Tax Policy and Local Labor Market Behavior*

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Abstract

Since 2002, the US government has encouraged business investment using accelerated depreciation policies that significantly reduce investment costs. We provide the first in-depth analysis of this stimulus on employment and earnings. Our local labor markets approach exploits cross-industry variation in policy generosity interacted with county-level industry location data. This strategy identifies the partial equilibrium effects of accelerated depreciation. Places that experience larger decreases in investment costs see an increase in employment and earnings. In contrast, the policy does not have positive effects on earnings-per-worker. Overall, our findings suggest federal corporate tax policy has large effects on local labor markets.

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The effectiveness of tax incentives for investment in stimulating labor demand is an article of faith among both policy makers and economists. As an example of this faith-based approach to tax policy, the Tax Cuts and Jobs Act (TCJA) of 2017 allows firms to immediately deduct or "expense" capital investments from their taxable income in the hopes of creating jobs and increasing wages. While previous research has shown that similar policies significantly increased capital investment during the previous two decades, the effects of these accelerated depreciation policies on the labor market have not been rigorously evaluated. This empirical void is startling given opponents of accelerated depreciation are concerned that these policies will incentivize firms to replace workers with machines.[1] If these concerns are real, the federal government may be spending billions of dollars – $119.4 billion over the next five years (JCT, 2017) – to destroy rather than create jobs.

We fill this void by providing the first in-depth analysis of the effects of accelerated depreciation policies on employment and earnings by estimating how these policies affect local labor markets. The particular policy we study – bonus depreciation – allows firms to deduct an additional percentage of capital expenditures in the first year of an asset's tax life. While this federal tax policy was not targeted at specific industries or locations, we show there is significant geographic variation in its benefits. This variation emerges from the fact that longer-lived assets experience a larger reduction in the present value cost of investment since bonus depreciation accelerates deductions from farther in the future. Bonus depreciation will therefore have larger effects on local labor markets where firms invest, on average, in longer-lived assets. To study the effects of this policy on local labor markets, we measure a county's exposure to bonus depreciation by interacting industry-level heterogeneity in the measured benefit of bonus depreciation with industry location data.

We measure the cumulative effect of exposure to bonus depreciation on employment, total earnings, and earnings-per-worker during the period 2002–2012. We find that bonus depreciation had a large and sustained effect on the level of local employment. Specifically, increasing a location's exposure to bonus depreciation by one Inter-quartile Range (IQR) unit – or from the 25^{th} to the 75^{th} percentile of the distribution – increased employment by 2.1 percent on average over our sample period. We benchmark this result by providing a back-of-the-envelope

[1] For instance, Robert Reich, former US Secretary of Labor, stated that bonus depreciation "will subsidize companies to cut even more jobs" in response to an accelerated depreciation policy proposed by the Obama White House in 2010 (Reich, 2010).

calculation of the cost-per-job created by bonus depreciation. We find a cost-per-job in the range of $20,000 to $50,000 depending on different assumptions used to quantify the fiscal cost of the policy. This range suggests that bonus depreciation had a cost-per-job in line with other policies more directly aimed at stimulating employment. These results suggest that the worst fears about accelerated depreciation policies are overblown. Bonus depreciation did not destroy jobs. Instead, employment increased in the locations where the cost of capital decreased the most.

While the worst fears of accelerated depreciation opponents did not come to pass, we also uncover dynamic effects of the policy that suggest that tax incentives for investment are not always a recipe for stimulating employment and earnings. We find that more exposed areas did not see an increase in employment after 2005. Similarly, we only find a short-lived increase in total earnings that crests in 2005. These gains retract and all but disappear by 2012. Finally, we do not find any positive effects on earnings-per-worker.

These dynamic patterns stand in contrast to the investment effects of the policy. Specifically, Zwick and Mahon (2017) find that bonus depreciation incentivized substantial capital accumulation in 2002–2005 and generated an even larger response in 2008–2012. The juxtaposition between the labor and capital market responses suggest bonus-incentivized investments made during the 2008–2012 period were less complementary to workers.

To establish our empirical findings, we rely on a difference-in-differences event-study approach. The assumption behind this research design is that our measure of policy exposure is not correlated with other shocks that coincide with the implementation of bonus depreciation and that also affect employment and earnings. We support this assumption in several ways. First, we show graphically that changes in employment and earnings are uncorrelated with bonus depreciation exposure prior to initial implementation. Second, all estimates include industry-by-year fixed effects, which control for industry-specific shocks. Third, state-level policies or shocks do not confound our results because they are robust to including state-by-year fixed effects. Fourth, our results are not affected by controlling for county characteristics or other within-state shocks, such as trade exposure. Fifth, we find no effects of a placebo treatment based on exposure to long duration industries with relatively little equipment. Our placebo test shows that our estimates are due to the policy itself and not to trends in industries with longer-lived assets. While the assumption underlying our research design is fundamentally untestable, our empirical strategies and robustness checks significantly limit the risk that our findings are the result of a spurious relation.

Our findings contribute to several literatures. First, we contribute to a growing literature that studies the impacts of accelerated depreciation policies by providing the first systematic analysis of the effects of federal bonus depreciation on the labor market (Hall and Jorgenson, 1967; Cummins et al., 1994; House and Shapiro, 2008; Edgerton, 2010; Kitchen and Knittel, 2016; Maffini et al., 2016; Zwick and Mahon, 2017; Ohrn, 2018b). Second, our findings improve our understanding of the effects of corporate taxation on economic behavior, labor markets, and inequality (Arulampalam et al., 2012; Yagan, 2015; Suárez Serrato and Zidar, 2016; Kovak et al., 2017; Fajgelbaum et al., 2018; Fuest et al., 2018; Nallareddy et al., 2018). In particular, this paper shows that national policies, such as a federal tax policy, can have large effects on local labor markets (Kline and Moretti, 2014; Autor et al., 2016; Dix-Carneiro and Kovak, 2017; Suárez Serrato, 2018).

Our results are immediately relevant for policy makers seeking to use tax incentives for investment to promote job creation. A priori, it is unclear how an investment incentive that lowers the cost of capital will affect workers. Firms could potentially use the incentive to increase automation, decreasing the number of jobs available. Alternatively, firms may respond to the incentive by installing capital that requires additional workers, increasing jobs. Our findings suggest that businesses do not use these incentives to directly replace workers. However, bonus depreciation does not raise local labor market earnings for the average worker.

I Bonus Depreciation and Local Labor Demand

Since 2002, the federal government has often relied on bonus depreciation to stimulate investment. The policy decreases the after-tax present value cost of new investments by allowing firms to deduct a 'bonus' percentage of the purchase price of a new investment from their taxable income in the year the investment is made.[2] A 30 percent bonus depreciation was first enacted in 2002 as part of the Job Creation and Worker Assistance Act. While the policy was initially understood to be temporary, it was increased to a higher 50 percent rate in 2003–2004. Bonus depreciation expired in 2005 before it was re-implemented in response to the 2008 recession. Apart from 2011, when the bonus rate was set at 100 percent (i.e., immediate expensing), bonus depreciation was

[2]Section 168(k) details the policy and the types of investments that qualify.

available at 50 percent between 2008–2017. In 2017, TCJA set the bonus rate at 100 percent for investments made after September 27, 2017, and before January 1, 2023. Overall, the average bonus depreciation rate during our sample period (2002–2012) was 39 percent and it decreased the after-tax present value cost of new investments by about 2.25 percent (Zwick and Mahon, 2017, henceforth ZM).

Previous studies show that federal bonus depreciation increased business investment. Based on industry-level investment data, House and Shapiro (2008) found substantial increases in investment when bonus depreciation was implemented in 2002. They also found evidence that temporary incentives had effects on investment that persisted after bonus depreciation was allowed to expire in 2005. Using financial statement data, Edgerton (2010) found that bonus depreciation created strong investment incentives even for firms with net-operating losses. ZM is the current gold-standard in the literature. Using corporate tax return data, ZM find sizable investment effects that were concentrated among smaller firms.[3]

All three of these studies use similar industry-level identification strategies based on Cummins et al. (1994). The crucial insight is that the types of assets that a business purchases determine the extent to which bonus depreciation affects its investment plans. Assets that are depreciated slowly for tax purposes benefit substantially from bonus depreciation because tax deductions are moved from farther into the future to the present. In contrast, assets that are depreciated quickly benefit very little from the policy. Therefore, industries that typically invest in long-lived assets see larger decreases in the average after-tax present value price of new capital than industries that invest in short-lived assets.

While policymakers often design incentives that target capital formation, increased investment is but a means to an end. For instance, the Council of Economic Advisers argued that capital deepening through policies including 100 percent bonus depreciation would substantially raise workers' wages (CEA, 2017).[4] Whether and to what extent increases in business investment generated by bonus depreciation translate into gains for workers depends on the interconnected roles of capital and labor. If capital complements labor, increased investment driven by bonus depreciation will increase labor demand and – by extension – employment, earnings, and wages.

[3] Other countries and US states also provide bonus-like policies. Maffini et al. (2016), Criscuolo et al. (2019), and Zhang et al. (2018) find strong investment responses to similar policies in the UK, US, and China and Ohrn (2018b) finds state-level bonus depreciation increased investment but not employment.

[4] In contrast, Barro and Furman (2018) argue that expensing may be desirable since it matches corporate tax deductions with investment cash out-flows.

If, however, investment incentivized by bonus depreciation is a substitute for labor, or even certain kinds of labor, bonus depreciation may decrease labor demand, employment, and wages and further increase the unequal distribution of income. This dichotomy motivates us to study how bonus depreciation affects employment and earnings to better understand whether new capital augments or supplants the efforts of workers.

II Measuring Local Exposure to Bonus Depreciation

This paper measures the cumulative effects of federal bonus depreciation on local labor markets. To identify these effects, we create a county-level measure of exposure to the policy by interacting industry-level treatment data from ZM and county-level industry composition data from the Quarterly Census of Employment and Wages (QCEW). We rely on QCEW composition data from 2001 to measure our exposure variable and use QCEW outcome variables from 1997–2012.

