inputs, inclusive of distortions from labor market power.

In addition, note that because $\frac{\partial\ln\left(\frac{w}{R}\right)}{\partial\text{Bonus}}$ is positive for any value of $\zeta>0$, we have that

$$sign\left(\frac{1}{1-\rho_2}\right)=sign(\beta^K-\beta^L).$$

Because we estimate that $\beta^K<\beta^L$, it follows that capital and labor are complements, i.e., $\frac{1}{1-\rho_2}<0$ for reasonable ranges of ζ. Even though the sign of $\frac{1}{1-\rho_2}$ does not depend on the value of ζ, we expect that lower values of ζ will shrink the value of $\frac{1}{1-\rho_2}$ toward zero.

Finally, we can derive some insight into the expression for ϕ by rewriting it as follows:

$$\tilde{s}_K\phi+\frac{1}{\zeta}\beta^L\tilde{s}_L = -\frac{1}{\eta}\beta^q$$

The left-hand side is the percentage change in unit costs across both wages and costs of capital. Because our model features a constant demand elasticity, we continue to have a unit pass-through to prices. The right-hand side shows that prices decrease by $-\frac{\beta^q}{\eta}$.

[67] Because $w=L^{\frac{1}{\zeta}}$, $d\ln w=\frac{1}{\zeta}d\ln L$ implies that $\beta^W=\frac{1}{\zeta}\beta^L$.

The equations above provide a natural empirical implementation of the model. As in our baseline case, we use data on cost shares to calibrate values of s_L, s_K, and s_J. We can then use calibrated or estimated values of ζ and η. Because the change in the wage rate is given by: $\beta^W = \frac{\beta^L}{\zeta}$, in our baseline case, $\beta^W \approx 0$ implies $\zeta \to \infty$. Estimates of ζ from the literature range between 4.8 in Azar et al. (2019) and 1.9 in Yeh et al. (2022). We can also estimate ζ in our empirical setting. Table A33 Panel C shows that we estimate a relatively larger effect of bonus on more concentrated labor markets. Because we show in Section 4.3 that the baseline average earnings is a composition effect, we use the relative wage effect of $\beta^W = 0.008$ together with the employment increase of $\beta^L = 0.08$ to estimate that $\frac{1}{\zeta} = \frac{0.008}{0.08} = 0.10$ and $\zeta = 10$. Given a value of ζ, we can compute the modified sale effect β^q. Because we have that $\beta^R = \left(1 - \frac{1}{\eta}\right)\beta^q$, the scale and revenue effects continue to identify η. For comparability, we calibrate η to the values used in our earlier analyses. Given values of ζ and η, we use Equations O.8, O.9, and O.10 to estimate ρ_1, ρ_2, and ϕ.

Table A26 implements the model with monopsony using our empirical estimates. Column (1) shows the case with $\zeta = \infty$, which is equivalent to our baseline case in Table A25. Column (2) reports results when we use our estimated value of $\zeta = 10$, which slightly attenuates the elasticity of substitution between production labor and capital, $\frac{1}{1-\rho_2}$. As discussed above, columns (3) and (4) show that we find estimates of $\frac{1}{1-\rho_2}$ that are closer to zero when we use smaller calibrated values of ζ from the literature. However, the conclusion that production labor and capital are complements ($\frac{1}{1-\rho_2} < 0$) and the result of our test of capital-skill complementarity in Panel C do not depend on the value of ζ. Columns (5)–(6) use a calibrated values of $\zeta = 4.8$ and vary the values of different cost shares, while columns (7)–(8) vary the values of η. Relative to column (3), we obtain a more negative value of $\frac{1}{1-\rho_2}$ when s_K or η are larger.

P 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 explore how our plant-level elasticity estimates may differ from those derived from industry-level data. This section explores the role of plant entry and exit and estimates the model using industry-level data. We then compute aggregate elasticities of substitution that account for within and across industry reallocation of production toward more capital intensive production units.

P.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 et al., 1971, 1973).

The translog cost function is a second-order approximation to a general cost function that can accommodate an arbitrary number of inputs and nests several alternative production technologies. The general form is given by:

$$\log C = \log Y + a_0 + \sum_i a_i \log w_i + 0.5 \sum_i \sum_j b_{ij} \log w_i \log w_j, \tag{P.1}$$

where

$$\sum_i a_i = 1; \quad b_{ij} = b_{ji}; \quad \sum_i b_{ij} = 0, \ \forall j, \tag{P.2}$$

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

$$\sigma_{ij} = [b_{ij} + s_i s_j]/s_i s_j, \quad i \neq j. \tag{P.3}$$

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 7. 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:

$$\sigma_{ii} = [b_{ii} + s_i^2 - s_i]/s_i^2. \tag{P.4}$$

Equations P.3 and P.4 demonstrate that the partial elasticities of substitution we estimate are linear functions of the analogous translog parameters b_{ij}. Panels A of Tables A22 and A23 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 A22 and A23 report p-values associated with the F-tests corresponding to these null hypotheses across the three-input model estimates presented in Table 7. 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 because 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 because $\sigma_{LJ} = \sigma_{KJ}$ 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.

P.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

$$\phi = -\frac{\bar{\beta}}{s_K \eta}. \tag{P.5}$$

Column (1) of Panel D of Table 6 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 $\phi \in [-0.30, -0.09]$.

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 6 shows that $\varepsilon^I_\phi = \frac{\beta^I}{\phi} = -1.40$.[68] This elasticity lies in the range $[-2.1, -0.68]$ 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

[68] This estimate uses the long-difference estimate on investment from Panel A of Figure 2.

-7.2. We estimate a smaller elasticity because our estimate of ϕ includes financing and other constraints.[69]

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 6 reports our baseline estimate of $\varepsilon_{\phi}^{K} = \frac{\beta^K}{\phi} = \frac{0.080}{-0.145} = -0.56$.[70] For context, Equation 3 and our baseline values for s_K and η would imply that $\varepsilon_{\phi}^{K} = -1.5$ 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 6 shows that we estimate an elasticity of $\varepsilon_{\phi}^{L} = \frac{\beta^L}{\phi} = \frac{0.116}{-0.145} = -0.80$ for production labor and $\varepsilon_{\phi}^{J} = \frac{\beta^J}{\phi} = \frac{0.090}{-0.145} = -0.63$ for non-production labor.[71] Both elasticities would equal -0.5 with Cobb-Douglas production. This comparison reinforces the dominance of the scale effect in our setting, because even a large degree of substitution would be overshadowed by the scale effect. In addition, because we estimate that $\varepsilon_{\phi}^{L} < \varepsilon_{\phi}^{J}$, 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. 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.

P.3 Constant Elasticity of Substitution Parameter Estimates

We now demonstrate that the elasticities in Panel D of Table 6 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

[69] In Appendix O.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 et al. (2019) estimate an investment tax elasticity of -2.2, which is comparable in magnitude to our estimates.

[70] This elasticity lies in the range $[-0.85, -0.27]$ across columns (1)–(5).

[71] Across our estimates in columns (1)–(5), $\varepsilon_{\phi}^{L} \in [-1.23, -0.39]$ and $\varepsilon_{\phi}^{J} \in [-0.96, -0.31]$.

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.[72]

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:

$$\frac{L}{K} = \left(\frac{(1-\mu_2)}{\mu_2}\frac{R}{w}\right)^{\frac{1}{1-\rho_2}}. \tag{P.6}$$

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

$$\varepsilon_\phi^L - \varepsilon_\phi^K = \frac{1}{1-\rho_2}, \tag{P.7}$$

which can be rearranged to yield an expression for ρ_2.[73]

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:

$$\frac{RK}{RK+wL} = \frac{\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}}{\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}} + (1-\mu_2)\left(\frac{w}{1-\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}} = \frac{s_K}{s_K+s_L}. \tag{P.8}$$

As with Equation P.6, we may also derive the following expression for the optimal quantity ratio of J and K using first-order conditions:

$$\frac{J}{K} = \left(\frac{R}{\mu_2}\right)^{\frac{1}{1-\rho_2}}\left(\frac{p_j}{\mu_1}\right)^{\frac{-1}{1-\rho_1}}\left[\frac{1}{(1-\mu_1)}\left[\mu_2\left(\frac{R}{\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}} + (1-\mu_2)\left(\frac{w}{1-\mu_2}\right)^{\frac{-\rho_2}{1-\rho_2}}\right]^{\frac{\rho_1-\rho_2}{-\rho_2}}\right]^{\frac{1}{1-\rho_1}} \tag{P.9}$$

Unlike Equation P.6, 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

[72] An alternative approach nests non-production labor and capital separately from production labor (e.g., as in Krusell et al., 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).

[73] Note that the left-hand-side expression in this equation and in Equation P.11 below are also Morishima elasticities of substitution.

logs and differentiating these expressions with respect to R allows us to link ρ_1 to Morishima elasticities. Equation P.8 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:

$$\varepsilon_\phi^J - \varepsilon_\phi^K \approx \frac{1}{1-\rho_2}\left[1 + \frac{\rho_1 - \rho_2}{1-\rho_1}\frac{s_K}{s_L + s_K}\right]. \tag{P.10}$$

The expression holds locally because 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 P.7, shows that ρ_1 is given by:

$$\varepsilon_\phi^J - \varepsilon_\phi^K \approx (\varepsilon_\phi^L - \varepsilon_\phi^K)\frac{s_L}{s_L + s_K} + \frac{1}{1-\rho_1}\frac{s_K}{s_L + s_K}. \tag{P.11}$$

According to Table 6, $\varepsilon_\phi^L - \varepsilon_\phi^K < 0$ and $\varepsilon_\phi^J - \varepsilon_\phi^K \approx 0$, implying that $\rho_2 > 1$ and $\rho_1 < 1$.[74] Panel A of Table A25 uses Equations P.7 and P.11 to show that we estimate $\rho_1 = -1.67$ and $\rho_2 = 5.03$. Panel B of Table A25 shows that our estimates imply that $\frac{1}{1-\rho_2} = -0.25 < 0.38 = \frac{1}{1-\rho_1}$. 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 et al. (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.

P.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 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.

[74] Table A24 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 et al. (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.

Panels A and B of Figure A20 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 6 over time. As in the main text, we define these elasticities as $\varepsilon^I_\phi = \beta^I/\phi$ and $\varepsilon^L_\phi = \beta^L/\phi$, respectively. These estimates are relatively stable over time. This result suggests that our estimates of ϕ capture the effects of the policy on the cost of capital, inclusive of financing and adjustment constraints that may prevent plants from adjusting their capital.

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

$$\sigma^t_{KL} = (1-\eta)\frac{\beta^L_t}{\beta^R_t} + \eta.$$

Figure A21 presents these estimates. While somewhat imprecise, these point estimates suggest the initial large negative estimate of σ_{KL} 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.

P.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:

$$\sigma_{KL} = \eta\left(1 - \frac{\beta^L}{s_L\beta^L + s_K\beta^K}\right). \tag{P.12}$$

To implement this equation, we set input cost shares so that $1-s_K = s_L = 0.8$. Panel A of Figure A19 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., $\sigma_{KL} < 0$.[75] Column (5) of Table A21 implements the classical minimum distance approach to estimate σ_{KL}, finding an estimate of $\sigma_{KL} = -0.106$. It is

[75] To be consistent with a Cobb-Douglas production function, Equation P.12 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 $\eta = 2$.

possible to specify restrictions that yield a constant-returns-to-scale production function in just capital and labor even if a third factor like materials is also part of production. When materials and another input can be combined via Leontief (i.e., so that $y = F(L, \min\{K, M\})$) it makes sense to assume that the production function F has constant returns to scale. We estimate that material use, M, increased by 8.3% in response to bonus, which is very close to the 8% increase in capital use, K. These results show that this CRS assumption is not necessarily at odds with the data. It is therefore possible to interpret our results as the elasticity of substitution conditional on the data-consistent assumption that capital and materials are combined in a Leontief fashion.

However, 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.[76] 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 A21 presents several three-input alternatives to the baseline model estimates presented in the text, which we reproduce in column (1). Column (2) shows that we obtain similar results when we also control for the factors of sectoral transformation discussed in Section 5. Columns (3) and (4) of Table A21 resemble our baseline model, but instead rely on difference-in-differences (instead of long-difference) moments and defines labor inputs as hours worked (instead of number of workers), respectively. In both cases, we estimate very similar values of σ_{KL}, which suggests that the finding that production labor and capital are complements is not driven by mismeasurement of labor inputs, nor by focusing on the ten-year effect of bonus depreciation on inputs. Column (6) of Table A21 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. Because 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 (7) 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

[76] Gechert et al. (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}.

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 A19 reports values of σ_{KL} implied by a five-input analogue of Equation P.12 across values of η. Once again, our estimates imply negative values of σ_{KL}.

P.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. 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.[77] 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 A29 for the outcomes log of production employment, log of non-production employment, and log of capital stock.[78] Our long-difference estimates show that bonus led to a relative increase in production employment of 22.7%, an increase in non-production employment of 17.0%, and an increase in capital stocks of 13.5% 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 A30 uses these industry-level results to estimate scale and substitution effects, and reports analogous statistics as those in Table 6. These tables show that our model has similar

[77] 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.

[78] 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.

implications when we use industry- or plant-level data. In column (1), we estimate that σ_{KL} is equal to -0.655, and we reject the null hypothesis that $\sigma_{KL} \geq 0$ with a p-value of 0.013. For reference, Table 6 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.

P.7 Interpretation of Plant- vs. Industry-Level Estimates

Our baseline estimates from ASM/CM microdata focus on plant production for a balanced panel of plants over the 1997 to 2011 period. The industry-level estimates discussed in Appendix P.6, on the other hand, capture both plant-level input changes as well as reallocation across plants and entry and exit. However, these estimates are still limited in that they are unable to separate all of these impacts. As mentioned above, our estimates of capital-labor substitution at the industry- and plant-levels are very similar in magnitude, which suggests that our plant-level estimates are quite representative of more aggregated industry-level effects. These patterns also support our interpretation that the estimated increases in employment in response to a decline in the cost of investment were driven primarily by the scale effect rather than by substitution across different factor inputs.

At the same time, the larger scale effect we estimate using industry-level data suggests that entry and exit over the 1997 to 2011 period likely contributed to the increases in manufacturing activity driven by bonus depreciation. We perform two sets of analyses to explore this possibility. The first approach, a Melitz and Polanec (2015) decomposition, isolates the effects of entry and exit from the effect of stayers over a 15-year period using confidential data from the Census of Manufacturers (CM). The second approach relies on public data from the US Census Business Dynamics Statistics (BDS) to decompose yearly flows into the share due to entry, exit, and intensive margin responses. Both approaches show that bonus depreciation increased job creation among stayers and entrants and decreased job destruction among stayers and exiters. Mechanically, we find a larger role for entry and exit using the approach of Melitz and Polanec (2015), which considers stayers to be only those plants that survive over a 15-year period. Using yearly employment flows from the BDS, we find that about 50% of the net employment change is driven by job creation, predominantly by continuing firms.

We now describe the Melitz and Polanec (2015) decomposition, following the generalization from Autor et al. (2020), in order to measure the magnitude of the observed industry dynamics that come from stayers, exiters, and entrants. Specifically, for each 6-digit NAICS manufacturing industry, we compute the following decomposition for the percent change in employment over the 1997 to 2012 period, ΔL:

$$\Delta L = \underbrace{\Delta \bar{L}_S + \Delta \left[\sum (\omega_i - \bar{\omega})(L_i - \bar{L})\right]_S}_{\text{Stayers}} + \underbrace{\omega_{X,0}(L_{S,0} - L_{X,0})}_{\text{Exiters}} + \underbrace{\omega_{E,1}(L_{E,1} - L_{S,1})}_{\text{Entrants}}.$$

This expression shows that the percent change in employment across two time periods can be decomposed into a stayers component, which is the sum of the average change in employment for plants that are open in both periods and a covariance term that captures the correlation of initial plant size and growth, an exiter component, which captures the total employment lost due to plant closures, and an entrant component capturing the total employment gained from new plant entry. Because we focus on the full 1997 to 2012 period, the "stayers" component closely corresponds to the balanced panel we study in our plant-level analyses.

We calculate each of these components using employment data from the CM in 1997 and 2012 for each 6-digit NAICS industry. We then regress each component on a binary bonus treatment variable along with controls for capital intensity, skill intensity, robot exposure, and import competition exposure as outlined in Section 5. These binary bonus treatment estimates represent the average percentage point change in employment for bonus industries relative to control industries for each component.

As in our industry-level analyses, we find that bonus depreciation leads to a large increase in the percent change on employment, ΔL, of 11.2%. We then estimate point estimates for each of the components, where we find that bonus increased net employment of stayers and entrants and decreased job losses from exiters. We then compare these point estimates to the total effect to calculate the percent contribution of each component. We calculate that the contributions of stayers, exiters, and entrants are 29.1%, 47.2%, and 23.7% of the total effect, respectively. However, these estimates are subject to considerable uncertainty. For instance, we cannot reject the hypotheses that the effect on stayers accounts for either 0% or 100% of the overall effect. While we can reject the hypotheses that exiters account for 0% ($p = 0.09$) and that entrants account for 100% of the effect ($p = 0.003$), ultimately this analysis is not conclusive.

We explore the role of entry and exit further using publicly-available data on job creation and destruction across plant cohorts from the US Census Business Dynamics Statistics (BDS).

The BDS provides annual, industry-level job creation and destruction data disaggregated by stayers and plant entrants and exiters. These data thus differ from our CM analysis by defining stayers, entrants, and exiters on an annual basis rather than over the full 1997–2012 period. Unfortunately, these data is are only available at the 4-digit NAICS industry level, which prevents us from including the granular controls we use in our main analysis.

Panel A of Figure A10 presents event study estimates corresponding to the effects of bonus depreciation on industry-level cumulative job flows relative to 2001 employment levels across plant cohorts. This figure shows that bonus depreciation increased job creation by stayers and entrants and decreased job destruction by stayers and exiters. The magnitudes in 2011 show a considerable degree of symmetry: destruction from firm deaths is quantitatively similar to creation from firm births and, similarly, job creation and destruction among stayers contribute equally to the net employment effect of bonus depreciation.

Panel B then shows how each of these components contribute to the total employment effect. As in our main analysis, we find that more exposed industries see a relative increase in employment by 2011. Even without our controls from the baseline analysis, we do not estimate statistical differences across industries in the pre-period.[79] Across the 2002–2011 period, we find that incumbent plants account for the largest share of employment effects induced by bonus through a combination of less job destruction and more job creation. Job flows from plant entry and exit account for a much smaller share of total employment effects. In the context of our decomposition using CM data, these results suggest that, while plants that enter or exit over the 1997–2012 are responsible for a large portion of the industry-level employment effects we estimate, annual employment effects are predominantly driven by the intensive margin of employment adjustments by existing plants.

P.8 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.

[79] Recall that we find more stable and precisely estimated null pre-trends when using plant-level data (Panel A Figure 3), state-by-industry data (Figure A7), and 6-digit NAICS industry-level data (Panel B of Figure A15).

To apply this method, we begin by using the industry-level elasticity estimates discussed in Appendix P.6 and presented in Panel D of Table A30. We use these estimates to compute the Morishima elasticities of substitution presented in Table A31. 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 analogs presented in Table A24, suggesting that reallocation within industries is a not a substantial margin of response to bonus depreciation. As in the framework of Oberfield and Raval (2021), these elasticities map to the parameters of a nested CES production function (see Appendix P.3).

Oberfield and Raval (2021) demonstrate that an aggregate capital-labor elasticity of substitution, σ_{KL}^{agg}, can be computed from 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. If we let $\alpha_n = \frac{rK_n}{rK+wL}$ 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 $\chi^{agg} = \sum \frac{(\alpha_n-\alpha)^2}{\alpha(1-\alpha)}\theta_n$. The parameter σ_{KL}^{agg} thus captures the degree to which aggregate capital-labor substitution will reflect within-industry substitution σ_{KL}^{N}; substitution across industries of varying capital intensity, captured by the cross-industry demand elasticity ε; or substitution toward non-production labor, captured by σ_{KJ}^{N}. 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 A32 presents the results of this analysis for different calibrated values of η and s_{NL}.[80] 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. Nevertheless, across all specifications, we estimate aggregate elasticities consistent with complementarity between

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

capital and production labor. Column (1) rejects values of σ_{KL}^{agg} greater than 0.0868 at the 5% level; across all columns we reject values of σ_{KL}^{agg} greater than 0.125 at the same significance level.

P.9 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. 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). We test for heterogeneous responses using 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 unionization is an indicator that equals 1 when more than 60% of workers at a plant are unionized. 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. RTW is an indicator equal to 1 for plants in RTW states (as of 2001), where employees have less bargaining power. 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 et al., 2021, Footnote 43). For these reasons, RTW laws lower workers' bargaining power and result in lower labor costs. We measure labor market concentration using a 3-digit NAICS-by-commuting-zone-level Herfindahl-Hirschmann Index (HHI) based on 2001 market conditions. 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 so that it can be easily interpreted as the differential effect of bonus depreciation between plants located in the average labor market concentration compared to plants located in a highly-concentrated labor market (according to FTC/DOJ guidelines, HHI>2500). In plants that operate in highly concentrated local labor markets, monopsony power may allow employers to set lower wages (see, e.g., Robinson, 1969; Manning, 2021).

Table A33 presents difference-in-differences estimates of the effects of bonus on investment, employment, and mean earnings while including 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 complementarity, which validates the results from our empirical model of factor demands. Further, these analyses highlight how labor market institutions can impact capital investment.

Table A33 also reports heterogeneous effects on employment and earnings. Two notable results stand out. First, negative interaction terms 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. Recent work by Yeh et al. (2022) finds evidence of significant monopsony power in the US manufacturing sector over the time period of our study. While our overall earnings result suggest minimal increases in earnings, our results in Table A33 are consistent with the notion that in monopsonistic labor markets, plants must raise wages to increase employment.

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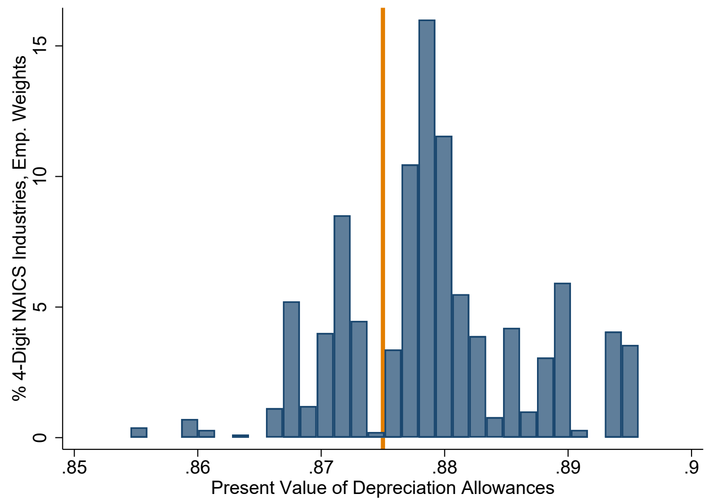
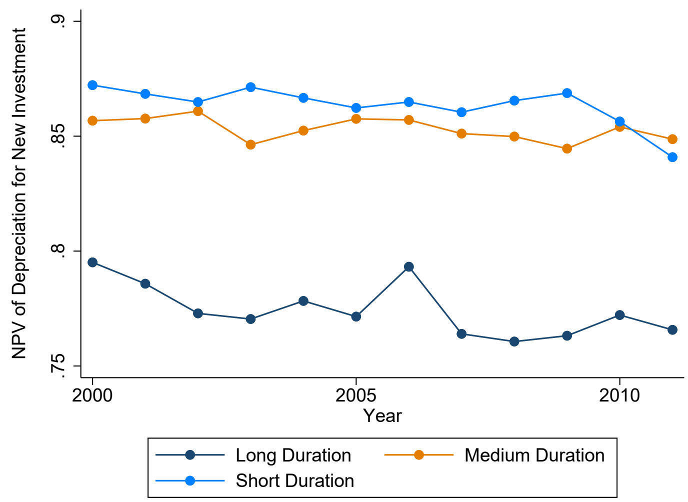


Panel A: Distribution of Depreciation NPV without Bonus



Panel B: Stability of Depreciation NPV Over Time

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

Note: 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 terciles 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 larger and more stable z_0 estimates. 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) data and IRS SOI sector-level corporation depreciation data from Form 4562.

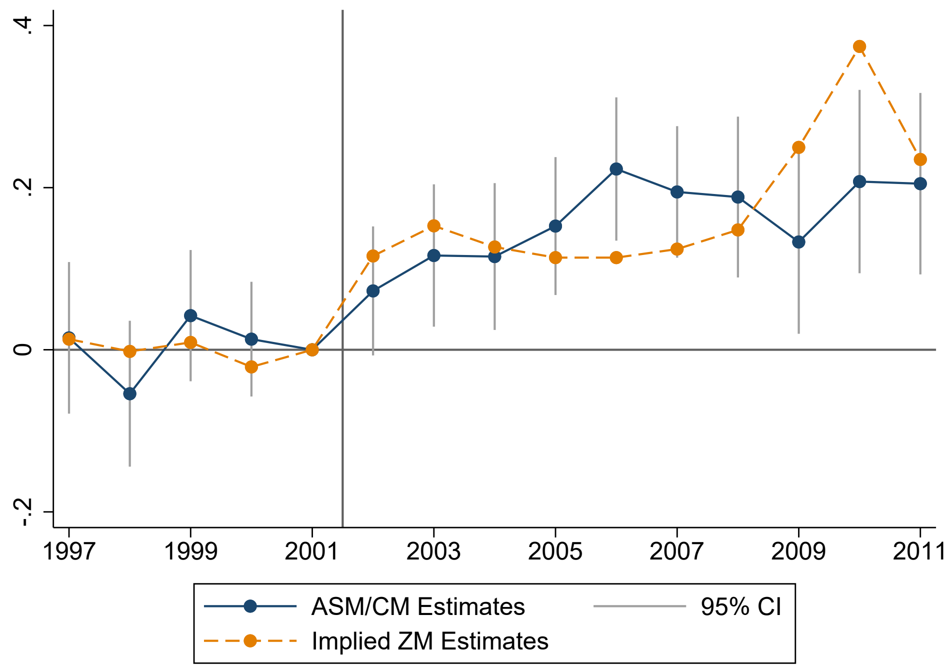
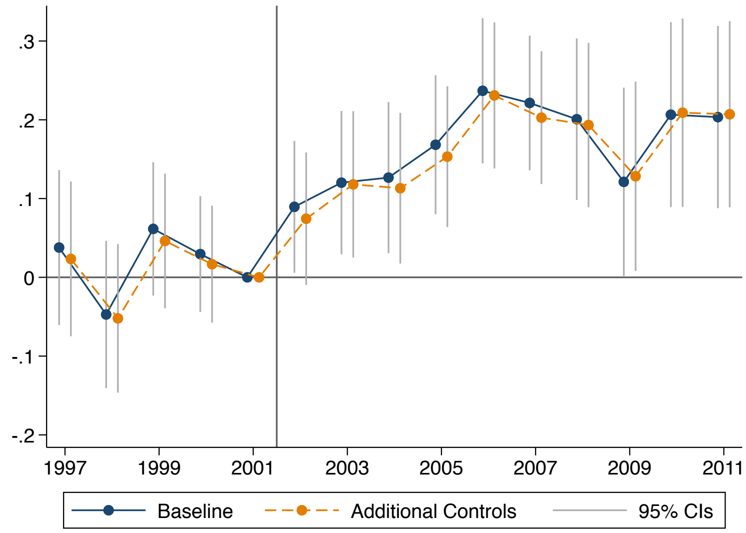


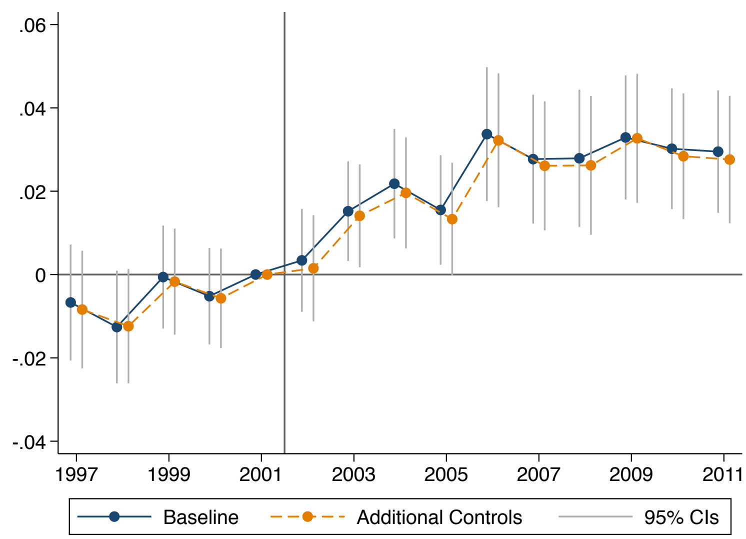
Figure A2: Comparison of Investment Event Study Results with Zwick and Mahon (2017)

Note: 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 E. 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.