A Bonus Depreciation Intensity Measure

Our measure of treatment intensity relies on estimates of which industries benefit most from bonus depreciation. In the absence of bonus depreciation, the Modified Accelerated Cost Recovery System (MACRS) details tax rules for the depreciation of new assets. The present value of depreciation deductions associated with \$1 of investment is equal to

$$z^0 = \sum_{t=0}^{T} \frac{1}{(1+r)^t} D_t,$$

where T is the class-life of the asset, D_t is the portion of the dollar that is depreciated in year t, and r is the rate used to discount future cash flows. MACRS rules specify T and D_t in each period for each type of investment. Long-lived assets — as compared to short-lived assets — are depreciated more slowly over longer lives and have smaller z^0s. Therefore, tax deductions generated by long-lived assets are worth less in present value terms.

Bonus depreciation allows firms to write off b percent of qualifying investments immediately; the remaining $1 - b$ percent are depreciated according to MACRS rules. Bonus depreciation reduces the present value cost of investment by $b(1 - z^0)$. Since this difference is larger when z^0 is smaller — when assets have longer class-lives and are depreciated more slowly — z^0 is a measure of bonus depreciation treatment intensity.

ZM calculate an industry-level measure of z^0 as follows. First, they calculate z^0 for each asset-class defined by MACRS assuming a 7 percent discount rate. Second, they use tax return data to calculate the share of each bonus-eligible asset-class purchased by each 4-digit NAICS industry. Finally, ZM weight the asset-class z^0s by the industry shares to create z^0_j, which measures the present value of depreciation deductions for the average asset in which industry j invests. It is worth noting that z^0_j's vary considerably even within a given sector. Figure 1A displays the within-sector coefficients of variation relative to the manufacturing sector. This figure shows that there is significant variation in z^0_j's across industries in the Accommodation and Food Services, Manufacturing, Retail Trade, and Health Care sectors.[5]

B Local Exposure to Bonus Depreciation

Our measure of exposure focuses on industries that typically invest in long-lived assets and have the smallest z^0_j's. As shown in Figure 1A, there is considerable within-sector variation in z^0_j's implying that industries that invest in long-lived assets are not in a specific sector.

We define an industry as *treated* if it is in the bottom third of the z^0_j distribution. We use this discretized treatment variable for two reasons. First, it eliminates the effects of outliers in the z^0_j distribution. The power generation industry, in particular, has a z^0_j that is much lower than other values. Second, z^0_j values depend on an assumption about the rate of return used to discount future cash flows. By discretizing our treatment measure, our estimates do not depend on this assumption. While there is a natural break at the 33^{rd} percentile, the Online Appendix shows our results are robust to splitting the distribution at the 25^{th} or 40^{th} percentiles of the z^0_j distribution.

The sector with the largest share of employment among treated industries is Accommodation and Food Services with 33 percent. Another 40 percent of employees in long-duration industries work in the Manufacturing, Retail Trade, and Health Care and Social Assistance sectors.[6]

We now map our industry-level treatment onto counties. QCEW provides county-by-industry employment data using 4-digit NAICS categories. Using these data, we construct **Exposure** (to Long-Duration Industries) as

$$\textbf{Exposure}_c = \frac{\sum_j Emp_{jc2001}\mathbb{I}(treated_j = 1)}{\sum_j Emp_{jc2001}}; \tag{1}$$

[5] Online Appendix Table F1 summarizes z^0_j's by 2-digit NAICS.

[6] Online Appendix Figure F1 shows the fraction of long-duration employment by 2-digit NAICS.

the percentage of employees in each county, c, working in treated 4-digit NAICS industries, j, in the year 2001. For example, our county-level Exposure measure would be 0.2 if 20 percent of employees work in treated industries and the remaining 80 percent work in untreated industries.[7]

Figure 1B plots our county-level Exposure measure relative to the state average. This map shows there is considerable variation in Exposure within a given state.[8] For example, only 16 percent of employees in Hunterdon County, New Jersey, work in long-duration industries. Meanwhile, 56 percent of employees in nearby Atlantic County, New Jersey, work in long-duration industries. These two locations on polar opposites of our Exposure distribution are only 120 miles apart.

Overall, our Exposure variable captures significant differences in tax incentives across local labor markets and allows us to measure the unequal geographic benefits of federal bonus depreciation.

C Estimating Equation and Identification Strategy

We use an event-study framework to measure the cumulative effects of bonus depreciation on local labor markets from 2002-2012. The regression specification we estimate is

$$\Delta Emp_{cjt} = \alpha + \sum_{y=1997}^{2012} \beta_y \Big[\mathbf{Exposure}_c \times \mathbb{I}(t=y)\Big] + \mathbf{X'}_c \gamma_t + \mu_{st} + \nu_{jt} + \epsilon_{cjt}, \qquad (2)$$

where c denotes county, j denotes NAICS 3-digit industry, and

$$\Delta Emp_{cjt} \equiv \frac{Emp_{cjt} - Emp_{cj2001}}{Emp_{cj2001}}$$

is defined as the county-by-industry percentage change in employment between year t and 2001. Because county-by-industries vary in size, we weight this regression by the national share of employment in each county-NAICS 3-digit industry in 2001.[9] We estimate similar specifications to quantify the effects of bonus depreciation on total earnings and earnings-per-employee. We scale Exposure so the coefficients β_y capture the dynamic effects of an increase in Exposure

[7] Our results are robust to redifining our shock based on employment patterns in 2008.

[8] Figure 1B plots Exposure relative to the state mean since our empirical analyses include state-by-year fixed effects. Online Appendix Figure F2 plots a raw measure of exposure. Online Appendix Table F2 lists the most and least Exposed counties.

[9] We choose to use a balanced-panel of county-by-3-digit NAICS industries as our observational unit as opposed to county-by-4-digit NAICS industries because QCEW data provide better coverage at this level. Our results are similar when using county-by-4-digit NAICS industry outcomes.

from the 25th to the 75th percentile of the distribution. Because Exposure is defined at the county-level, we cluster standard errors within counties (Cameron and Miller, 2015).

The identifying assumption of Equation 2 is that ϵ_{cjt} is not correlated with our measure of Exposure. The differenced county-industry outcomes eliminate any concerns that permanent level differences across county-industry can be correlated with Exposure and drive our results.[10] Our preferred specification includes state-by-year fixed effects, μ_{st}, which account for the effects of time-varying state-level policies such as changes in state-level corporate tax rates (Suárez Serrato and Zidar, 2018) or state-level adoption of bonus depreciation (Ohrn, 2018b). We also include industry-by-time fixed effects, ν_{jt}, which rule out the concern that other industry-by-time variation may be responsible for our empirical results.[11]

Additionally, we include county-level controls, $\mathbf{X_c}$, to isolate the portion of Exposure that is unrelated to contemporaneous policy shocks, initial business conditions, and demographic characteristics. $\mathbf{X_c}$ includes exposure to trade from NAFTA and China (Hakobyan and McLaren, 2016; Autor et al., 2016), the domestic production activities deduction (Ohrn, 2018a), the share of routine labor (Autor and Dorn, 2013), tangible and intangible capital stock measures (IP), and demographic characteristics from the 2000 Census.[12]

By ruling out level differences, state-by-year shocks, industry-by-year shocks, and other observable shocks, we significantly reduce the risk that our results are driven by some spurious relation and increase the likelihood that we provide unbiased estimates of the local labor market effects of bonus depreciation. By controlling for these shocks and focusing on the differential effects of the policy across local labor markets, this strategy does not measure the overall effect of the policy. In particular, we cannot measure whether the policy led to aggregate increases or decreases in employment.

III Local Labor Market Effects of Bonus Depreciation

We begin by examining the effects of bonus depreciation on employment in Figure 2A. This figure shows that High and Low Exposure county-industries were on similar paths before the

[10]This eliminates the need to include county-industry fixed effects in our regressions.

[11]This specification addresses a major criticism of studies that measure the effects of tax policy using industry-by-time variation (Cummins et al., 1994; House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2018a).

[12]Capital measures come from BEA data on the Current-Cost Net Capital Stock of Private Fixed Assets. Demographic characteristics include the share of population with less then a high-school degree and the share with a college degree, as well as white and black shares of the population. See Online Appendix B for more detail.

onset of the policy in 2002. Upon implementation and through 2005, employment in more Exposed county-industries increased relative to other units. The effect tapered slightly during years 2005–2007 when bonus depreciation was allowed to expire. The difference in employment levels then stabilized during the 2009–2012 period after the policy was re-implemented in 2008.[13]

One way to interpret these results is to think of them as a response to a permanent 39 percent bonus depreciation (the average level during the 2002–2012 period) that was implemented in 2002. In a neoclassical model (e.g., Auerbach and Poterba, 1987), a permanent policy of this nature leads to level increases in employment and the capital stock. To quantify this level increase, we replace the year dummies in Equation 2 with a Post indicator for years after 2002. The coefficient on Exposure $\times$ Post is a difference-in-differences estimate of the average effect of bonus depreciation on employment for years 2003–2012 relative to 1997–2001, where we omit 2002 as a transition year. We present these difference-in-differences estimates in Table 1. Our main specification in column (3), which includes 3-digit NAICS industry-by-year fixed effects, state-by-year fixed effects, and county characteristics, shows that increasing the Exposure to bonus depreciation from the 25th to the 75th percentile of the Exposure distribution increased employment by 2.1 percent. Column (1) only includes 3-digit NAICS industry-by-year fixed effects while column (2) includes both 3-digit NAICS industry-by-year and state-by-year fixed effects. Column (4) winsorizes the employment treatment weights at the 1 percent level and column (5) limits the analysis to county-industries with more than 1,000 employees in 2001. Our estimate in the absence of state-by-year fixed effects suggests that state shocks are largely uncorrelated with Exposure while the stability of our results with winsorized treatment weights and without small county-industries suggests neither very large nor very small units of observation are primarily responsible for our estimates.[14]

An alternative interpretation of Figure 2A is that expectations about future costs of capital may lead bonus depreciation to incentivize investment in different types of capital. When the policy was first implemented, firms may have seen it as a temporary policy and used this opportunity to replace aging equipment or to invest in projects they had planned to pursue in the

[13]The Online Appendix reports point estimates for all graphs, as referenced in figure notes. For brevity, we discuss estimates that include the controls mentioned in Section II. Online Appendix C lists additional robustness checks. In particular, Appendix Figure F3 shows that both the parallel pre-trends and large employment effects we estimate do not rely on state-by-year fixed effects or county-level controls.

[14]Online Appendix D discusses the role of corporate losses and Section 179 in interpreting these estimates. Adjusting for these time-varying factors has relatively small effects on our results.

future. It is likely that these investments complemented human work, which is consistent with the large effects on employment we observe between 2002 and 2004.

In contrast, after 2008, firms may have believed that the policy would be extended indefinitely. After all, bonus depreciation has been in place since 2008 and is expected to be part of the tax code through 2022. Facing a decrease in the future expected costs of capital, firms may have responded by increasing the capital intensity of their production processes. This dynamic would be consistent with a smaller impact of bonus depreciation on employment. Indeed, while we see persistent employment levels until 2012, we do not see additional job gains. The dual investment responses documented by ZM are consistent with this interpretation.

We view these interpretations as complementary. When comparing the fiscal cost of the policy to the number of jobs created, as we do in Section IV, we use the average effects of the policy. However, as we consider how the policy may affect earnings, as we do below, it is useful to recall that bonus depreciation evolved over time and that expectations over its persistence may influence its effects on local labor markets.

A Effects on Earnings and Earnings-per-Worker

We extend our analysis of bonus depreciation to county-industry total earnings and earnings-per-worker in Figures 2B-2C.[15] Cumulative earnings patterns do not differ by Exposure in the pre-period. Upon bonus depreciation implementation in 2002, earnings in more Exposed county-industries increase substantially relative to less Exposed units. In contrast to employment, the effects on earnings decline after 2005 and are no longer statistically significant by 2008–2012. Our estimates in Table 1 suggest that one unit of IQR Exposure to bonus depreciation increased cumulative earnings by 1.9 percent from 2003–2012, on average.[16]

Figure 2C shows that bonus depreciation had no effect on earnings-per-worker during the pre-period or during the years 2002–2006. Earnings-per-worker in more exposed county-industries then decrease during the 2009–2012 period. Table 1 shows that a one unit of IQR Exposure decreases cumulative earnings-per-worker by 0.5 percent during the treatment period. The timing of the decline in earnings-per-worker coincides with the decrease in the earnings effects, suggesting

[15]Earnings do not include non-wage compensation. However, since bonus depreciation does not affect the relative cost to the employer or wage vs. non-wage compensation, we do not see a reason to suspect a change in the wage share of total compensation.

[16]Figures F4 and F5 present graphical results for earnings and earnings-per-worker with without state-by-year fixed effects and county-level controls. Our graphical and empirical results are similar across all specifications.

changes in earnings-per-worker explain some of the later-period decline in total earnings.

There are two reasons that our earnings-per-worker results cannot speak directly to the effect of the policy on wages. First, earnings-per-worker are affected by changes in the number of hours worked. In particular, the observed decreases in earnings-per-worker after 2008 could be due to fewer hours worked per worker as opposed to decreases in wages. Second, changes in the composition of workers – as opposed to changes in wages – may be driving the estimated effects. If, for example, more low-income workers were hired in years 2008–2012, earnings-per-worker would decrease even if wages were unaffected. In light of these caveats, our earnings and earnings-per-worker results suggest that any wage increases resulting from capital deepening were not large enough to overcome changes in hours or the composition of the labor force.

B Heterogeneous Effects by Automation Likelihood

The earnings-per-worker declines during the later half of the treatment period may be driven by a shift in the types of jobs created by bonus depreciation. To explore this hypothesis, we estimate the employment effects of Exposure on county-industries that were most likely to lose jobs to automation (as defined by Autor, 2015) during the 2007–2012 period.[17] Figure 3 presents the results of this exercise and shows that county-industries that were most likely to lose jobs to automation were extra responsive in the early years of the policy. These same county-industries then saw more rapid declines in cumulative employment after 2006. As many jobs lost to automation were well-paid jobs in production, administration, and sales, the rapid decline in these county-industries likely explains some of the later-period declines in earnings and earnings-per-worker.

C Placebo Test

We use the fact that structures and IP were not eligible for bonus depreciation to conduct a natural placebo test. We create a placebo exposure — mirroring Equation 1 — to long-duration industries that own five times as much stock in structures and IP as in equipment. Figure 2D reports the results of this test. Contrasting these flat patterns with Figures 2A–2C suggests that

[17] We classify a county-industry as High Automation if the county-industry is in the top third of county-industries in terms of the percentage of jobs classified by Autor (2015) as the fastest declining industries in 2007–2012. We link occupations to industries using 2002 data from the Bureau of Labor Statistics' Occupational Employment Statistics. We then regress percentage changes in employment on Exposure and Exposure interacted with High Automation to produce Figure 3.

the effects of bonus depreciation are driven by the policy itself and not by trends in industries that invest in ineligible but long-lived assets.

IV Cost-per-job Calculations

To better appreciate the magnitude of our estimates, we compare the fiscal cost of the policy to the number of jobs it created. We estimate the total number of jobs created by multiplying the average Exposure by the estimated effect from specification (3) in Table 1. Relative to the 109.3 million workers in the US in 2001 (QCEW, 2018), this implies an increase in employment of 6.24 million jobs.[18]

While estimating the number of jobs created is fairly straightforward, the fiscal cost of bonus depreciation depends on several factors and warrants some discussion. Recall that bonus depreciation changes only the *timing* of deductions. The government allows firms to deduct more now in exchange for lower future deductions. This lowers tax revenue now, but may increase future revenue. The fiscal cost to the government of offering bonus depreciation on \$1 of qualifying investments is

$$\text{Fiscal Cost} = \sum_{t=0}^{T} \frac{\tau_t}{(1+r)^t} \times (D_t^{\text{Bonus}} - D_t^{\text{Baseline}}) \times \mathbb{I}(\text{Firm is Taxable})_t.$$

The fiscal cost of allowing firms to depreciate according to the sequence D_t^{Bonus} depends on four factors. The first is the schedule of baseline deductions, D_t^{Baseline}, against which the cost is calculated. When the fiscal cost is calculated against a relatively accelerated baseline, such as MACRS, the cost is lower than when it is calculated against a slower baseline, such as economic depreciation.

The second factor is the tax rate, τ, against which the deductions are taken. Bonus depreciation is more costly when the tax rate is higher. The dynamics of the corporate tax rate also affect the cost of the policy. As an example, consider a qualifying investment made in 2011 that is typically depreciated over 12 years. Given the 100 percent bonus depreciation rate in 2011, the full cost of the investment could be deducted against the prevailing 35 percent corporate tax rate. Because the equipment is fully depreciated, the firm will have fewer deductions and higher taxable income over the next 11 years. If the tax rate decreases during this time, the increase

[18] This follows from an average value of Exposure of 2.72 (IQR units), an effect of 2.1 percent, and base employment of 109.3 million jobs: $6.24 = 109.3 \times 0.021 \times 2.72$.

in taxable income will yield less nominal revenue and increase the cost of the policy. In fact, the new 21 percent corporate tax rate ushered in by the TCJA increased the fiscal cost of bonus depreciation for many investments made prior to 2018.

The rate at which the government discounts future cash flows, r, also affects the cost of the policy. When the government discounts future cash flows more (higher r), the cost of the policy increases.

Finally, the taxable status of a firm in a given period, which we represent using the indicator function, $\mathbb{I}(\text{Firm is Taxable})_t$, affects the cost of policy. The cost increases if a firm depreciates an investment under bonus depreciation rules and experiences losses or goes out of business in the future. In this case, the government collects less revenue now and no additional revenue in the future.

We now calculate the cost-per-job for bonus depreciation and show how this varies based on several different assumptions. The first estimate of the fiscal cost comes directly from the US Treasury. The US Treasury estimates the fiscal cost using an economic depreciation baseline, the 'current law' sequence of tax rates, a discount rate approximating interest rates offered by the US government, and a microsimulation model to capture the transitions of firms into tax loss status. These estimates imply a cost of $311 billion over the period 2003–2012.[19] Dividing this cost by the 6.24 million jobs yields a cost-per-job of approximately $50,000.

This method may overestimate the true fiscal cost and resulting cost-per-job estimate because it uses an economic depreciation benchmark. In the absence of bonus depreciation, firms deduct investments using MACRS, which is more generous than economic depreciation. Using a MACRS baseline would yield a lower fiscal cost and a lower cost-per-job.

To estimate the fiscal cost relative to MACRS, we rely on ZM estimates of the after-tax present value cost of investments under bonus depreciation relative to MACRS. ZM estimate that 39 percent bonus depreciation (the average rate during our sample period) decreases the present value of deductions by 2.13 percent, on average. Relative to the $5.82 trillion of investments that took advantage of bonus depreciation during the years 2003–2012, this estimate implies a cost of $124 billion or just under $20,000 per job.[20]

[19]These estimates are presented in US Treasury "Tax Expenditures" reports. For example, see IRS (2013) for the 2013 report. Using Treasury estimates for 2004–2012, we calculate an average cost of $31.1 billion per year. 'Current law' tax rates assume Congress will not deviate from planned changes in the tax code.

[20]Kitchen and Knittel (2016) note that, while there were were $9.7 trillion in eligible investments made during the sample period, bonus depreciation had only a 60 percent take-up rate.

While this estimate improves upon the Treasury-based number because it uses the MACRS baseline, it does not account for changes in the tax rate and transitions into and out of tax loss status. If some percentage of firms are taxable now but will not be in the future, then this would increase the cost-per-job. On the other hand, this approach assumes that the government has a 7 percent discount rate, which likely overestimates the fiscal cost of the policy.

We view the assumptions underlying these estimates as plausible but imperfect. Nonetheless, both estimates are comparable to cost-per-job numbers in the literature. For instance, Suárez Serrato and Wingender (2016) and Chodorow-Reich (2019) place the cost-per-job from government spending close to $30,000. Zidar (Forthcoming) also finds a cost-per-job of $30,000 when personal income tax cuts are directed to earners in the bottom 10 percent of the income distribution. Suárez Serrato (2018) finds that repealing tax credits for US multinationals resulted in a cost-per-job of $48,000.