Panel A: IHS Investment



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

Figure A3: Effects of Bonus Depreciation on Alternative Investment Outcomes

Note: 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 A3, respectively. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

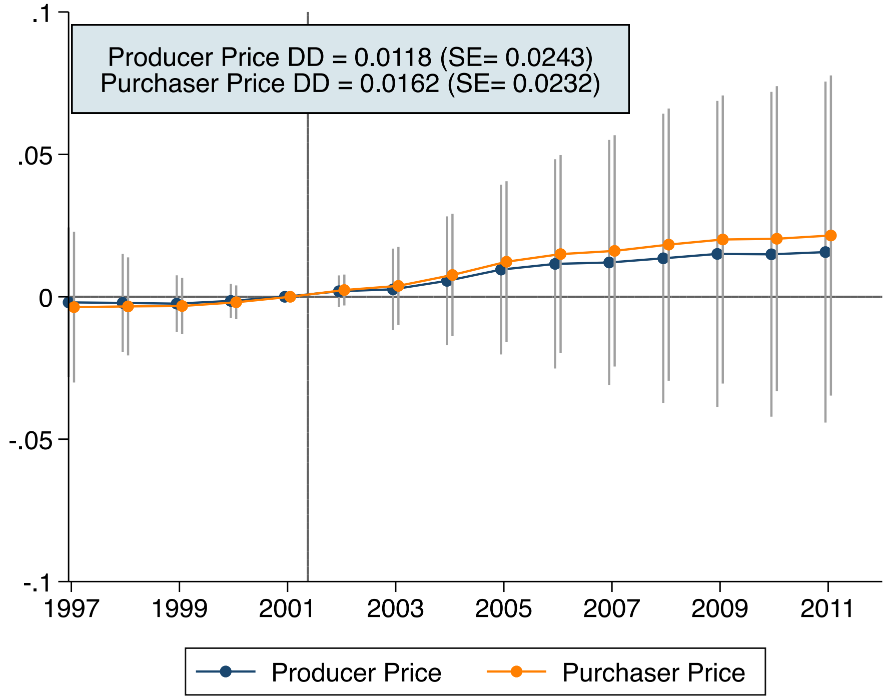


Figure A4: Effects of Bonus Depreciation on Input Price Indices

Note: Figure A4 presents event study estimates of the effect of bonus on input prices. Input prices are measured as the log of 6-digit NAICS industry-specific price indices constructed using BEA data as detailed in Appendix G.3. Estimates are presented for both producer prices and purchaser prices where purchaser prices are inclusive of transportation costs, taxes, and retailer/wholesaler markups. Observations are weighted by 2001 industry employment levels. The regression includes 6-digit NAICS fixed effects and year fixed effects. 95% confidence intervals are included for each point estimate with standard errors clustered at the 4-digit NAICS level. The text box reports the associated DD estimates.
Source: Authors' calculations based on BEA Underlying Detail Table 5.5.4U, 1997 and 2002 Benchmark I-O accounts from the BEA, the NBER-CES Manufacturing Industry Database, and Zwick and Mahon (2017) data.

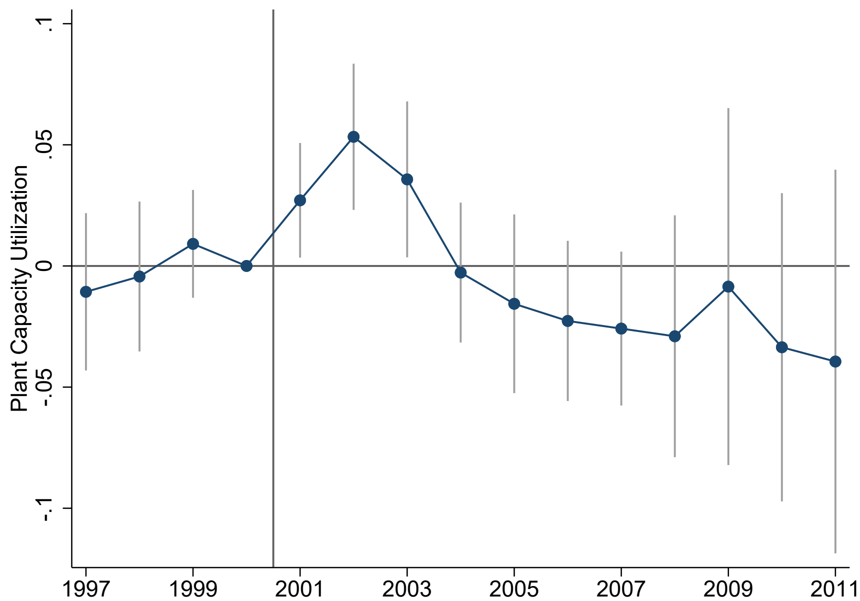
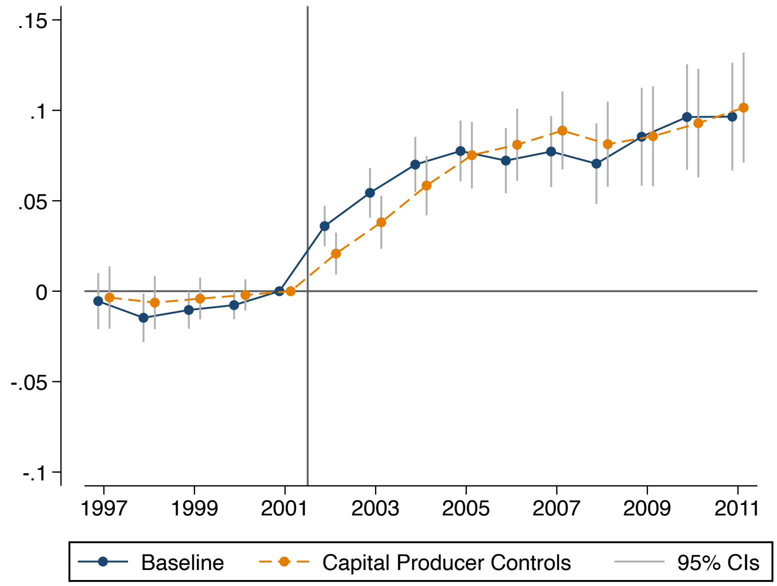
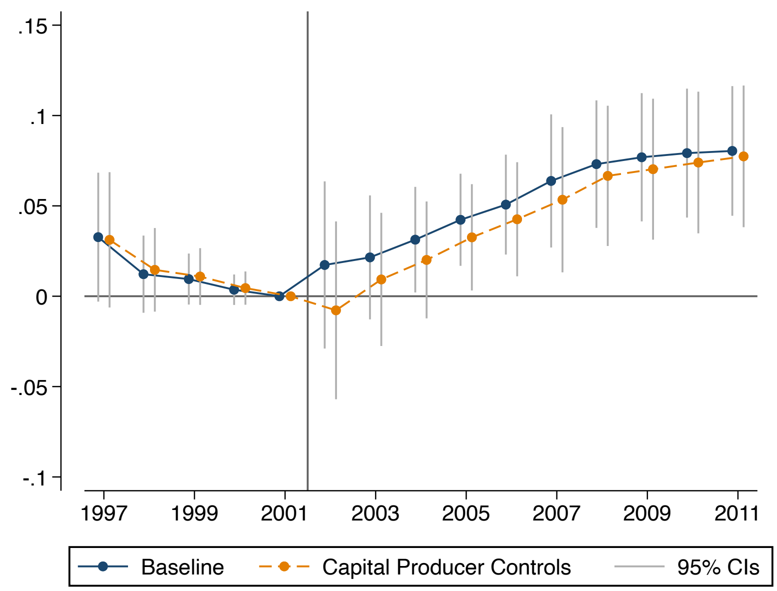


Figure A5: Effects of Bonus Depreciation on Plant Capacity Utilization

Note: Figure A5 estimates how much capacity utilization changes for plants in industries most impacted by bonus. Plant capacity utilization averages at the industry level come from the Census' Quarterly Survey of Plant Capacity Utilization (QPC) fourth quarter estimates. Industry-year observations are weighted according to the inverse standard deviation of the industry average estimates. 1997–2006 data were converted from PDFs to Excel files using the Adobe Online converter. 2008–2011 data are available directly on the QPC website while 2007 is imputed from the average of 2006 and 2008. The regression includes year fixed effects and standard errors are clustered at the industry level. While there is a short-run increase in utilization by treated industries through 2003, the long-difference estimate shows a statistically insignficant 3.9pp decrease in capacity utilization in bonus industries.
Source: Authors' calculations based on the Quarterly Survey of Plant Capacity Utilization and Zwick and Mahon (2017) data



Panel A: Log Employment



Panel B: Log Capital

Figure A6: Effects of Bonus Depreciation on Employment and Capital, Controls for Capital Producer Share

Note: Figure A6 displays estimates of the effect of bonus depreciation on the log employment in Panel A and log 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 capital producer controls specification includes capital producer share interacted with year fixed effects to allow plants who sell more or less of their output as equipment capital goods to have flexible time trends. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on ASM, CM, BEA, and Zwick and Mahon (2017) data.

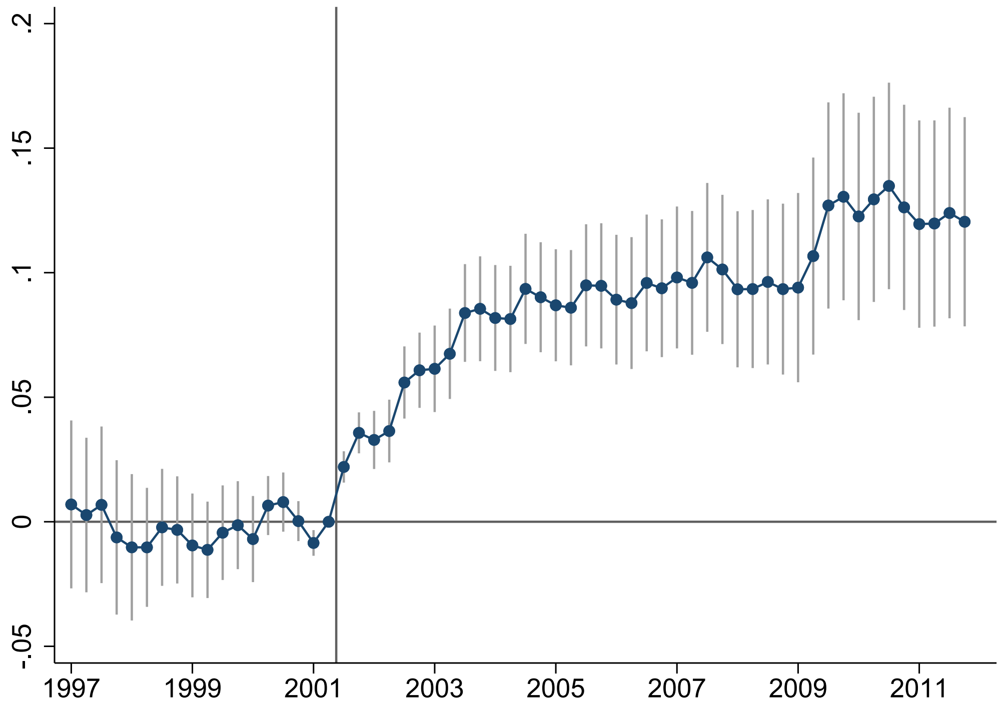
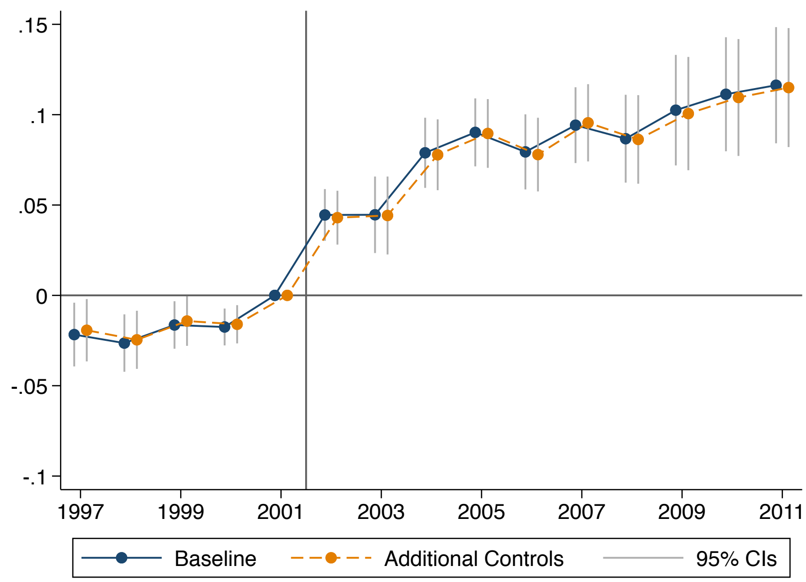


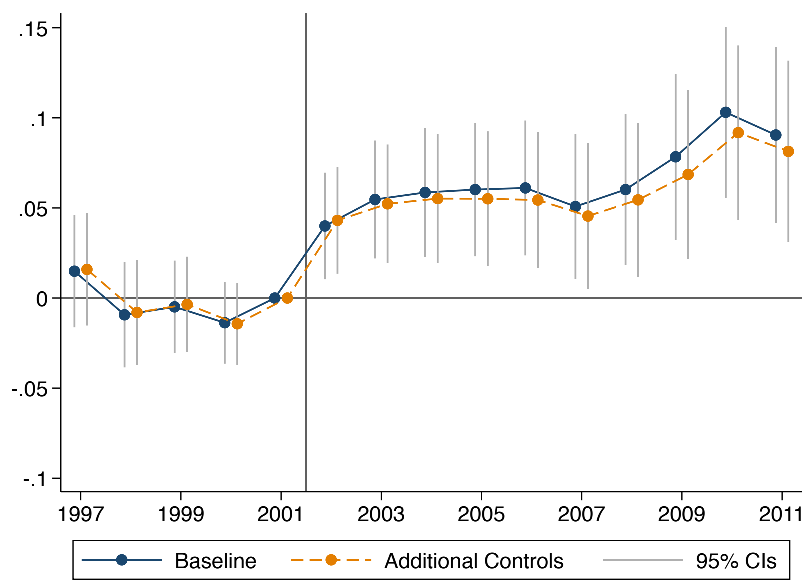
Figure A7: Effects of Bonus Depreciation on Log Employment; QWI Data

Note: Figure A7 displays estimates of 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. 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 A7. 95% confidence intervals are included for each quarterly point estimate with standard errors clustered at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data.



Panel A: Log Production Employment

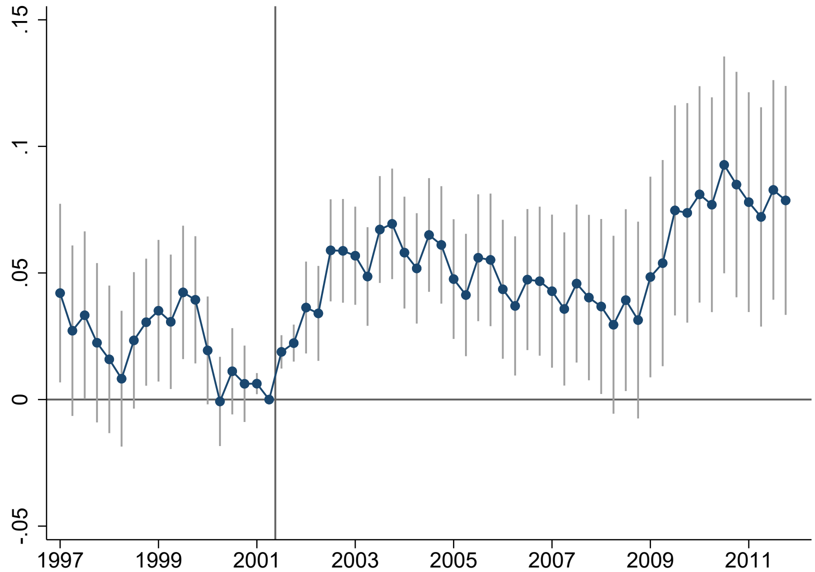


Panel B: Log Non-Production Employment

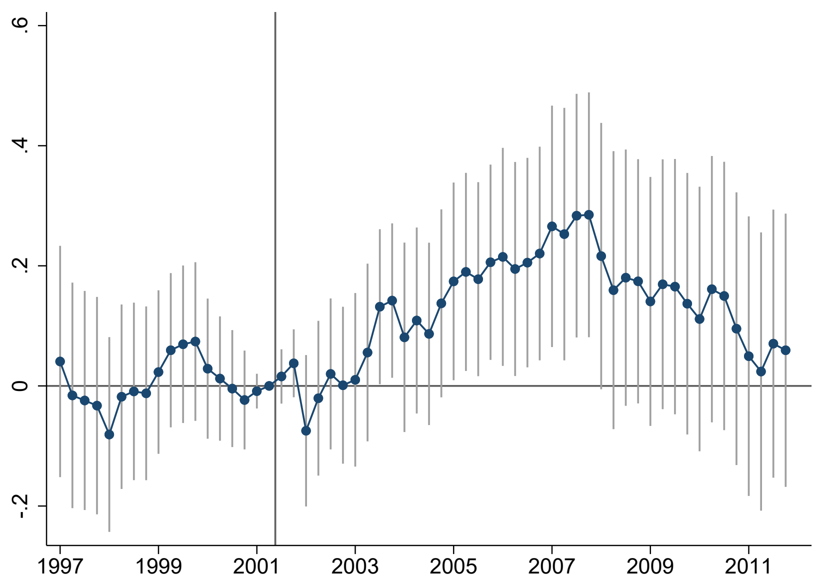
Figure A8: Effects of Bonus Depreciation on Production and Non-Production Employment

Note: Figure A8 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 Panels B and C, columns (6) and (7) of Table 3. 95% confidence intervals are included for each annual point estimate with standard errors clustered at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.



Panel A: Firms with 1–50 Employees

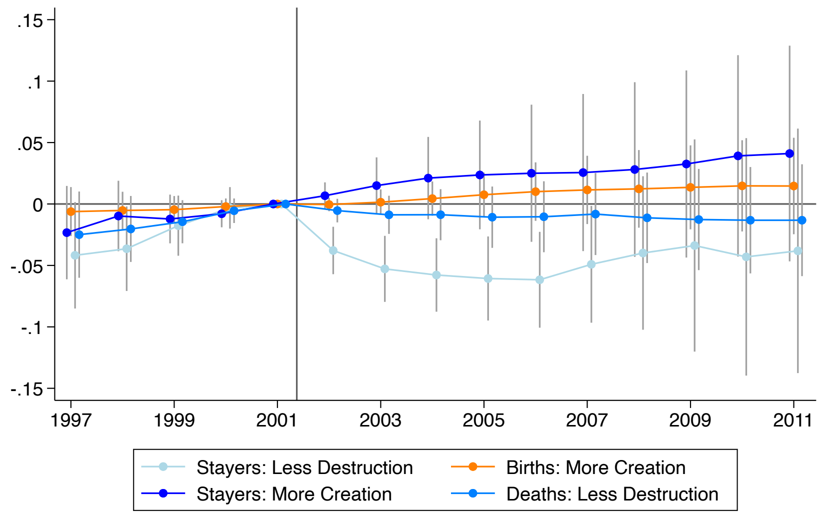


Panel B: Firms 0–5 Years Old

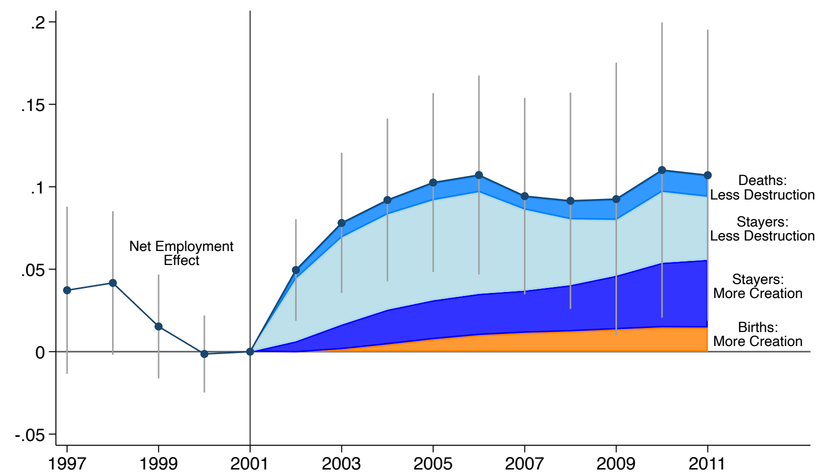
Figure A9: Effects of Bonus Depreciation on Smaller and Younger Firm Employment; QWI

Note: Figure A9 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 at the 4-digit NAICS-by-state level.

Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data.



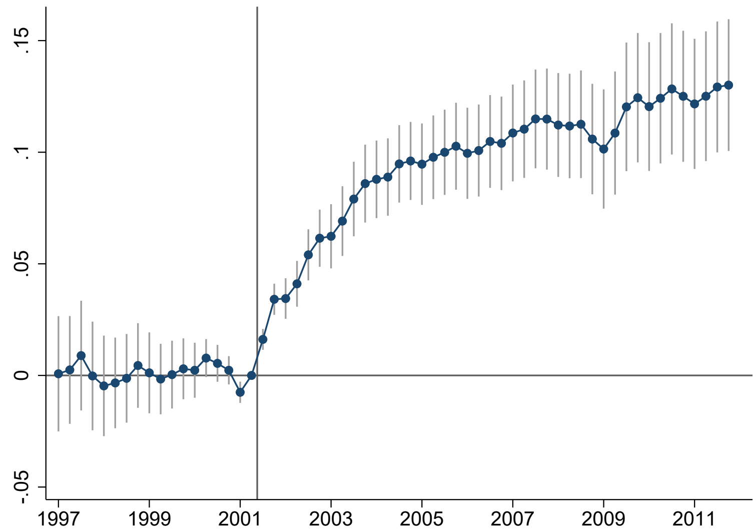
Panel A: Cumulative Employment Flows



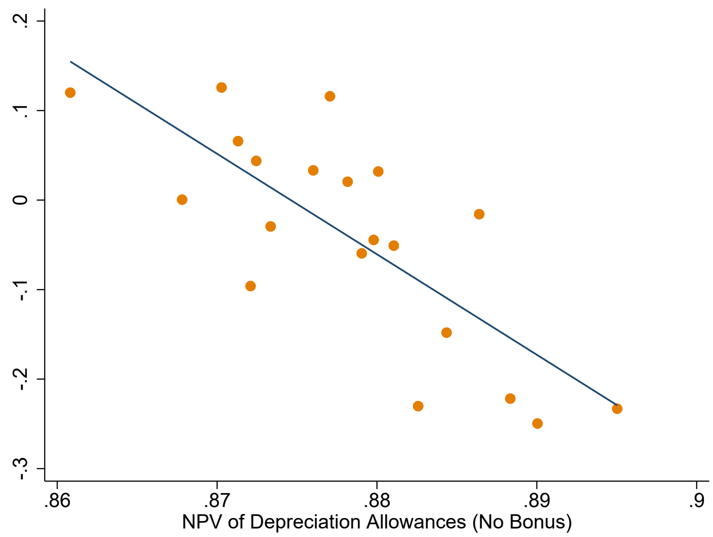
Panel B: Net Employment Effect Decomposition

Figure A10: Effects of Bonus Depreciation Job Creation and Destruction; BDS

Note: Figure A10 describes the effect of bonus depreciation on job creation and destruction using Business Dynamic Statistics data from the US Census. Panel A shows the effect of bonus depreciation on four types of cumulative flows: job destruction from plants that do not exit (stayers), job destruction due to plant deaths, job creation from new plants (births), and job creation from stayers. To calculate cumulative flow in a given year, t, we sum flows between 2001 and t then scale them by 2001 total employment. Panel B presents event study estimates and standard errors of the effect of bonus depreciation on net employment flows. The shaded regions illustrate the respective contributions of the employment flow components in Panel A, which by definition aggregate to the net effect. We define the net employment change as jobs created minus jobs destroyed. Regressions include 4-digit NAICS and year fixed effects. 95% confidence intervals are based on standard errors clustered at the 4-digit NAICS level.
Source: Authors' calculations based on BDS and Zwick and Mahon (2017) data.



Panel A: Effect of Bonus Depreciation on QWI Log Employment, Continuous Treatment

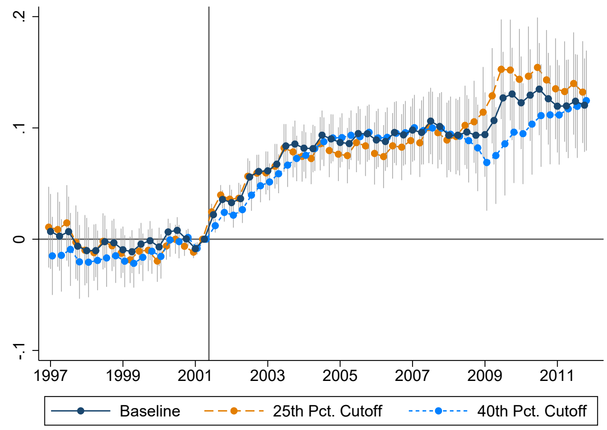


Panel B: Binscatter; Industry-Level Changes in Employment vs. z_0

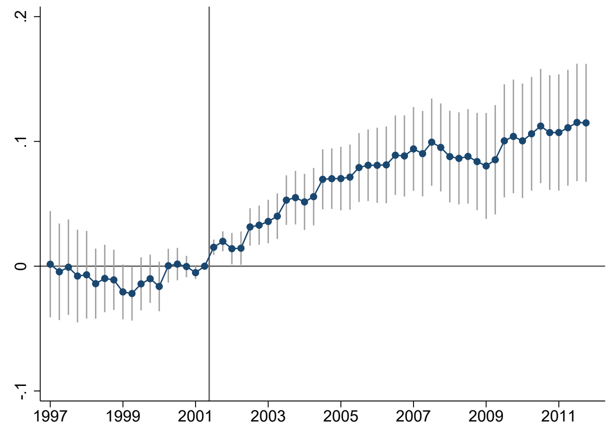
Figure A11: Effects of Bonus Depreciation on Employees, Continuous Treatment

Note: Panel A of Figure A11 displays estimates describing the effect of bonus depreciation on log employment using state-by-industry QWI data as in Figure A7, but using the continuous measure (1-z_0)τ*0.0375 in place of the treatment indicator. Panel B plots industry-level changes in QWI log employment between the pre- and post-periods against z_0 using a binned scatterplot. Each industry-level change is derived from a regression in the form of Equation 2 with treatment dummies for each industry.

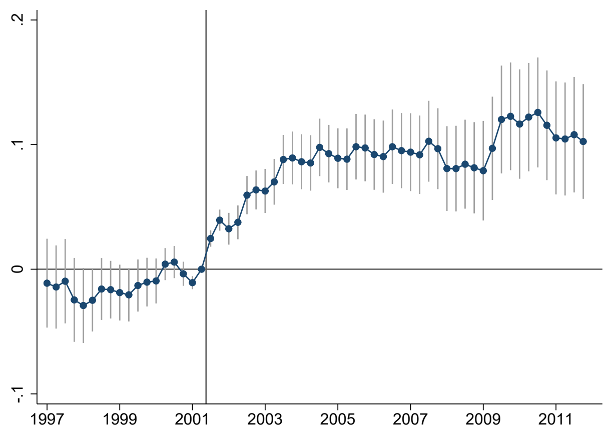
Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data.



Panel A: Different Treatment Cutoffs



Panel B: Capital Producer Controls

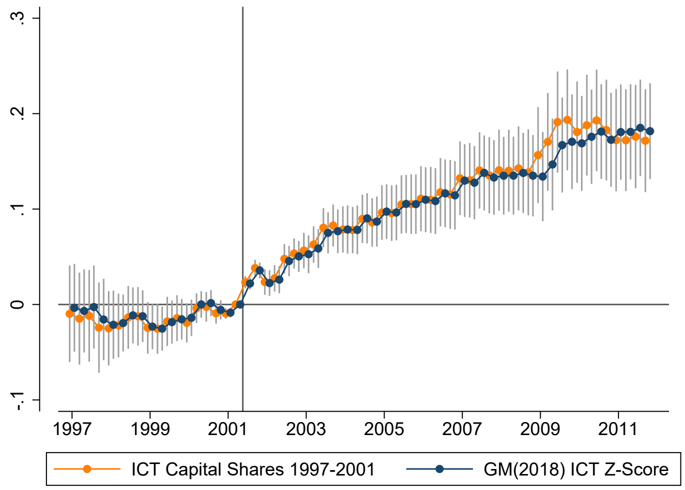


Panel C: Cost of Capital Controls

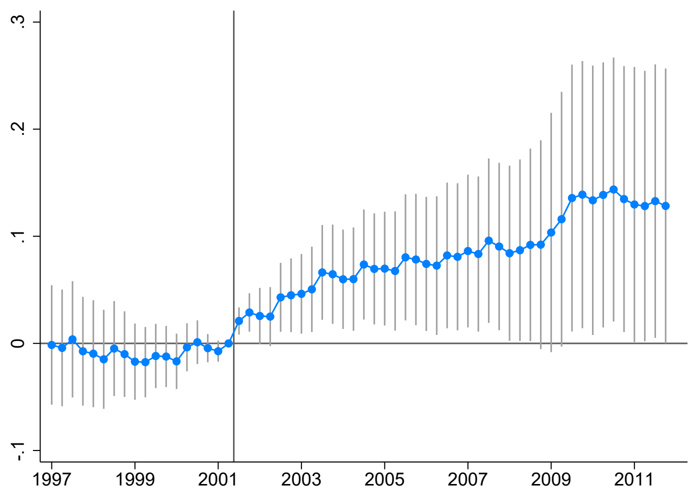
Figure A12: Effects of Bonus Depreciation, QWI Employment Robustness Checks

Note: Figure A12 presents additional estimates of the effect of bonus depreciation on log employment using state-by-industry QWI data as in Figure A7. 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.