While these estimates provide a valuable back-of-the-envelope calculation that benchmarks our results relative to the prior literature, we caution that they depend on two important assumptions. First, our estimates are based on cross-sectional variation that does not account for general equilibrium effects or other major effects of the policy.[21] Second, our estimates do not account for migration induced by the policy. See Fuchs-Schuendeln and Hassan (2016) for related approaches to estimate effects of macroeconomic policies.

V Conclusion

This is the first study to provide a detailed analysis of the labor market effects of bonus depreciation. We find that local labor markets with more exposure to the policy experience a large and stable increase in employment. These same markets experience a short-run increase in total earnings, but no increase in the average earnings-per-worker. While these results alleviate the concern that accelerated depreciation policies will be used to replace workers with machines, our employment and earnings results from the 2008–2012 period suggest that policies designed to promote capital deepening do not always benefit workers.

[21] These major effects might include increased employment by firms selling equipment goods to meet the additional demand stimulated by bonus depreciation.

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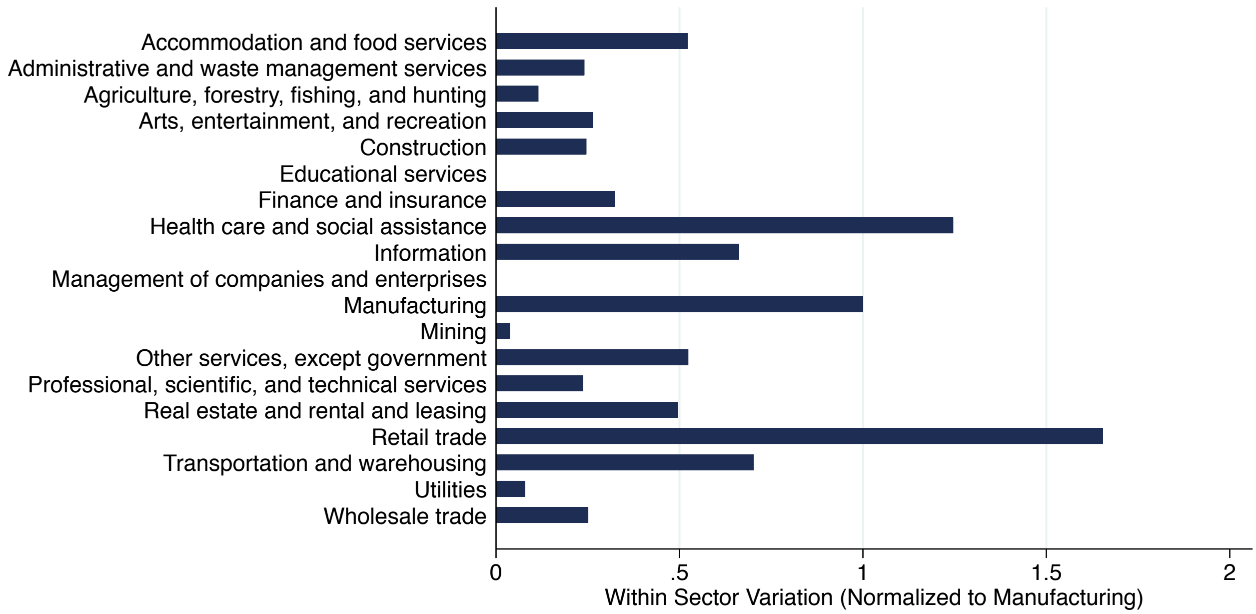
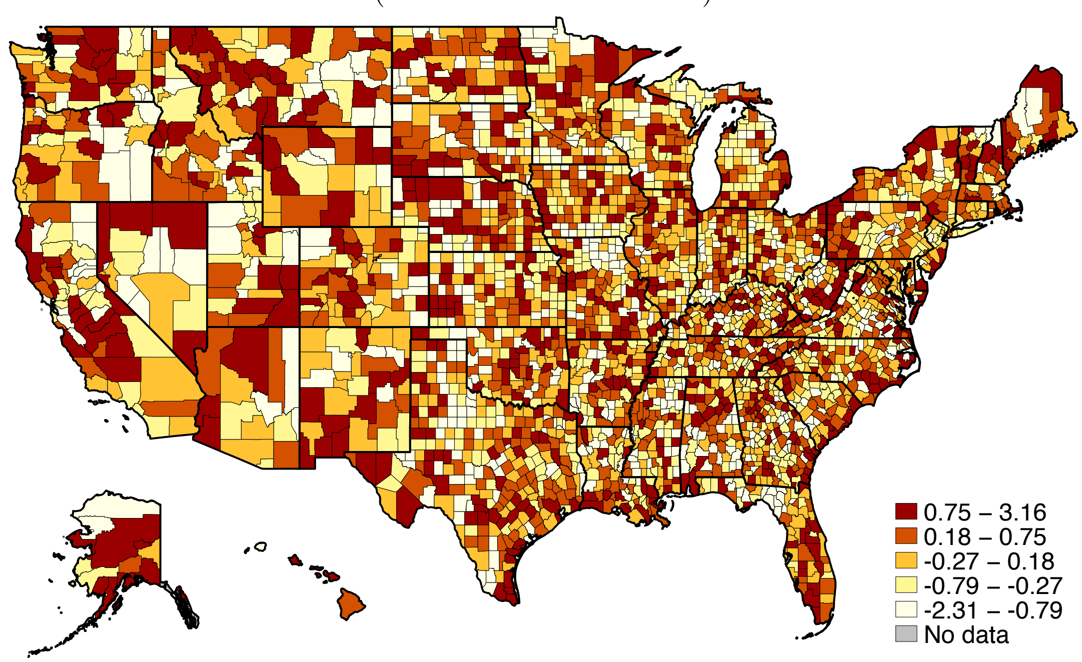
Figure 1: Exposure to Long Duration Industries

A. Within 2-digit NAICS Variation in Duration



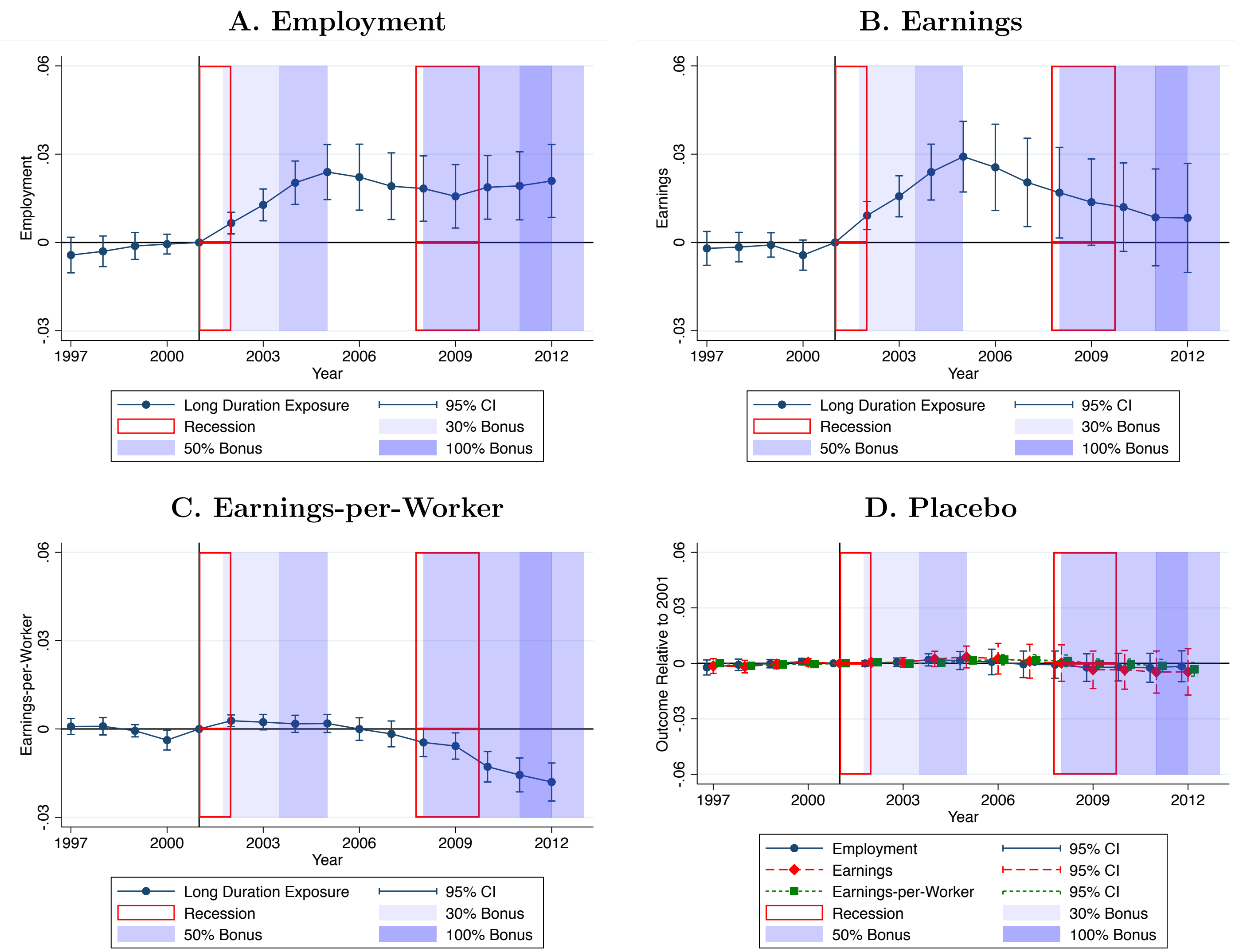
B. Percent of Employment in Long Duration Industries

(Relative to State Mean)



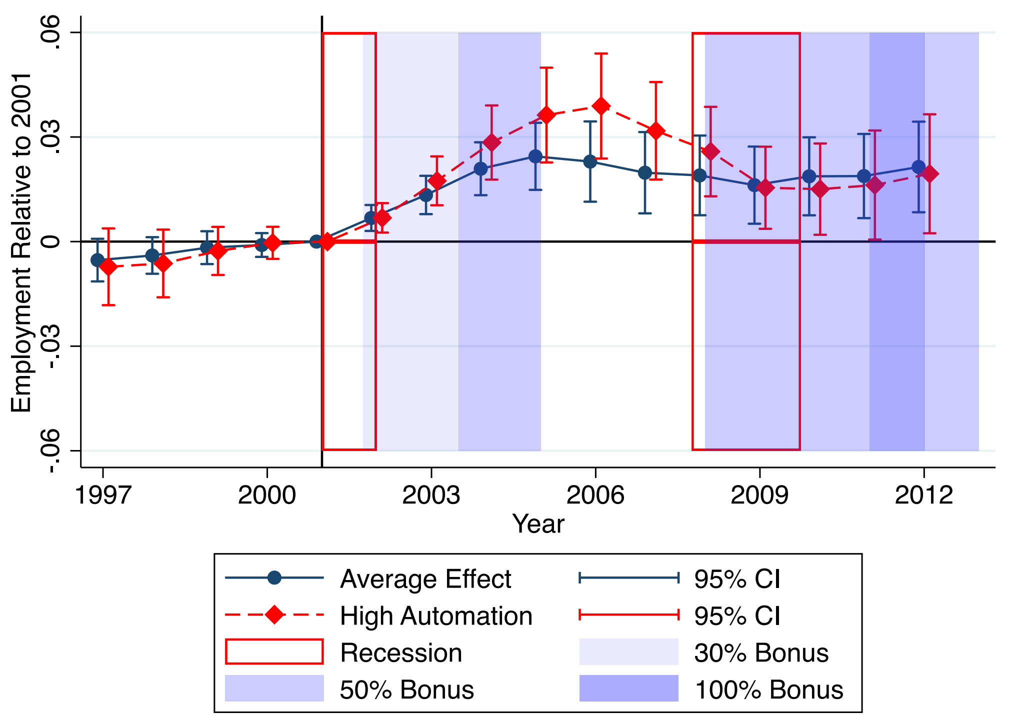
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). Figure 1A shows the within-2-digit-NAICS variation in duration of industries relative to manufacturing. For each 2-digit-NAICS, we calculate the within-2-digit-NAICS coefficient of variation of the measure of duration from Zwick and Mahon (2017) and multiply that by the share of 2-digit-NAICS capital and 2-digit-NAICS employment, respectively. We normalize each measure of weighted variation to the manufacturing sector (NAICS 31-33). Figure 1B shows the standardized percent of employment in each county that comes from the top three deciles of employment-weighted industries by average duration of investment. The exposure measure is normalized by average exposure at the state level so the coefficients are interpretable as standard deviations in exposure from the state average exposure. Long duration exposure values are shown in Figure E2 without adjusting for state means.

Figure 2: Effects of Bonus Depreciation by Exposure to Long Duration Industries



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation following the structure of Equation 2. The dependent variable is Employment in Figure 2A, earnings in Figure 2B, earnings-per-worker in Figure 2C, and a placebo for all outcomes in Figure 2D. The variable of interest is the percent of employment that resides in long duration industries normalized to the inter-quartile range (IQR). See Section III for more discussion regarding the interpretation of the event study results. Figure 2D shows the coefficients from regressions of outcomes on exposure to long duration industries that use more than five times more structures and intellectual property products than equipment in 2001. Structures and intellectual property products are not eligible for bonus depreciation. The set of long duration industries that use relatively little equipment includes the following NAICS codes: 2111, 4821, 5311, 7111, 7112, 7211, 7212, and all of 81. The results of Figure 2D give evidence that structures and land investment are not driving the results. All of the results are robust to the exclusion of the local controls as shown in Figures E3, E4, and E5, as well as the definition of a long-duration industry exposure as shown in Figures E6 and E7. Tables E4, E5, and E6 show the annual coefficients for employment, earnings, and earnings-per-worker, respectively, with additional specifications. Standard errors are clustered at the county level.

Figure 3: Heterogeneity by Automation Likelihood



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). Figure 3 shows the heterogeneous effect of exposure to bonus depreciation on local employment. The regression matches Figure 2A and is estimated separately for the full sample and interacted with industry automation categories. The coefficients for high automation likelihood industries rise in a similar manner to the coefficients of the full sample of industries and are not statistically different.

Table 1: **Local Labor Market Effects of Bonus Depreciation**

	(1)	(2)	(3)	(4)	(5)
Employment					
Exposure × Post	0.021**	0.019***	0.021***	0.018***	0.020**
	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
Earnings					
Exposure × Post	0.022**	0.023***	0.019***	0.017**	0.021**
	(0.011)	(0.008)	(0.007)	(0.007)	(0.010)
Earnings-per-Worker					
Exposure × Post	-0.002	0.000	-0.005**	-0.004**	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Dropping Small County-Industries					Yes

Notes: This table shows difference-in-differences estimates from Equation 2 where β is not allowed to vary by year. The outcomes are employment in the first row, earnings in the second, earnings-per-worker in the third. Column (1) shows estimates with only 3-digit NAICS industry-by-year fixed effects while column (2) adds state-by-year fixed effects. Column (3), the main specification, adds county level economic and demographic characteristics as control variables. The last two columns show robustness of the results to winsorizing the weights at the 5% level and to dropping county-3-digit industries with less than 1,000 workers in 2001. The sample for this table excludes 2002 as a transition year. Standard errors are clustered at the county level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix: Not For Publication

This Online Appendix includes additional information on the data and methods used in the paper as well as supplementary results. Appendix A contains additional details on our data sources. Appendix B lists results from robustness checks that are mentioned in the body of the paper. Appendix C discusses the role of tax losses and Section 179 expensing rules in the interpretation of our results. Appendix D shows that we obtain similar results when we analyze the effects of bonus depreciation on the employment-to-population ratio. Finally, additional tables and figures are included in Appendix E.

A Variable Definitions

Variable name	Definition
	Accelerated Depreciation Variables
Industry	We define the industry at the 4-digit NAICS level and 3-digit NAICS level in different cases and denote the difference by mentioning the number of digits.
Employment	Number of average workers listed in a geographic area and industrial grouping in a given year according to QCEW (2017), *annual_avg_emplvl*.
Duration	The present value of depreciation deductions for the average asset in which each industry invests from Zwick and Mahon (2017).
Long Duration Exposure	Share of employment in each county in industries in the top tercile of industries as ranked by duration of average investment. This variable is always normalized to the interquartile range (IQR).
	Other Outcome Variables
Earnings	Total payments made to workers in a geographic area and industrial grouping in a given year according to QCEW (2017), *total_annual_wages*.
Earnings-per-Worker	Total payments made to workers in a geographic area and industrial grouping in a given year divided by *employment*. From QCEW (2017), this variable is created as *total_annual_wages* divided by *annual_avg_emplvl*.
	Other Control Variables
DPAD	Share of employment in each county in industries in the top tercile of industries as ranked by Qualified Production Activities Income as a percent of sales in 2005 derived from data compiled in Ohrn (2018a).
Trade (China)	County-level exposure to trade from China from Autor et al. (2016).
Trade (NAFTA)	County-level exposure to trade related to NAFTA from Hakobyan and McLaren (2016).
Routine Jobs	County-level share of routine labor from Autor and Dorn (2013).
Capital Stock	Total capital stock, including structures, equipment, and intellectual property products, in 2001 from Bureau of Economic Analysis (2017) allocated to counties using employment shares at the 3-digit NAICS level.
IP Stock	Total intellectual property products in 2001 from Bureau of Economic Analysis (2017) allocated to counties using employment shares at the 3-digit NAICS level.
Demographics	County-level education outcomes including percent of population with college degrees and with less than a high school education as well as racial demographics percent white and black from the American Community Survey. Data compiled in Suárez Serrato and Zidar (2018).

B Additional Results

This appendix describes tables and figures that report additional details of the specifications in Figure 2, as well as additional results.

- **Descriptive Statistics.** We include several figures and tables to more completely describe the variation in duration both across space and across industries that we use as identifying variation in exposure to accelerated depreciation.
  - Figure E1 provides a summary description of the source of employment in long duration industries.
  - A map of the geographic distribution of long duration industries without normalizing within-state means to zero is shown in Figure E2.
  - Table E1 describes the within sector variation in duration as well as shares of national employment from QCEW (2017) and capital stock from Bureau of Economic Analysis (2017). The final column shows total variation (coefficient of variation multiplied by employment weight) with the manufacturing variation normalized to be equal to one.
  - A list of the top and bottom ten counties with over 100,000 population in 2001 based on the percent of their employment coming from long duration industries is shown in Table E2.
  - Table E3 shows additional county descriptive statistics associated with exposure to long duration, population, and local capital stock.
- **Robustness to Controls.** We show the robustness of the county-level regressions of employment, earnings, and earnings-per-worker in a series of expanded results with different controls and different definitions of key variables. The primary results displayed in Figure 2 are robust to the inclusion or exclusion of the controls.
  - Figures E3, E4, and E5 show the robustness of the specifications in Figure 2 to taking away the county-level controls or to removing the state-by-year fixed effects. Although the 3-digit NAICS industry-by-year fixed effects are fundamental to the identification strategy, the county controls and state-by-year fixed effects are included as extra controls. We show that the additional controls do not have qualitative impacts on the main results.
  - Tables E4, E5, and E6 show the annual coefficients from Figure 2 for employment, earnings, and earnings-per-worker, respectively. The tables all include five specifications where column

(3) is the preferred specification with state-by-year and 3-digit NAICS industry-by-year fixed effects as well as controls for county economics and demographics.