Panel A: ICT Controls



Panel B: Dropping Tech Industries

Figure A13: Effects of Bonus Depreciation, Controlling for ICT Growth

Note: Figure A13 presents additional estimates of the effect of bonus depreciation on log employment in the state-by-industry QWI data. Panel A includes tercile indicators for two measures of the use of information and communications technology (ICT) interacted with year fixed effects. The first uses BEA Detailed Data for Fixed Assets and Consumer Durable Goods to measure ICT capital intensity as the share of capital stock in ICT 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 from 2002–2016. Panel B presents estimates that exclude tech industries. Excluded industries represent 16.6% of 2001 manufacturing employment and 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: Authors' calculations based on QWI, BEA, Gallipoli and Makridis (2018), and Zwick and Mahon (2017) data.

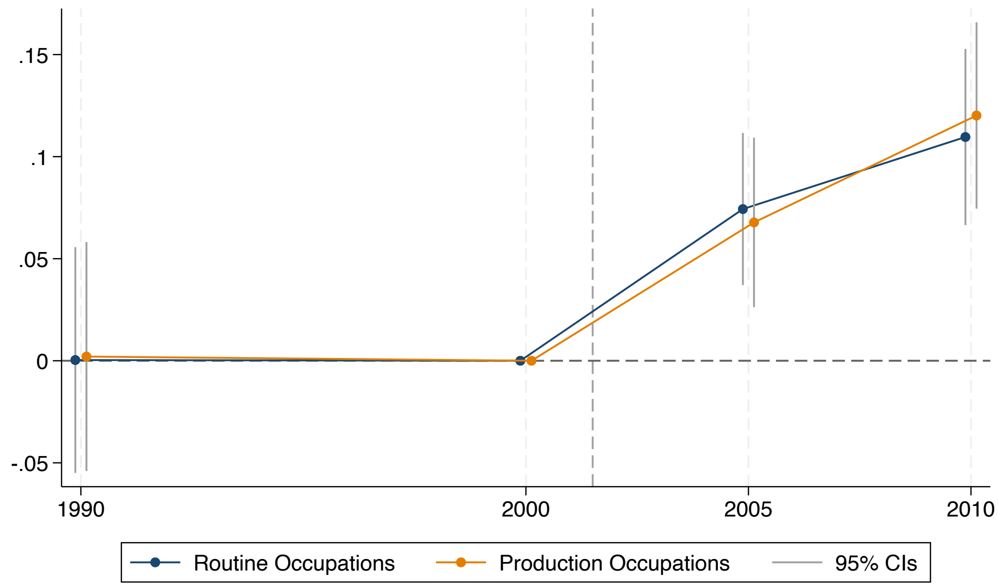
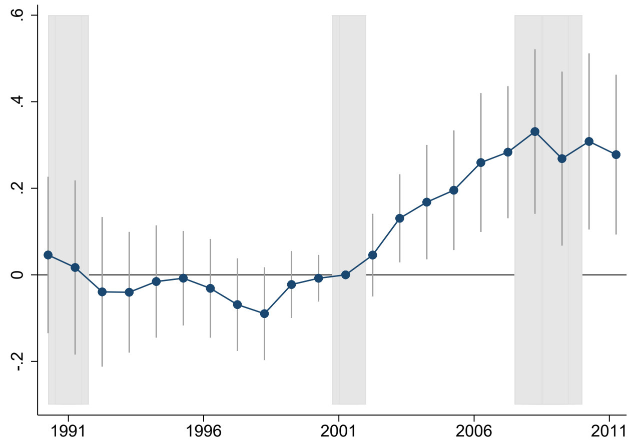


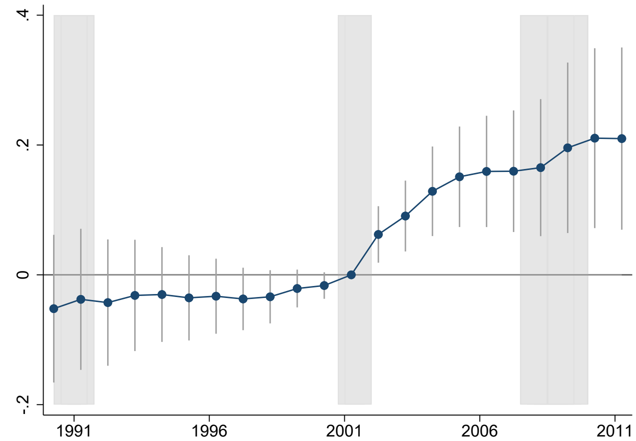
Figure A14: Effect of Bonus Depreciation on Employment by Task Content

Note: Figure A14 displays estimates of the effect of bonus depreciation on employment in routine occupations and production occupation. 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.

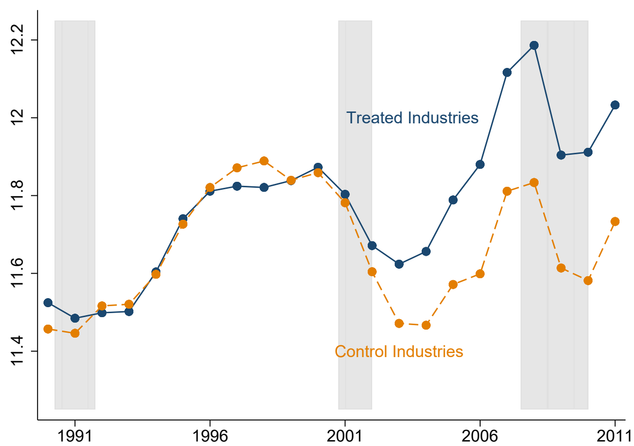
Source: Authors' calculations based on Census, ACS, Zwick and Mahon (2017), and Acemoglu and Autor (2011) data.



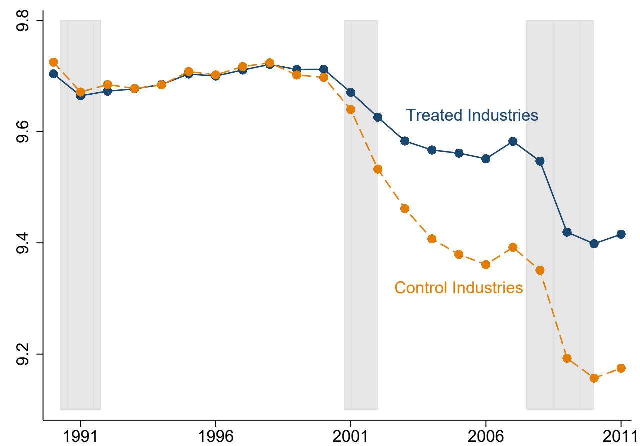
Panel A: Log Investment



Panel B: Log Employment



Panel C: Log Investment Plus Trends



Panel D: Log Employment Plus Trends

Figure A15: US Manufacturing Over the Business Cycle

Note: Panels A and B of Figure A15 present event study regression coefficients representing the effect of bonus depreciation on log investment and log employment in 6-digit NAICS industries over the 1990 to 2011 period. Coefficients are obtained from industry-year-level regressions akin to Equation 1 with observations weighted by 2001 industry employment levels. These regressions include industry and year fixed effects. Standard errors are clustered at the 4-digit NAICS level. Shaded regions correspond to business cycle contractions by the National Bureau of Economic Research. In Panels C and D, the event study estimates are added or subtracted from the aggregate trends in each outcome based on NBER-CES data following the same procedure as in Figure 6.
Source: Authors' calculations based on NBER-CES Manufacturing Industry Database, NBER Business Cycle Expansions and Contractions, and Zwick and Mahon (2017) data.

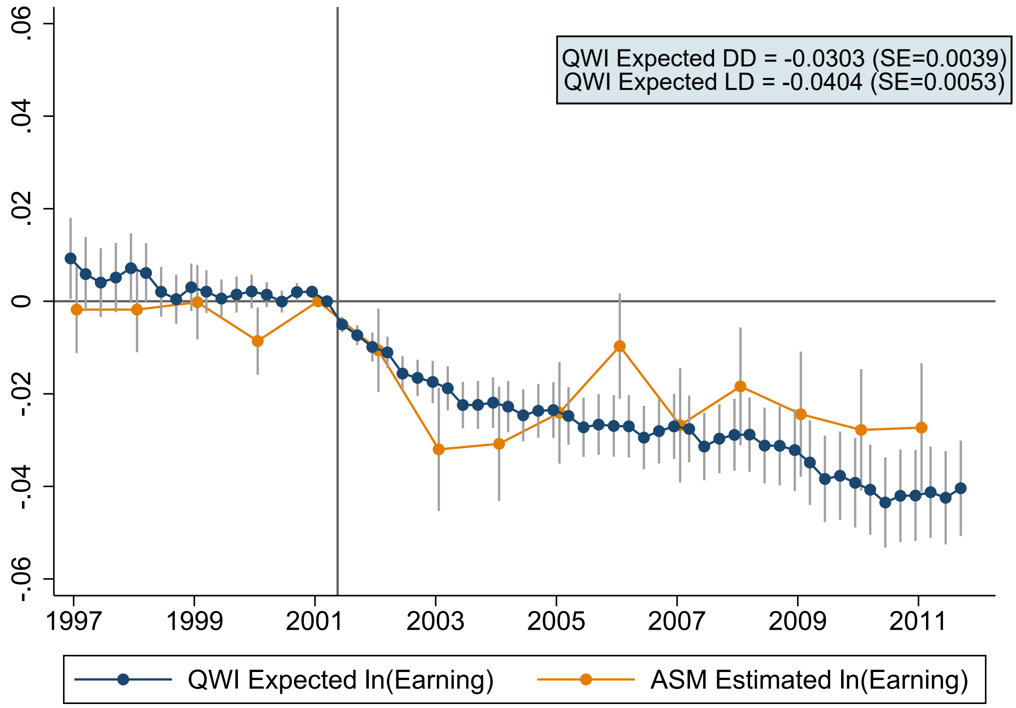


Figure A16: Comparing Counterfactual and Observed Earnings Changes

Note: Figure A16 presents two event studies. The first event study, in orange, depicts the effect of bonus depreciation on log mean earnings per worker (as in Panel B of Figure 3). The second plot, in blue, displays the effect of bonus depreciation on the average earnings predicted by worker demographic industry-state shares in the pre-period. These counterfactual earnings were estimated using a regression that included industry-by-state and state-by-year fixed effects. Standard errors are clustered at the state-industry level.

Source: Authors' calculations based on ASM, CM, QWI, and Zwick and Mahon (2017) data.

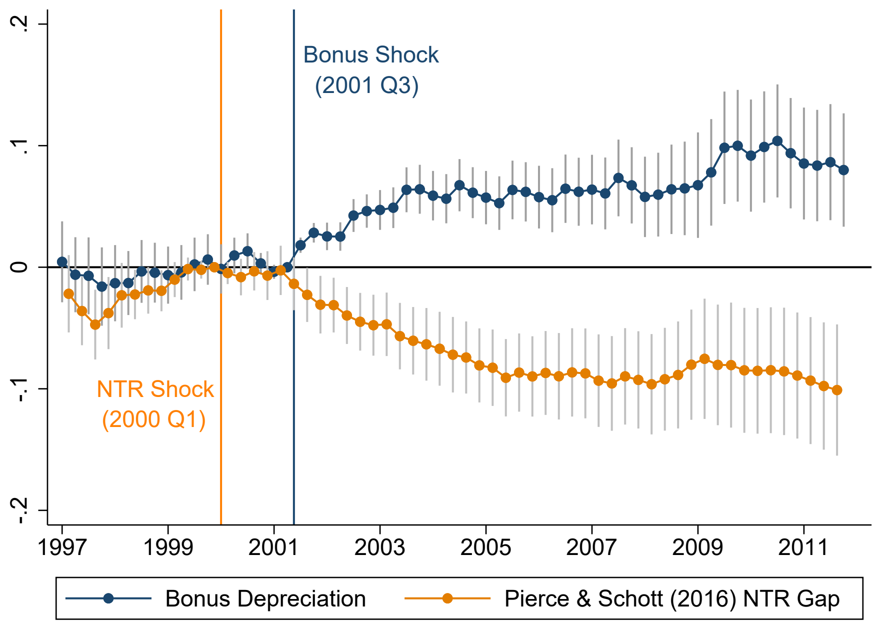
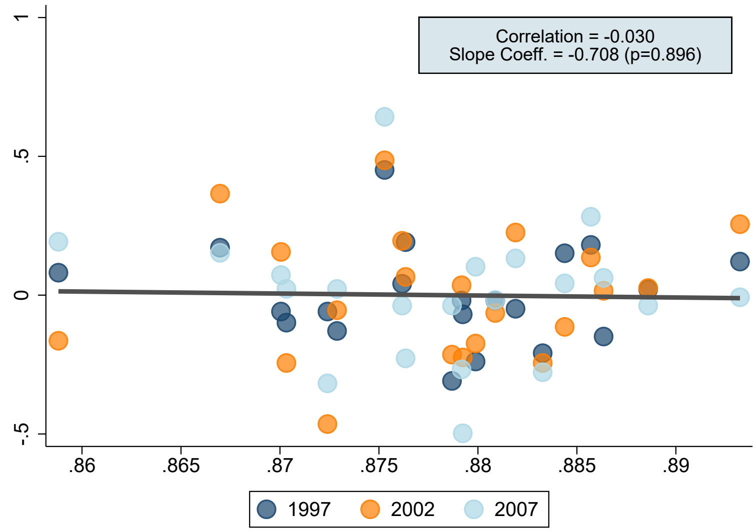
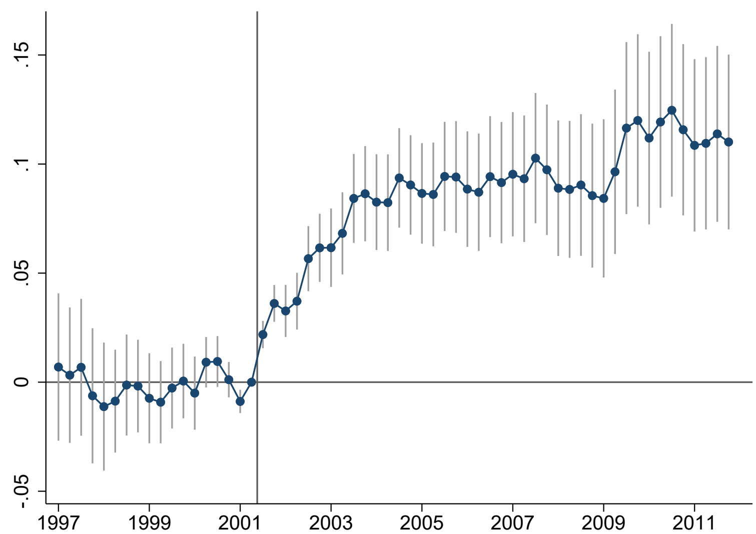


Figure A17: Joint Effects of Bonus Depreciation and NTR Gap on Log Employment; QWI Data

Note: Figure A17 depicts the concurrent effects of bonus depreciation and the normal trade relations gap of Pierce and Schott (2016) on log employment using state-by-industry QWI data. The regression estimates displayed in this figure correspond to quarterly analogs of β_y from Equation 1. The "Bonus Shock" estimates describe the change in log employment relative to 2001q2 in industries affected most by bonus relative to industries that are less affected by bonus. The "NTR Shock" estimates describe the change in log employment relative to 2000q1 in industries with above median NTR Gap exposure compared to those with below median NTR Gap exposure. 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 at the 4-digit NAICS-by-state level.
Source: Authors' calculations based on QWI, Pierce and Schott (2016) and Zwick and Mahon (2017) data.