- **Robustness to Definition of Exposure and Placebo Tests.** We also show the robustness of the baseline results shown in Figure 2 to the definition of the long duration exposure at the county level. Instead of defining firms in the top tercile of industries ranked by duration to be "long" duration, we change the threshold to the top 25% and 40% of industries and show that the results are unchanged. We also include a placebo with exposure to long duration industries that primarily invest in structures and intellectual property, NAICS 2111, 4821, 5311, 7111, 7112, 7211, 7212, and all of 81, which are long duration industries with more than five times more structures and IP than equipment.
  - The choice to use the percentile instead of a continuous measure of average duration is twofold: (1) the continuous measure is influenced by larger outliers in NAICS 22 that invest in much longer duration assets than any other industry, so much of the variation is driven by outliers and (2) the measurement of industry-level duration of investment is a function of assumptions on discount rates that are avoided by discretizing the set of long-duration industries. In order to check that the results are not sensitive to the decision to discretize bonus exposure, we define other cutoffs and examine the stability of the coefficients of the other exposure measures. The analogue of Figure 2 is shown using exposure to the top 25% of long duration firms in Figure E6 and using the exposure to the top 40% of long duration firms in Figure E7.
  - Tables E7, E8, and E9, show the annual coefficients from Figure 2D for employment, earnings, and earnings-per-worker, respectively. The labor market outcomes tables each include five specifications where column (3) is the preferred specification with state-by-year and 3-digit NAICS industry-by-year fixed effects as well as county economic and demographic controls.

C Adjusting for Losses and Section 179

This appendix discusses the role of losses and Section 179 expensing rules in interpreting our results. In particular, we clarify that the interpretation of our main result is that of an intent-to-treat (ITT) effect. Our main estimate differs from the treatment on the treated (ATOT) for three reasons. First, some companies may rely on Section 179 expensing instead of bonus. Second, some companies may not take up the incentives of bonus depreciation if they plan to report tax losses. A third complication is that bonus depreciation has varied in intensity across our time period. This section clarifies the interpretation of our results in light of these three factors.

We make three related points in this appendix:

1. First, accounting for Section 179 has small effects on our reduced-form estimates of the effects of bonus depreciation. Specifically, our estimates would be 11% smaller in the absence of Section 179 expensing.

2. Second, accounting for the fraction of firms with losses implies that the ATOT would be 33% larger than the ITT. Accounting for both losses and Section 179 results in estimates of the ATOT that are 19% larger than our ITT estimates.

3. Finally, we show that the time-pattern of losses and Section 179 expensing limits has negligible effects on the time-path of our reduced-form effects in Figure 2.

Marginal Investment Incentives with Losses and Section 179

As noted by Kitchen and Knittel (2016), the effects of bonus depreciation interact with two important factors. The first is corporate losses. Since firms can only get the immediate benefit from the bonus depreciation deduction if they owe corporate taxes, we would expect to find smaller effects when a larger fraction of firms experience year-end losses. Second, Section 179 allows firms to fully expense capital investments if the investment value is below a given threshold. A higher Section 179 limit could therefore confound the effects of bonus.

In order to explore the role of these interactions, we start by characterizing the present discounted value (PDV) of depreciation deductions. To do so, we make use of the following definitions:

- Under the modified accelerated cost recovery system (MACRS), the PDV of depreciation deductions for the marginal dollar is z^0.

- Under Bonus, the PDV of depreciation deductions for the marginal dollar is $b + (1-b)z^0$. Figure C1A shows how the policy parameter b varies over time. The average value of b over our sample period is 39%.

- Under Section 179, the PDV of depreciation deductions for the marginal dollar is 1 if $I_{j,t} < \bar{I}_t$, where $\bar{I}_t$ is the Section 179 limit. Moreover, Share $179_t = E[\mathbb{I}[I_{j,t} < \bar{I}_t]]_t$ is the share of investment that is eligible for Section 179 expensing. Figure C1B reports data from Kitchen and Knittel (2016) that describes the time variation in Share 179_t. The Share 179_t is relatively stable over out time period with an average value that is close to 8%.

- Let $\mathbb{I}[\text{Gains}_{j,t}]$ be the event that a firm is in the gains domain and Share $\text{Gains}_t = E[\mathbb{I}[\text{Gains}_{j,t}]]_t$. Figure C1C uses data in corporate losses by industry from the IRS Statistics of Income and describes the time variation in Share Gains_t. Over our sample period, the average value of Share Gains_t is close to 75%.

For an individual firm j, the general value of depreciation deductions for the marginal dollar of investment is:

$$\begin{aligned} z &= (b + (1-b)z^0) \times (1 - \mathbb{I}[I_{j,t} < \bar{I}_t]) + 1 \times \mathbb{I}[I_{j,t} < \bar{I}_t] \\ &= (b + (1-b)z^0) + \mathbb{I}[I_{j,t} < \bar{I}_t][1 - b - (1-b)z^0)] \\ &= (b + (1-b)z^0) + \mathbb{I}[I_{j,t} < \bar{I}_t][(1-b)(1-z^0)]. \end{aligned}$$

Taking the difference between this value and z^0 we have :

$$\begin{aligned} z - z^0 &= (1-z^0)b + \mathbb{I}[I_{j,t} < \bar{I}_t][(1-b)(1-z^0)] \\ &= (1-z^0)[b + (1-b)\mathbb{I}[I_{j,t} < \bar{I}_t]]. \end{aligned}$$

Intuitively, Section 179 gives $b = 1$ when $I_{j,t} < \bar{I}_t$ so the combined policy of bonus and Section 179 has a larger effect on $z - z^0$ whenever the event $\mathbb{I}[I_{j,t} < \bar{I}_t]$ is more likely.

Assume now that a firm only values depreciation deductions in the gains domain. The average value of the shock in a county is then:

$$\begin{aligned} E[z - z^0]_{c,t} &= (1-z^0) \times \text{Share Gains}_t \times [b + (1-b)\text{Share } 179_t] \\ &\approx \text{Exposure}_c \times \text{Share Gains}_t \times [b + (1-b)\text{Share } 179_t], \end{aligned} \tag{C.1}$$

where we use our Exposure_c measure as the empirical approximation of $(1 - z^0)$.

Adjusting Average Reduced-Form Effects for Losses and Section 179

Equation C.1 formalizes the notion that estimates that rely on Exposure_c for identifying variation will result in estimates of intent-to-treat effects. To see this, assume average values of $b = 39\%$ and

Share Gains$_t$ = 75% and temporarily ignore the role of Section 179 by setting Share 179$_t$ = 0. Equation C.1 then suggests that to recover the ATOT we would need to divide our estimates by Share Gains$_t$ = 75%, which would increase their magnitude by 33% ($\approx \frac{1}{0.75}$).

To understand the role of Share 179$_t$, assume that Share Gains$_t$ = 1 and b = 39%. To obtain the equivalent effect of an average bonus rate of b = 39% absent Section 179, we would need to multiply our estimates by: $\frac{39\%}{39\%+(1-39\%)\times 8\%} \approx 0.89$, which would make them 11% smaller. For instance, column (2) in Table 1 shows that the average increase in employment from an IQR increase in exposure to bonus depreciation was 1.9%. Accounting for the role of Section 179, our estimate would be $1.7\% = 1.9\% \times 0.89$.

To offset the effects of both losses and Section 179, we would have to multiply our estimates by $\frac{39\%}{75\%\times[39\%+(1-39\%)\times 8\%]} \approx 1.19$. The combined effect of losses and Section 179 would be to make our estimates 19% larger. Absent Section 179 and in a world where no firms were constrained in claiming bonus due to loss effects, we would expect to find an increase in employment of $2.3\% = 1.9\% \times 1.19$.

Similarly, suppose that we are interested in evaluating the effects of a policy where b = 50% for a decade. Again, assuming no Section 179 and no frictions from corporate losses, we would expect an increase in employment of $2.9\% = 1.9\% \times 1.52$ where $1.52 = \frac{50\%}{75\%\times[39\%+(1-39\%)\times 8\%]}$.

Adjusting Dynamics of Reduced-Form Effects for Losses and Section 179

As discussed above, while corporate losses and Section 179 expensing interact with bonus depreciation, accounting for these interactions has small effects on the interpretation of our average estimates. An additional concern is that the time patterns in b, Share Gains$_t$, and Share 179$_t$ influence the dynamics of the effects shown in Figure 2. We now perform similar adjustments as above to show that this is not the case.

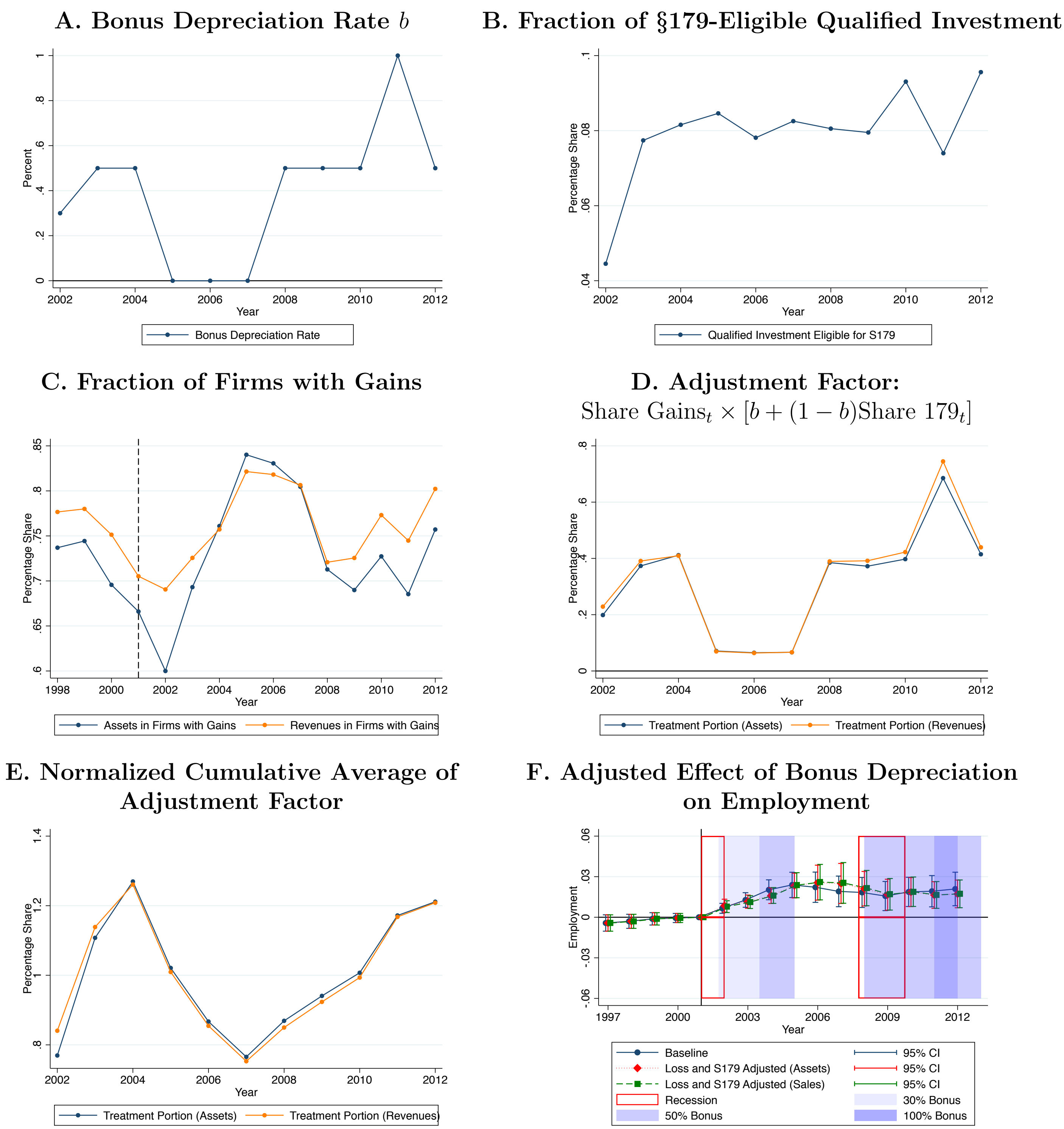
Conceptually, Equation C.1 shows that our treatment is time-varying, and that the intensity of the policy depends on the time patterns of b, Share Gains$_t$, and Share 179$_t$. The goal of this exercise is to use our estimates and the time patterns in b, Share Gains$_t$, and Share 179$_t$ from Figures C1A-C1C to compare the observed policy to a counterfactual policy where b, Share Gains$_t$, and Share 179$_t$ are held constant at their average values over our time period.

To do so, Figure C1D plots the value of the adjustment factor Share Gains$_t$ $\times [b + (1-b)$Share 179$_t]$ over time. This plot mostly follows the time path of b; however, the amplitude of the curve is diminished by Share Gains$_t$ and the minimum value is augmented by Share 179$_t$. Because outcomes in a given year t are affected by the policy in previous years, we adjust our estimates by the cumulative average of Share Gains$_t$ $\times [b + (1-b)$Share 179$_t]$ from 2001 until a given year t. Figure C1E plots this cumulative average relative to the average value of Share Gains$_t$ $\times [b + (1-b)$Share 179$_t]$ over the time period. We can then divide our estimates in Figure 2 by the values of Figure C1E to obtain the reduced-form effects of a policy where b, Share Gains$_t$, and Share 179$_t$ are held constant at their average values over our time period. Figure C1D shows that a time-consistent policy would result in larger effects in years 2002 and 2006-2009. Similarly, this adjustment would imply smaller effects in years 2003-2004 and 2011-2012.

Figure C1F shows that adjusting our estimates on the effects of bonus depreciation on employment so that they have a time-consistent interpretation results in very similar effects. The largest change is that we observe a slightly larger effect in years 2006-2007.

Overall, the pattern of losses and Section 179 expensing do not play a material role in explaining the dynamics of how bonus depreciation affects the labor market. For this reason, we present the unadjusted results in the paper. This result is also consistent with results in Zwick and Mahon (2017) that show that business investment was similarly responsive to bonus depreciation in the early and latter years of our sample.

Figure C1: Adjusting for Losses and Section 179 in the Employment Effects of Bonus Depreciation



Notes: Author's calculations using employment data from QCEW, industry duration data from Zwick and Mahon (2017), net operating loss shares from IRS (2017), and Section 179 use from authors calculations and results reported in Kitchen and Knittel (2016). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation that is adjusted for national net operating losses and access to Section 179. Section C discusses a correction to our baseline estimates that adjusts for the intensity of treatment from Bonus in a given year due to interactions with losses and Section 179. Figure C1A shows the bonus rate b for each year. Figure C1B shows the fraction of total investment that is eligible for Section 179 deductions. Figure C1C shows the percent of assets and revenues in firms that do not have losses. Figures C1A, C1B, and C1C combine into Figure C1D, the adjustment factor, and Figure C1E, the normalized cumulative average adjustment factor. Dividing the regression results from Figure 2A by the adjustment factor yields the adjusted effect of Bonus on Employment shown in Figure C1F.

D Effects of Bonus Depreciation on the Employment-to-Population Ratio

One potential mechanism behind the increase in employment is the geographic relocation of workers. In order to account for this factor, we estimate the effects of our shock on the employment-to-population ratio, as in Autor et al. (2013).

Figure D1 plots the results of this analysis and shows that, similar to Figure 2, the effects of bonus depreciation on employment crest in 2006.[22] This figure shows that, by 2006, a unit IQR increase in Exposure increases the employment-to-population ratio by 1 percentage point.

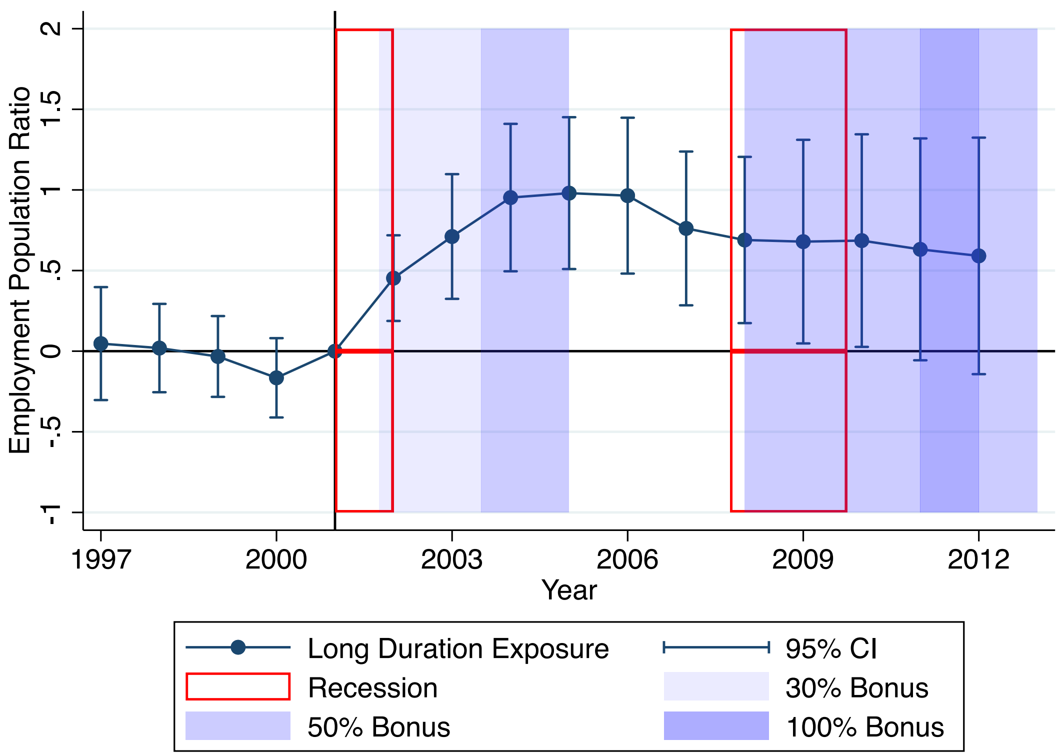
Overall, the average effect for years 2003-2012 is that a unit IQR increase in Exposure raised the employment-to-population ratio by 0.76 percentage points. Relative to the average US working-age population during our period of 195 million, this implies that the average effect of Exposure would be to raise employment by 4.06 million jobs. Comparing this employment effect with the cost of the policy implies a cost-per-job of \$73,000 $\left(\approx \frac{297.5}{4.06}\right)$.

Our discussion in the paper focuses on the cost of creating a job in a given location. For this reason, our main estimate of \$53,000 is smaller than the estimate of \$73,000, which applies to the cost of creating a job relative to a given population. We choose to focus on the percentage change in employment since this outcome is comparable to previous work on local fiscal multipliers.

Finally, it is worth noting that the dynamics of the effects of bonus depreciation in Figure D1 are similar those of our main result in Figure 2A. Specifically, bonus depreciation has temporary effects on employment. While these level effects are persistent, bonus depreciation does not lead to sustained increases in the rate of employment growth.

[22] These regressions use the county-year outcome as the unit of observations, which does not allow us to control for industry by year fixed effects. For details regarding this specification, see Appendix F of an earlier version of this article in NBER Working Paper 25546.

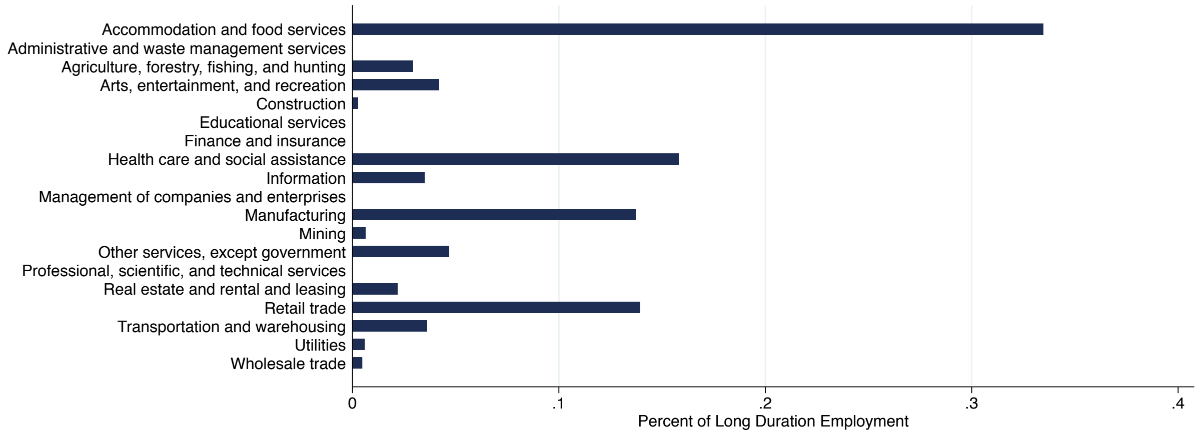
Figure D1: Effects of Bonus Depreciation on Employment-to-Population Ratio



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is the change in in the Employment-to-Population ratio. The variable of interest is the percent of employment that is resides in long duration industries normalized to the interquartile range (IQR). For more information on this calculation, see Appendix D. Standard errors are clustered at the county level.