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

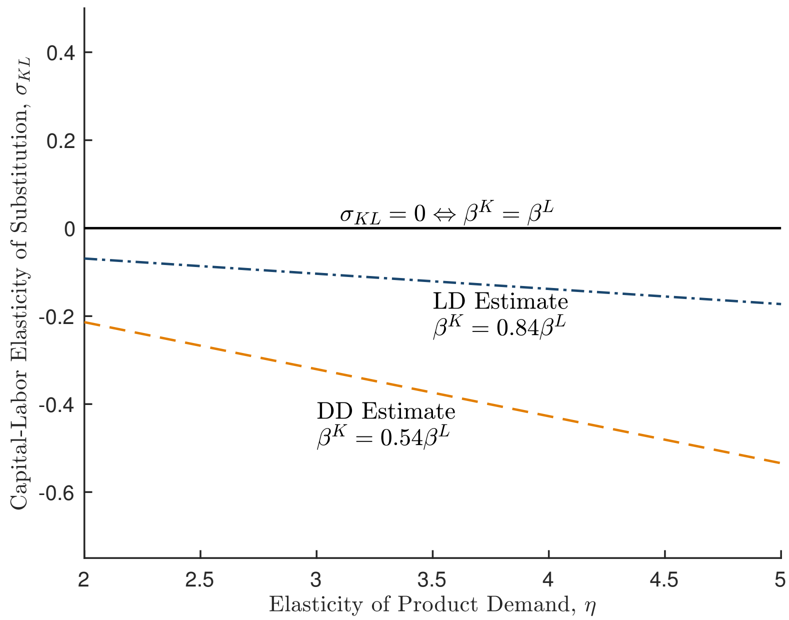


Panel B: Effect of Bonus Depreciation Employment Controlling for σ_{KL}

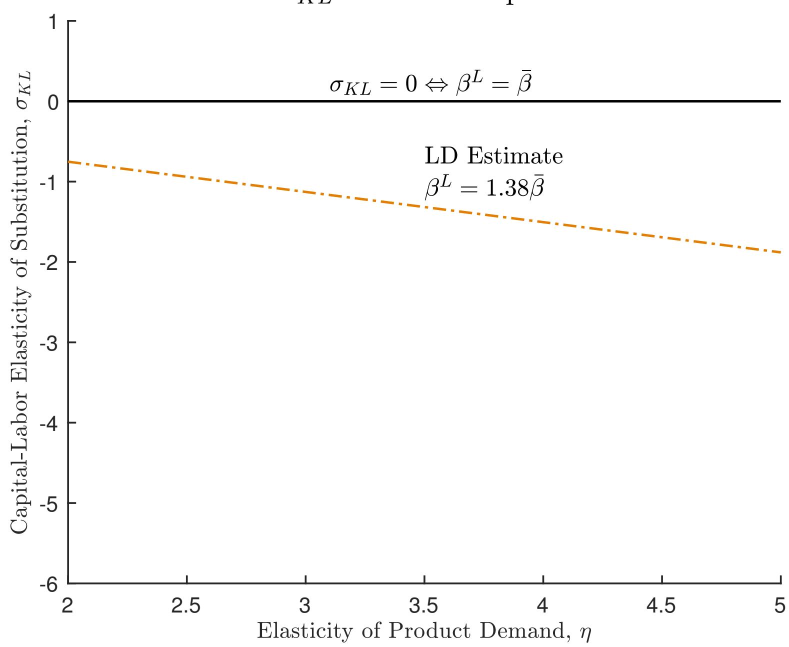
Figure A18: Bonus Depreciation Treatment and Differences in σ_{KL}

Note: Panel A of Figure A18 shows the relationship between de-meaned 1997, 2002, and 2007 estimates of σ_{KL} from Raval (2019) and the 3-digit NAICS level average of z_0. The fitted linear relationship is based on 2002 data. Panel B shows the effect of bonus depreciation on log employment using state-by-industry QWI data, 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).



Panel A: σ_{KL} in a Two-Input Model

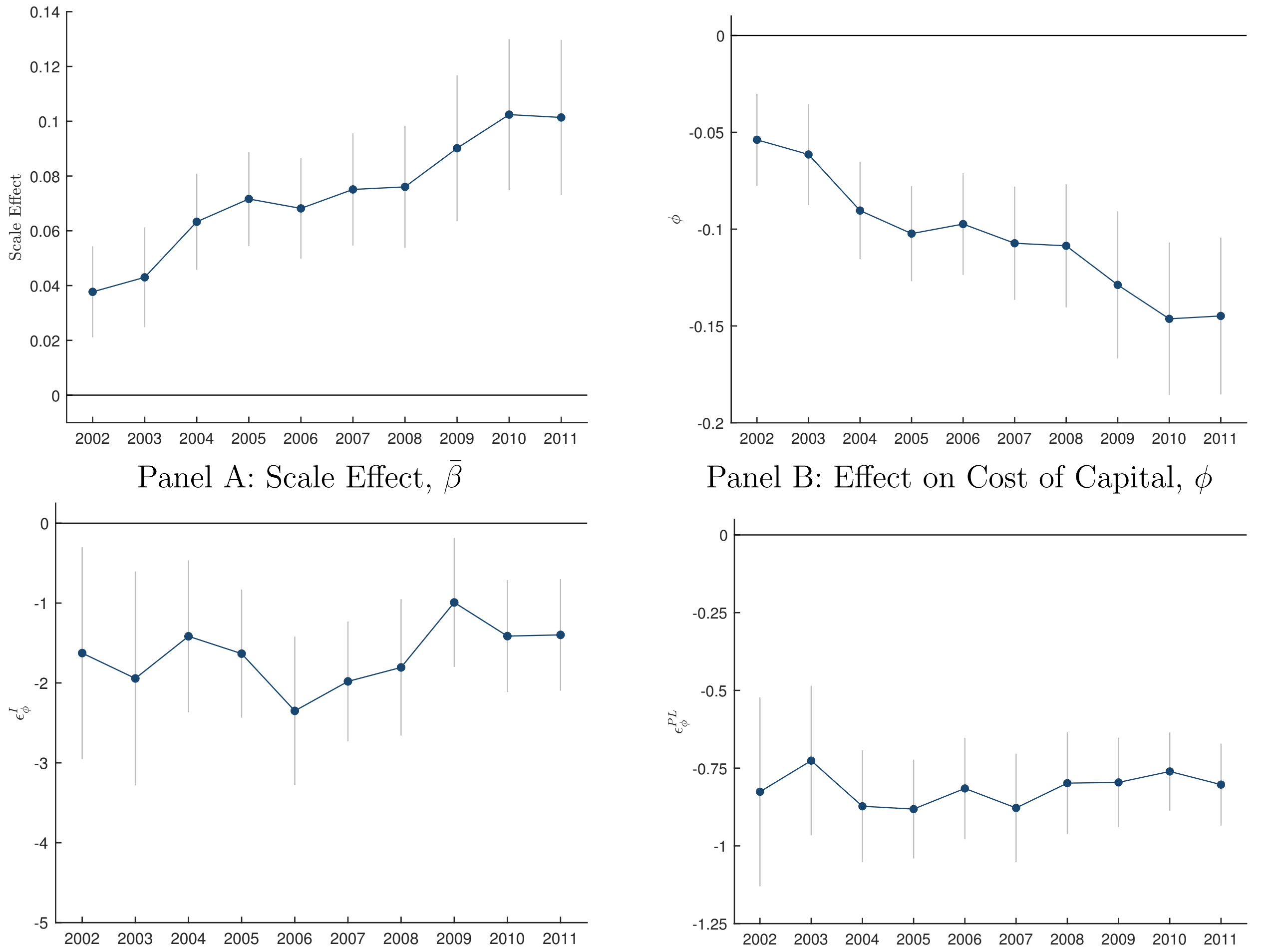


Panel B: σ_{KL} in a Five-Input Model

Figure A19: Additional Estimates of Capital-Labor Substitution

Note: Figure A19 implements versions of Equation P.12 for two- and five-input models and for a range of values of η. Panel A shows that neither our long-difference nor our difference-in-differences reduced-form estimates are 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 because profit maximization requires a non-negative value of σ_{KL}. Panel B implements a five-input analogue of Equation P.12 where the inputs 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.



Panel A: Scale Effect, $\bar{\beta}$

Panel B: Effect on Cost of Capital, ϕ

Panel C: Investment Elasticity, ε^I_ϕ

Panel D: Production Employment Elasticity, ε^{PL}_ϕ

Figure A20: Scale, Cost of Capital, and Elasticity Estimates over Time

Note: Figure A20 displays select model estimates over the 2002–2011 period using event study regression estimates from Equation 1. Panel A presents the scale effects implied by our reduced-form estimates over the 2002–2011 period. Scale effects for year t are defined using Equation 7 as $\bar{\beta}_t = s_J\beta^J_t + s_K\beta^K_t + s_L\beta^L_t$. Panel B displays estimates of the effect on the cost of capital. Effects for year t are defined using Equation 7 as $\phi = -\hat{\beta}_t/(s_K\eta)$. Panels C and D present estimates of the elasticity of investment and production labor, respectively, with respect to changes in the cost of capital over time. Elasticities are calculated as $\varepsilon^I_\phi = \beta^I/\phi$ and $\varepsilon^L_\phi = \beta^L/\phi$, respectively.

Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

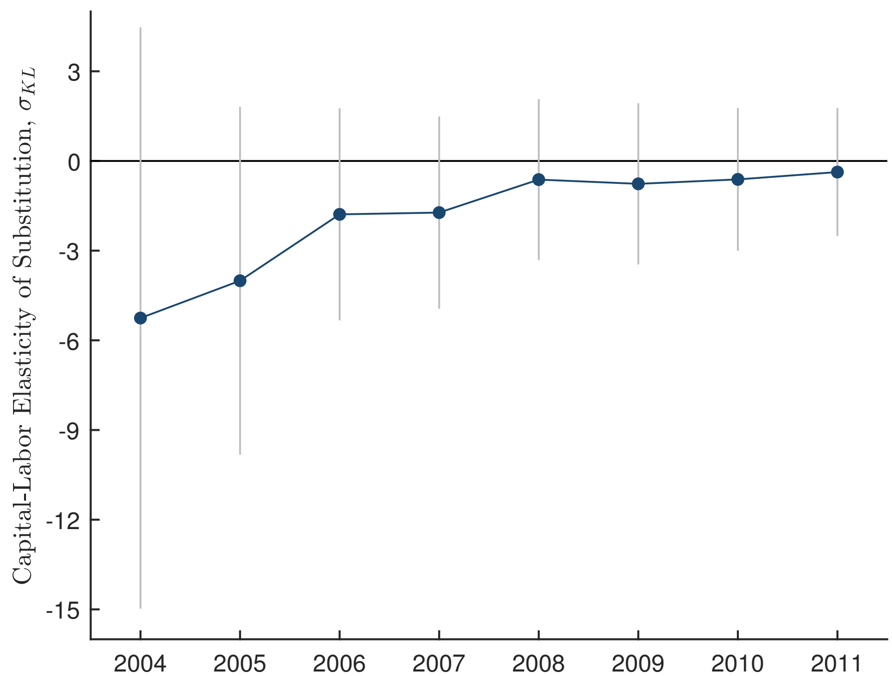


Figure A21: Capital-Production Labor Substitution over Time

Note: Figure A21 estimates σ_{KL} over the 2004–2011 period. For each year t, σ_{KL} estimates are obtained using the estimated event study coefficients from Equation 1, an annualized long-difference 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.

Table A1: Data from Zwick and Mahon (2017) Figure 1

	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

Note: Table A1 uses data from Figure 1 of Zwick and Mahon (2017) as a way to benchmark our investment results. We construct these data using WebPlotDigitizer (see `https://apps.automeris.io/wpd/`). 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 data from Figure 1 of Zwick and Mahon (2017).

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
	Panel A: 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]
	Panel B: 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	✓	✓	✓	✓	✓	✓

Note: Table A2 displays estimates of the effect of bonus depreciation on various outcomes. Standard errors are clustered at the 4-digit NAICS level. Panel A shows the Bonus×Post coefficient estimates from specifications in the form of Equation 2 while Panel B shows Bonus×$[t = 2011]$ coefficient estimates from specifications in the form of Equation 1. Outcome variables in columns (1)–(6) are the log of investment, total employment, mean earnings, total capital, 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.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A3: Effects of Bonus Depreciation on Capital Investment

	Panel A: IHS Investment				
	(1)	(2)	(3)	(4)	(5)
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 B: 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					✓

Note: Table A3 displays difference-in-differences estimates of Equation 2 of the effects of bonus depreciation on the inverse hyperbolic sine of investment (Panel A) and investment over pre-period capital (Panel B). Column (1) estimates include year and plant fixed effects. Column (2) estimates include state-by-year fixed effects and plant fixed effects. Columns (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.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A4: Effects of Bonus on Hours Worked and Materials

	(1) Log Prod. Hours	(2) Log Non-prod. Hours	(3) Log Materials
Bonus	0.0863	0.0582	0.0832
	(0.0181)	(0.0310)	(0.0344)
	[0.000]	[0.061]	[0.016]
Plant FE	✓	✓	✓
State×Year FE	✓	✓	✓

Note: Table A4 displays long-difference 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.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A5: Effects of Bonus with Capital Producer Controls

	(1)	(2)	(3)	(4)
	Log Capital		Log Employment	
1997	0.0327	0.0312	-0.0055	-0.0035
	(0.0182)	(0.0191)	(0.0079)	(0.0088)
1998	0.0122	0.0146	-0.0147	-0.0063
	(0.0109)	(0.0118)	(0.0068)	(0.0075)
1999	0.0095	0.0109	-0.0104	-0.0041
	(0.0072)	(0.008)	(0.0053)	(0.0059)
2000	0.0036	0.0045	-0.0077	-0.0021
	(0.0043)	(0.0047)	(0.0040)	(0.0044)
2002	0.0173	-0.0078	0.0360	0.0208
	(0.0236)	(0.0251)	(0.0057)	(0.0059)
2003	0.0215	0.0093	0.0544	0.0381
	(0.0175)	(0.0188)	(0.0070)	(0.0075)
2004	0.0313	0.0201	0.0700	0.0584
	(0.0149)	(0.0165)	(0.0078)	(0.0084)
2005	0.0423	0.0326	0.0775	0.0752
	(0.0130)	(0.015)	(0.0086)	(0.0094)
2006	0.0507	0.0426	0.0722	0.081
	(0.0141)	(0.0161)	(0.0092)	(0.0102)
2007	0.0638	0.0534	0.0772	0.0888
	(0.0188)	(0.0205)	(0.0100)	(0.011)
2008	0.0731	0.0666	0.0705	0.0813
	(0.0180)	(0.0198)	(0.0114)	(0.012)
2009	0.0769	0.0703	0.0854	0.0857
	(0.0181)	(0.0199)	(0.0138)	(0.0141)
2010	0.0792	0.074	0.0963	0.0929
	(0.0182)	(0.02)	(0.0149)	(0.0153)
2011	0.0804	0.0774	0.0965	0.1015
	(0.0183)	(0.02)	(0.0152)	(0.0155)
Plant FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Capital Producer Controls		✓		✓

Note: Table A5 shows dynamic difference-in-differences estimates of the effect of bonus with and without capital producer share controls. The outcome in columns (1) and (2) is log capital while the outcome in columns (3) and (4) is log employment. Columns (1) and (3) replicate the baseline results with plant and state-by-year fixed effects, while columns (2) and (4) add the capital producer share interacted with year fixed effects. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. These coefficients are graphed in Figure A6.
Source: Authors' calculations based on ASM, CM, BEA, and Zwick and Mahon (2017) data.

Table A6: Effects of Bonus with Capital Producer Share Interactions

	(1) Log Investment	(2) Log Employment	(3) Log Total Value of Shipments
Bonus	0.1316	0.0737	0.0393
	(0.0305)	(0.0107)	(0.0149)
	[0.000]	[0.000]	[0.008]
Bonus × CapProd_{2001}	0.0134	0.0151	-0.0041
	(0.0461)	(0.0115)	(0.0204)
	[0.771]	[0.189]	[0.841]
Plant FE	✓	✓	✓
State × Year FE	✓	✓	✓

Note: Table A6 shows difference-in-differences estimates of the effect of bonus and bonus interacted with the share of equipment capital in 2001 industry-level output on key outcomes. Capital production is standardized to the 75th percentile but not demeaned. As such, the bonus coefficient with the interaction term represents the impact of moving from zero to the 75th percentile of capital production relative to an industry with zero capital production. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, BEA and Zwick and Mahon (2017) data.

Table A7: Effects of Bonus Depreciation, QWI Sample

	(1) Log(Emp)	(2) Log(Earn)	(3) % $\leq$ HS	(4) % $<$ 35 years	(5) % Female	(6) % Black	(7) % Hispanic
	Panel A: Difference-in-Differences						
Bonus	0.09409	-0.02966	0.00395	0.01289	0.01219	0.00104	0.01764
	(0.01550)	(0.00542)	(0.00119)	(0.00203)	(0.00229)	(0.00127)	(0.00256)
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.413]	[0.000]
	Panel B: Long Differences						
Bonus	0.12045	-0.04722	0.00837	0.01480	0.01241	0.00599	0.01176
	(0.02143)	(0.00832)	(0.00153)	(0.00257)	(0.00301)	(0.00250)	(0.00354)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.017]	[0.001]
Share2001			0.46	0.30	0.32	0.09	0.11
State×NAICS FE	✓	✓	✓	✓	✓	✓	✓
State×Quarter FE	✓	✓	✓	✓	✓	✓	✓
Pre-Period Growth FE					✓	✓	✓

Note: Table A7 shows the effect of bonus depreciation on outcomes using state-industry data from QWI. Panel A shows the Bonus×Post coefficient estimates from specifications in the form of Equation 2 while Panel B shows Bonus×[t = 2011q3] coefficient estimates from specifications in the form of Equation 1. The outcomes across columns (1)–(4) are the log total employment, log mean earnings, the fraction of employees with a high school degree or less, and the fraction of employees who are 34 years or younger. The outcomes across columns (5)–(7) 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 bins of pre-period growth rate 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.

Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data

Table A8: Effects of Bonus Depreciation on Employment by Task-Content and Demographics: 2000–2010 Changes

	(1) All Occupations	(2) Routine	(3) Non-routine	(4) Professional Cognitive Non-routine	(5) Administrative Cognitive Routine	(6) Production Manual Routine	(7) Services Manual Non-routine
All Workers	0.06841	0.10961	0.01609	0.02109	0.06341	0.12016	0.04300
	(0.02087)	(0.02202)	(0.02226)	(0.02322)	(0.02425)	(0.02329)	(0.04798)
				Demographic Subgroups			
< HS Education	0.13670	0.14488	0.07999	0.07701	0.11056	0.14531	0.05619
	(0.02226)	(0.02283)	(0.02850)	(0.03469)	(0.02822)	(0.02374)	(0.05636)
Ages 18-35	0.11809	0.16721	0.01423	0.00880	0.08461	0.18112	0.05308
	(0.02815)	(0.02990)	(0.03578)	(0.03960)	(0.04093)	(0.03210)	(0.09690)
Female	0.10721	0.14811	0.00816	0.04222	0.09945	0.12403	-0.00547
	(0.02434)	(0.02602)	(0.03005)	(0.03180)	(0.02796)	(0.03262)	(0.08900)
Hispanic	0.13578	0.19649	-0.05102	0.01179	0.16127	0.20388	-0.03174
	(0.04018)	(0.04393)	(0.08337)	(0.09582)	(0.10626)	(0.04682)	(0.11456)
Black	0.08321	0.13784	-0.11438	0.07373	-0.03588	0.14141	-0.00500
	(0.04359)	(0.04621)	(0.09699)	(0.10341)	(0.09763)	(0.05146)	(0.14799)
Industry FE	✓	✓	✓	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓	✓	✓	✓

Note: Table A8 displays long-difference 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 A9: Effects of Bonus Depreciation on Employment, Capital Producer Share Robustness

	(1)	(2)	(3)	(4)
	Panel A: Difference-in-Differences			
Bonus	0.0941	0.0831	0.0960	0.0780
	(0.0155)	(0.0187)	(0.0163)	(0.0211)
	[0.000]	[0.000]	[0.000]	[0.000]
	Panel B: Long Differences			
Bonus	0.1205	0.1149	0.1394	0.1022
	(0.0214)	(0.0241)	(0.0222)	(0.0259)
	[0.000]	[0.000]	[0.000]	[0.000]
State × NAICS FE	✓	✓	✓	✓
State × Quarter FE	✓	✓	✓	✓
Capital Producer Control × Quarter FE		✓		
Below 90th Percentile			✓	
Below 70th Percentile				✓

Note: Table A9 displays QWI difference-in-differences (Panel A) and long-difference (Panel B) estimates of employment. The first column is the baseline specification matching Figure A7. Column (2) includes a control for producer share interacted with year fixed effects, mirroring Panel B of Figure A12. Column (3) drops industries in the top 10% of the capital producer share variable. Column (4) drops industries in the top 30% of the capital producer share variable, which focuses on variation in industries whose output is less than 10% equipment capital usable in another business. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on QWI, BEA, and Zwick and Mahon (2017) data.

Table A10: Effects of Bonus Depreciation, Interactions with Firm-Level Bonus Exposure

	(1)	(2)	(3)	(4)
	Panel A: Log Investment		Panel B: Log Employment	
Bonus	0.158	0.1578	0.0824	0.08
	(0.0276)	(0.0286)	(0.0095)	(0.0096)
	[0.000]	[0.000]	[0.000]	[0.000]
Bonus × Untreated Share	-0.0197	-0.0234	-0.0136	-0.0122
	(0.0098)	(0.01)	(0.0032)	(0.0033)
	[0.044]	[0.019]	[0.000]	[0.000]
Mean Untreated Share	0.142			
75th Quantile Untreated Share	0.132			
Plant FE	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓
PlantSize_{2001} ×Year FE		✓		✓
TFP_{2001}×Year FE		✓		✓
FirmSize_{2001}×Year FE		✓		✓

Note: Table A10 displays difference-in-differences estimates describing the interaction between difference-in-differences terms and "Untreated Share," the share of firm-level employment located in plants that were not exposed to bonus depreciation in 2001. The Untreated Share interaction variable is standardized such that reported coefficients express the effect of moving from full firm-level exposure to the 25th percentile of firm-level exposure across plants in our treatment sample. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, LBD, and Zwick and Mahon (2017) data.

Table A11: 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		✓		✓		✓

Note: Table A11 displays difference-in-differences estimates describing the heterogeneous effects of bonus depreciation according to 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 of exposure across plants in our 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.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A12: Effect of Bonus on Earnings, Controlling for Endogenous Worker Composition

	(1)	(2)	(3)	(4)	(5)
	Difference-in-Differences				
Bonus	-0.031	-0.026	-0.005	-0.007	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
	[0.000]	[0.000]	[0.298]	[0.182]	[0.802]
Industry × State FE	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓
Age Shares		✓	✓	✓	✓
Education Shares			✓	✓	✓
Race and Ethnicity Shares				✓	✓
Sex Shares					✓

Note: Table A12 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 workers who are younger, have fewer years of education, are non-White, and are female in 2001, interacted with year fixed effects. Column (5) yields a statistically insignificant estimated effect of 0.1%. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented below in brackets.
Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data

Table A13: Effect of Worker Composition on Observed Earnings, Decomposition Regressions

	(1) Treat Pre	(2) Treat Post	(3) Control Pre	(4) Control Post
Share Young	-0.773	-0.020	-0.678	-0.246
	(0.130)	(0.110)	(0.103)	(0.072)
	[0.000]	[0.855]	[0.000]	[0.001]
Share High School or Less	-1.592	-1.711	-2.288	-1.980
	(0.182)	(0.166)	(0.265)	(0.125)
	[0.000]	[0.000]	[0.000]	[0.000]
Share Non-White	0.084	-0.079	0.429	0.195
	(0.094)	(0.086)	(0.144)	(0.066)
	[0.369]	[0.354]	[0.003]	[0.003]
Share Female	-0.571	-0.634	-0.914	-0.410
	(0.144)	(0.111)	(0.165)	(0.070)
	[0.000]	[0.000]	[0.000]	[0.000]
Industry × State FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Mean Share Young	0.320	0.263	0.311	0.240
Mean Share High School or Less	0.495	0.491	0.428	0.423
Mean Share Non-White	0.320	0.332	0.285	0.282
Mean Share Female	0.262	0.261	0.334	0.318

Note: Table A13 presents the regression estimates and independent variable means needed to to perform the Kitagawa-Oaxaca-Blinder decomposition in Appendix K. Each column reports estimates from 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.
Source: Authors' calculations based on QWI and Zwick and Mahon (2017) data.

Table A14: Heterogeneity in Effects of Bonus Depreciation by Local Labor Market Tightness

	(1) Log Investment	(2) Log Employment	(3) Log Mean Earnings
Bonus	0.1548	0.082	-0.0202
	(0.0277)	(0.0097)	(0.0043)
	[0.000]	[0.000]	[0.000]
Bonus × $LAU_{1997\text{-}2001}$	-0.0216	0.0141	-0.0045
	(0.0245)	(0.0087)	(0.0039)
	[0.378]	[0.105]	[0.249]
Plant FE	✓	✓	✓
State × Year FE	✓	✓	✓

Note: Table A14 displays difference-in-differences estimates of the interaction between the difference-in-differences term and a measure of the average unemployment rate over the 1997–2001 period in the county in which each plant operates. We demean and standardize our unemployment rate measure such that the interaction coefficient corresponds to the interquartile range of our plant-level sample. The outcome variable in column (1) is the log investment. The outcome variable in column (2) is the log total employment. The outcome variable in column (3) is the log mean earnings per worker. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, BLS and Zwick and Mahon (2017) data.

Table A15: Effects of Bonus Depreciation, Industry Wage Markdown Robustness

	(1)	(2)	(3)
	Panel A: Log Production Labor		
Bonus	0.1163	0.0999	0.0858
	(0.0164)	(0.017)	(0.018)
	[0.000]	[0.000]	[0.000]
	Panel B: Log Non-Production Labor		
Bonus	0.0905	0.076	0.0824
	(0.0249)	(0.0254)	(0.0275)
	[0.000]	[0.003]	[0.003]
	Panel C: Log Total Capital		
Bonus	0.0804	0.0744	0.0759
	(0.0183)	(0.0184)	(0.0183)
	[0.000]	[0.000]	[0.000]
Plant FE	✓	✓	✓
State × Year FE	✓	✓	✓
Continuous Markdown × Year FE		✓	
Markdown Quintiles × Year FE			✓

Note: Table A15 displays long-difference estimates of employment and capital outcomes in the presence of controls for industry-level average wage markdowns. Column (1) reproduces the baseline specifications in Tables 2 and 3. Column (2) controls for average industry markdowns by interacting the continuous 2002 industry-level average markdown measure from Yeh et al. (2022) with year fixed effects. Column (3) implements this control by interacting quartile bins of the markdown measure 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.
Source: Authors' calculations based on ASM, CM, Yeh et al. (2022) and Zwick and Mahon (2017) data.

Table A16: Effects of Bonus Depreciation on Labor Productivity and Labor Share

	(1)	(2)	(3)	(4)
	Labor Productivity		Labor Share	
Bonus	0.0073	0.0123	0.0129	0.0068
	(0.018)	(0.0166)	(0.0183)	(0.0176)
	[0.685]	[0.459]	[0.481]	[0.699]
Plant FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
$\text{PlantSize}_{2001} \times$Year FE		✓		✓
$\text{TFP}_{2001} \times$Year FE		✓		✓
$\text{FirmSize}_{2001} \times$Year FE		✓		✓

Note: Table A16 displays long-difference estimates of the effect of bonus depreciation on labor productivity and labor share at the plant level. Labor productivity is defined as total output divided by total hours worked. Labor share is defined as total payroll divided by total value of shipments. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM and Zwick and Mahon (2017) data.

Table A17: 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 Control×Year FE	✓		✓		✓	
Shock×Year FE		✓		✓		✓

Note: Table A17 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, columns (2), (4), and (6) also include binned 6-digit NAICS industry-level controls for drivers of sectoral transformation interacted with year fixed effects. These drivers include increases in skill intensity, capital intensity, Chinese import exposure, and robotization. Standard errors are presented in parentheses and are clustered at the 4-digit NAICS-by-state level. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), Acemoglu et al. (2016), and Acemoglu and Restrepo (2020) data.

Table A18: Difference-in-Differences Estimates of the Effect of Bonus Depreciation on Investment and Employment, with Quartile and Decile Sector Shock Controls

	(1)	(2)	(3)	(4)
	Log Investment		Log Employment	
Bonus	0.1566	0.1634	0.0691	0.0655
	(0.0315)	(0.0333)	(0.0104)	(0.0105)
	[0.000]	[0.000]	[0.000]	[0.000]
Plant FE	✓	✓	✓	✓
State×Year FE	✓	✓	✓	✓
Sector Quartiles ×Year FE	✓		✓	
Sector Deciles ×Year FE		✓		✓

Note: Table A18 compares the difference-in-differences estimates of bonus depreciation on log investment and log employment with full controls for 6-digit NAICS industry-level sectoral shocks binned as quartiles and deciles, respectively, and interacted with year FEs. This table uses the Acemoglu et al. (2016) measure for trade exposure. Standard errors are reported in parentheses. p-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), Acemoglu et al. (2016), and Acemoglu and Restrepo (2020) data.

Table A19: Difference-in-Differences Estimates of the Effect of Bonus Depreciation on Investment and Employment, Different Intensity Control Definitions

	Panel A: Log Total Employment					
	(1)	(2)	(3)	(4)	(5)	(6)
Bonus	0.0864	0.0889	0.0812	0.0751	0.0755	0.0808
	(0.0098)	(0.0099)	(0.0097)	(0.0101)	(0.0098)	(0.0097)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
	Panel B: Log Investment					
Bonus	0.1422	0.2103	0.152	0.1384	0.1342	0.1385
	(0.0285)	(0.0289)	(0.0266)	(0.0291)	(0.0279)	(0.0281)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Capital Intensity$_{01}$	✓					
Δ Capital Intensity$_{97\text{-}01}$		✓				
Δ Capital Intensity$_{97\text{-}11}$			✓			
Skill Intensity$_{01}$				✓		
Δ Skill Intensity$_{97\text{-}01}$					✓	
Δ Skill Intensity$_{97\text{-}11}$						✓

Note: Table A19 shows the difference-in-differences estimates of the effect of bonus on log employment and log investment, controlling for different measures of capital and skill intensity. Intensity is measured in three specifications: as binned intensity in 2001, the change in intensity between 1997 and 2001, and the change in intensity between 1997 and 2001. All three measures of intensity are interacted with year fixed effects. Capital intensity is measured as total capital assets divided by employment at the 6-digit NAICS level in the listed year. Skill intensity is defined as non-production employment divided by total employment at the 6-digit NAICS level in the listed year. Standard errors are reported in parentheses. *p*-values are presented in brackets.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), Acemoglu et al. (2016), and Acemoglu and Restrepo (2020) data.

Table A20: Effects of Bonus Depreciation Interacted with 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	✓	✓

Note: Table A20 displays difference-in-differences estimates and coefficients describing the full set of interactions between DD terms and variables capturing the four manufacturing sector trends described in Charles et al. (2019). The outcome variable in column (1) is the log investment. The outcome variable in column (2) is the log total employment. All specifications include state-by-year and plant fixed effects. To control for trends in the manufacturing sectors, both specifications include 6-digit NAICS industry-level controls for drivers of sectoral transformation: 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.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), Acemoglu et al. (2016), and Acemoglu and Restrepo (2020) data.

Table A21: Additional Classical Minimum Distance Estimates of Production Elasticities

	(1) Baseline	(2) Controls	(3) DD	(4) Hours	(5)	(6)	(7)
	Panel A: Estimated Parameters						
Demand elasticity, η	3.500	3.500	3.500	3.500	3.500	3.500	3.500
Labor-capital, σ_{KL}	-0.440	-0.312	-0.603	-0.332	-0.106	-0.138	-0.474
	(0.346)	(0.378)	(0.305)	(0.498)	(0.144)	(0.142)	(0.952)
Non-production labor-capital, σ_{KJ}	0.733	0.652	1.006	0.786			
	(0.639)	(0.711)	(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	0.107	0.101	0.086	0.097	0.097	0.097
Non-production labor	0.090	0.080	0.068	0.058			
Structures						0.041	
Materials							0.083
Capital	0.080	0.103	0.042	0.080	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	0.107	0.098	0.080	0.094	0.094	0.091
Non-production labor	0.076	0.080	0.060	0.057			
Structures						0.041	
Materials							0.076
Capital	0.096	0.104	0.084	0.080	0.080	0.105	0.080
Cost shares:							
Labor	0.50	0.50	0.50	0.50	0.80	0.80	0.25
Non-production labor	0.30	0.30	0.30	0.30			
Structures						0.09	
Materials							0.65
Capital	0.20	0.20	0.20	0.20	0.20	0.11	0.10
Effect on Cost of Capital, ϕ	-0.14	-0.14	-0.12	-0.10	-0.13	-0.23	-0.23

Note: Table A21 presents classical minimum distance estimates across several alternative models. Column (1) reproduces column (1) of Table 7 for reference. Column (2) estimates our model using long-difference moments in the presence of the 6-digit-NAICS industry-level controls for manufacturing trends discussed in Section 5. Columns (3) and (4) demonstrate that these baseline results are robust to using difference-in-differences estimates and estimates on labor hours, respectively. Column (5) estimates a two-input model of total labor employment and capital. Columns (6) and (7) consider three-input models with either two types of capital or materials, respectively. Depending on the column, labor-capital substitution elasticities correspond either to that of total capital and total labor, capital and production labor, or 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 A22: 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
Non-Production 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

Note: Table A22 presents estimates of translog cost parameters implied by select estimated substitution elasticities from Tables 7 and A21 and tests whether various production functions are consistent with the associated translog parameters. The specified columns correspond to three-input models with production labor, non-production labor, and total capital. 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 7, $\hat{\sigma}_{LJ} = -(s_K/s_J)\hat{\sigma}_{KL}$. 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 A23: 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
Non-Production 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

Note: Table A23 presents estimates of translog cost parameters implied by select estimated substitution elasticities from Tables 7 and A21 and tests whether various production functions are consistent with the associated translog parameters. The specified columns correspond to three-input models with production labor, non-production labor, and total capital. Panel A displays estimated translog cost parameters where σ_{LJ} is assumed to be equal the upper bound implied by our model estimates, $\hat{\sigma}_{LJ} = \hat{\sigma}_{KJ}$. 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 A24: 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)
Non-Production 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
Non-production 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

Note: Panel A of Table A24 presents estimates of Morishima elasticities of substitution. Panel B presents p-values associated with tests of the substitutability and complementarity of the above elasticities. Standard errors are presented in parentheses.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A25: 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				
Non-Production 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				
Non-Production 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
Non-production 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

Note: Panel A of Table A25 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. Standard errors are presented in parentheses.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A26: CES Parameter Estimates with Firm Labor Market Power

	(1) Baseline	(2) $\zeta = 10$	(3) $\zeta = 4.8$	(4) $\zeta = 1.9$	(5) Low s_K	(6) High s_K	(7) Low η	(8) High η
	Panel A: CES Parameter Estimates							
Non-Production Labor, ρ_1	-1.662	-1.517	-1.390	-1.131	-1.072	-1.857	-3.183	-0.673
	(4.158)	(3.762)	(3.433)	(2.804)	(2.429)	(5.254)	(6.008)	(2.403)
Production Labor, ρ_2	5.034	6.480	8.230	14.588	15.472	5.816	11.617	6.875
	(2.300)	(3.046)	(3.949)	(7.238)	(7.779)	(2.673)	(5.859)	(3.185)
	Panel B: Implied CES Substitution Elasticities							
Non-Production Labor, $\frac{1}{1-\rho_1}$	0.376	0.397	0.418	0.469	0.483	0.350	0.239	0.598
	(0.587)	(0.594)	(0.601)	(0.618)	(0.566)	(0.644)	(0.343)	(0.859)
Production Labor, $\frac{1}{1-\rho_2}$	-0.248	-0.182	-0.138	-0.074	-0.069	-0.208	-0.094	-0.170
	(0.141)	(0.101)	(0.076)	(0.039)	(0.037)	(0.115)	(0.052)	(0.092)
	Panel C: p-values for Skill Complementarity Test							
$H_0 : \frac{1}{1-\rho_2} - \frac{1}{1-\rho_1} - 1 > 0$	0.004	0.005	0.005	0.007	0.003	0.008	0.000	0.021
Cost shares:								
Production labor	0.50	0.50	0.50	0.50	0.55	0.45	0.50	0.50
Non-Production labor	0.30	0.30	0.30	0.30	0.35	0.25	0.30	0.30
Capital	0.20	0.20	0.20	0.20	0.10	0.30	0.20	0.20
Labor Supply Elasticity, ζ	∞	10.00	4.80	1.88	4.80	4.80	4.80	4.80
Demand Elasticity, η	3.50	3.50	3.50	3.50	3.50	3.50	2.00	5.00
Effect on Cost of Capital, ϕ	-0.15	-0.19	-0.24	-0.43	-0.50	-0.15	-0.49	-0.18

Note: Table A26 presents estimates of parameters from a constant elasticity of substitution (CES) production function when firms face an upward sloping labor supply elasticity given by ζ when setting wages. Panel A presents estimates of CES substitution parameters. 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. Column (1) assumes perfect competition in labor markets. Column (2) calibrates ζ using the estimates implied by our high HHI earnings effects in Table A33. Columns (3) and (5)–(8) calibrate ζ to the value estimated in Azar et al. (2019). Column (4) calibrates ζ to the value estimated in Yeh et al. (2022). Standard errors are presented in parentheses.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A27: 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)
Non-production 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
Non-production 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
Non-production 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
Non-production 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

Note: Table A27 reproduces Table 7 using an unconstrained classical minimum distance estimation procedure. Estimation is identical to that conducted in Table 7 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 A28: 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
Non-production 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

Note: Table A28 presents estimates of elasticities of substitution between capital and production labor under cash flow constraints as described in Appendix O.4. Standard errors are presented in parentheses.
Source: Authors' calculations based on ASM, CM, and Zwick and Mahon (2017) data.

Table A29: Effects of Bonus Depreciation; NBER-CES Industry-Level Data

	(1) Log Prod. Emp.	(2) Log Non-prod. Emp.	(3) Log Capital
Bonus	0.227	0.170	0.135
	(0.075)	(0.069)	(0.042)
	[0.003]	[0.015]	[0.002]
Year FE	✓	✓	✓
NAICS FE	✓	✓	✓

Note: Table A29 presents estimates the effect of bonus depreciation on manufacturing inputs at the industry level using data from NBER-CES. 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-values are presented in brackets.
Source: Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A30: Model-Based Implications of Industry-Level 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, $\bar{\beta}$	0.191	0.198	0.185	0.191	0.191
	(0.030)	(0.026)	(0.035)	(0.030)	(0.030)
	Panel B: Allen Elasticities of Substitution				
Production labor-capital, σ_{KL}	-0.655	-0.521	-0.798	-0.374	-0.936
	(0.295)	(0.279)	(0.381)	(0.169)	(0.422)
Non-production labor-capital, σ_{KJ}	0.401	0.501	0.294	0.229	0.572
	(0.646)	(0.553)	(0.760)	(0.369)	(0.923)
	Panel C: p-values for Substitutability Tests				
Substitutability of production labor	0.013	0.031	0.018	0.013	0.013
$H_0 : \sigma_{KL} \geq 0$					
Complementarity of non-production labor	0.732	0.817	0.651	0.732	0.732
$H_0 : \sigma_{KJ} \leq 0$					
	Panel D: Cost of Capital Elasticity Estimates				
Effect on cost of capital, ϕ	-0.274	-0.565	-0.176	-0.479	-0.191
	(0.043)	(0.074)	(0.033)	(0.076)	(0.030)
Capital, ε_{ϕ}^{K}	-0.493	-0.238	-0.764	-0.281	-0.704
	(0.189)	(0.100)	(0.266)	(0.108)	(0.270)
Production Labor, ε_{ϕ}^{L}	-0.831	-0.402	-1.289	-0.475	-1.187
	(0.059)	(0.028)	(0.114)	(0.034)	(0.084)
Non-production Labor, ε_{ϕ}^{J}	-0.620	-0.300	-0.962	-0.354	-0.886
	(0.129)	(0.055)	(0.228)	(0.074)	(0.185)
Cost shares:					
Production labor	0.50	0.55	0.45	0.50	0.50
Non-production 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

Note: Table A30 relates the reduced-form estimates in Table A29 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.
Source: Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A31: 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}	-0.338	-0.164	-0.525	-0.193	-0.483
	(0.217)	(0.100)	(0.355)	(0.124)	(0.310)
Non-production labor-capital, σ^M_{KJ}	-0.127	-0.062	-0.197	-0.073	-0.182
	(0.295)	(0.141)	(0.464)	(0.168)	(0.421)
	Panel B: p-values for Substitutability Tests				
Substitutability of production labor $H_0 : \sigma^M_{KL} \geq 0$	0.060	0.051	0.070	0.060	0.060
Complementarity of non-production labor $H_0 : \sigma^M_{KJ} \leq 0$	0.333	0.331	0.335	0.333	0.333
Cost shares:					
Production labor	0.50	0.55	0.45	0.50	0.50
Non-production 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

Note: Panel A of Table A31 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.
Source: Authors' calculations based on NBER-CES and Zwick and Mahon (2017) data.

Table A32: 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}	-0.338	-0.164	-0.525	-0.193	-0.483
	(0.217)	(0.100)	(0.355)	(0.124)	(0.310)
Aggregate Elasticity, σ_{KL}^{agg}	-0.257	-0.095	-0.431	-0.126	-0.389
	(0.209)	(0.099)	(0.338)	(0.120)	(0.299)
Cost shares:					
Production labor	0.50	0.55	0.45	0.50	0.50
Non-production 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

Note: Table A32 reproduces industry-level Morishima elasticities of substitution from Table A31 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.

Table A33: 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	✓	✓	✓

Note: Table A33 displays coefficient estimates describing the interaction between difference-in-differences terms and variables capturing labor market characteristics. The outcome variables in columns (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.
Source: Authors' calculations based on ASM, CM, Zwick and Mahon (2017), and Valletta and Freeman (1988) data.