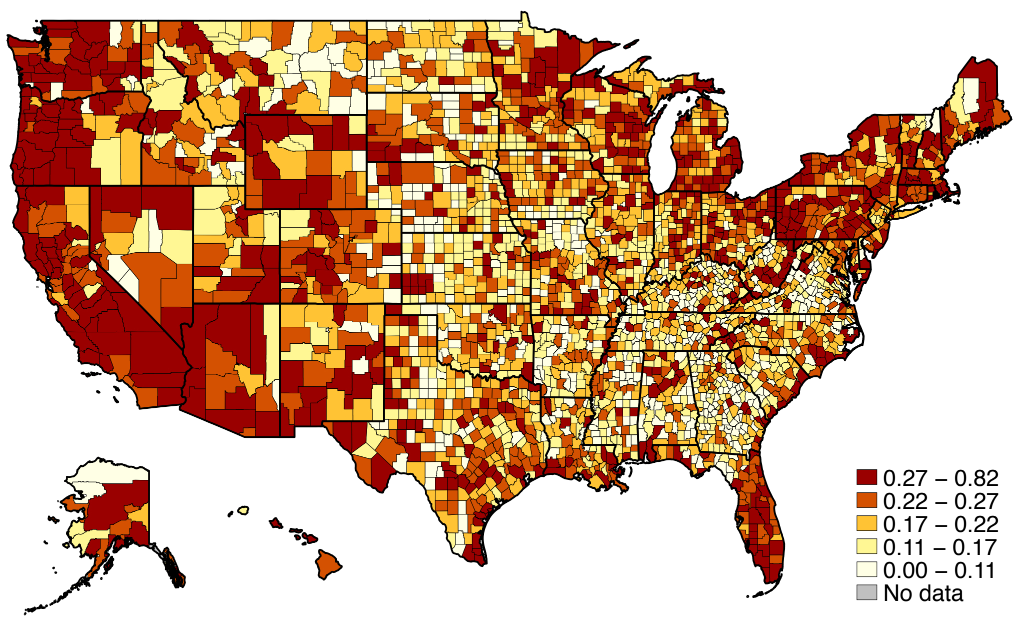
E Additional Figures and Tables

Figure E1: Percent of Long Duration Employment Derived from Each 2-digit NAICS



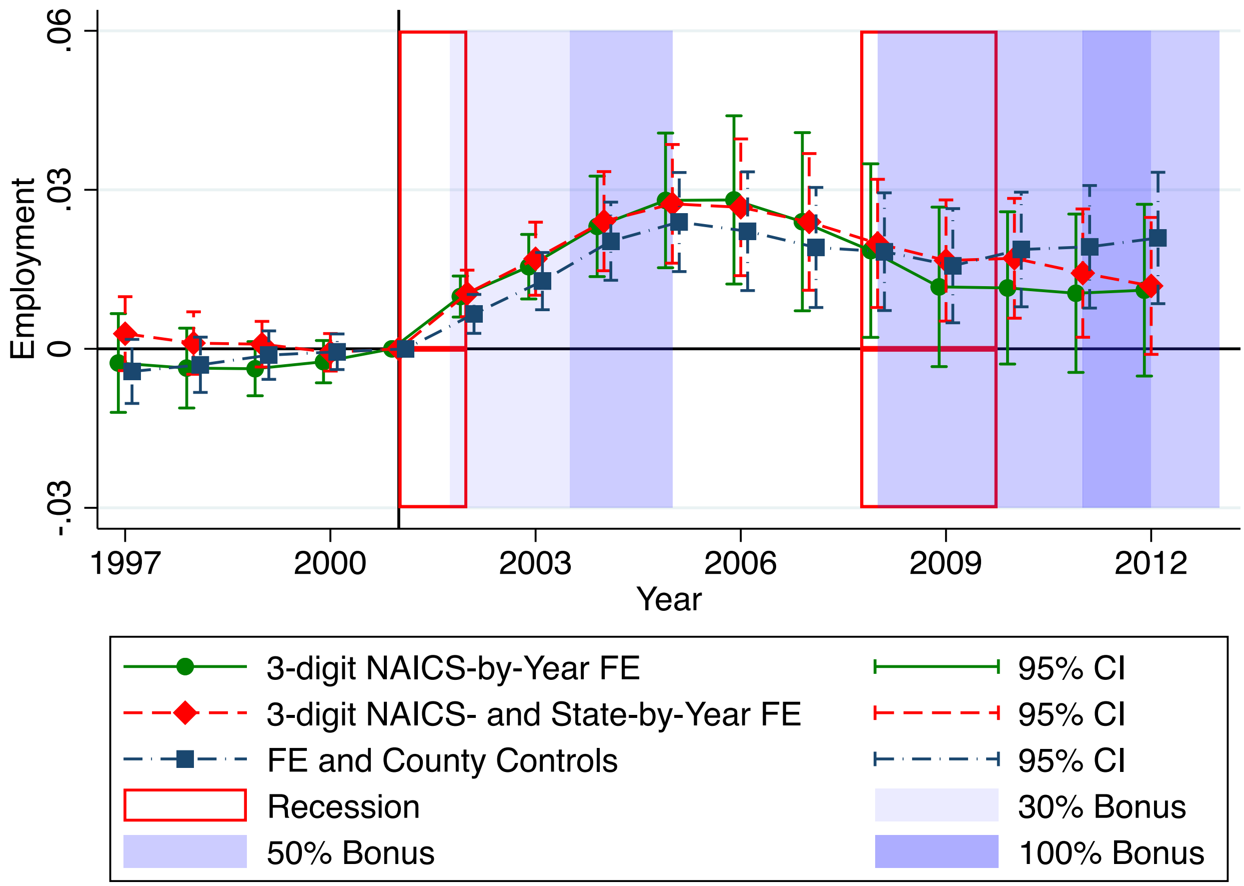
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the percent of long duration employment coming from each sector as defined by 2-digit NAICS in 2001. Data are at the national level.

Figure E2: Exposure to Long Duration Industries in 2001, Raw



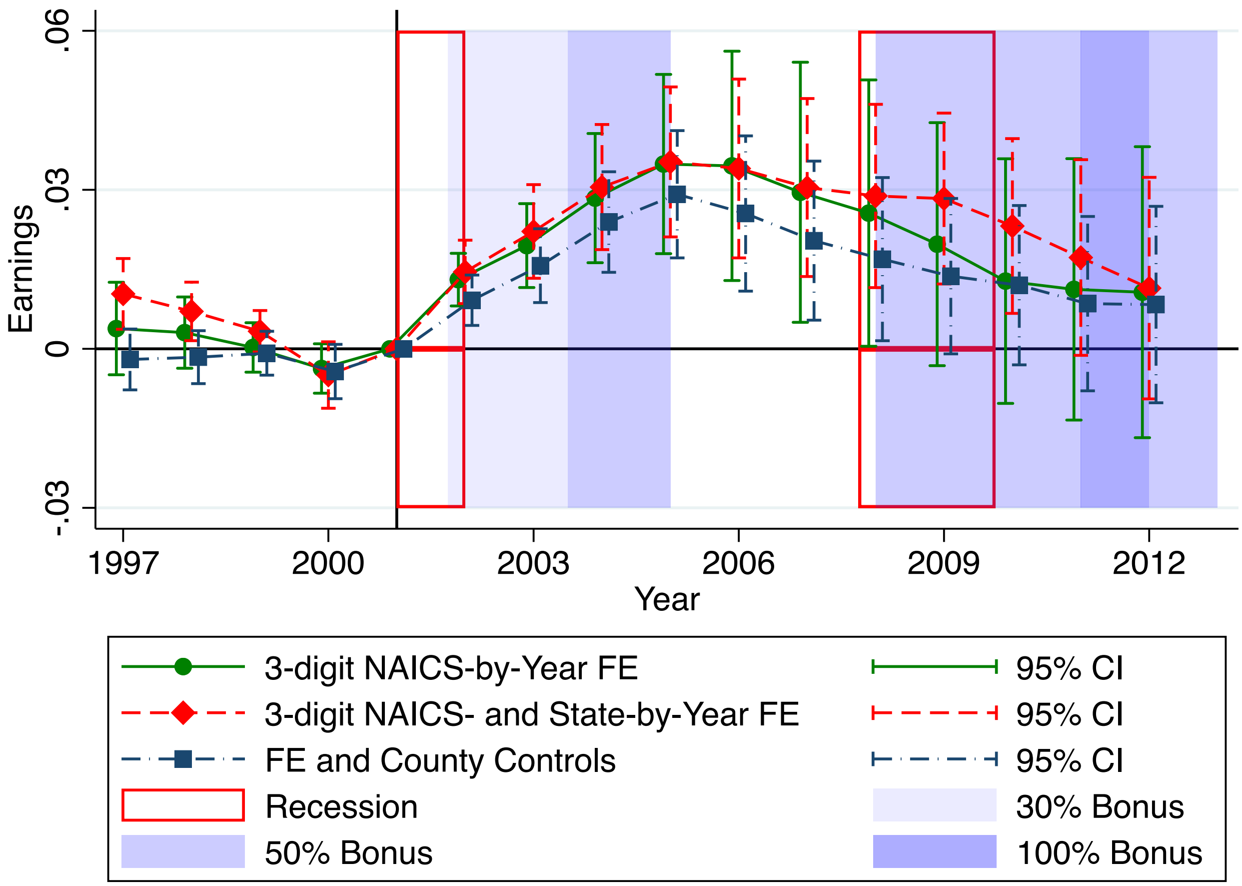
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the percent of employment in each county that comes from the top three deciles of employment-weighted industries by average duration of investment. Industries are defined by 4-digit NAICS codes. A version of this map normalized to standard deviations from state-level mean is shown in Figure 1.

Figure E3: Employment Effects of Bonus Depreciation, Controls Robustness



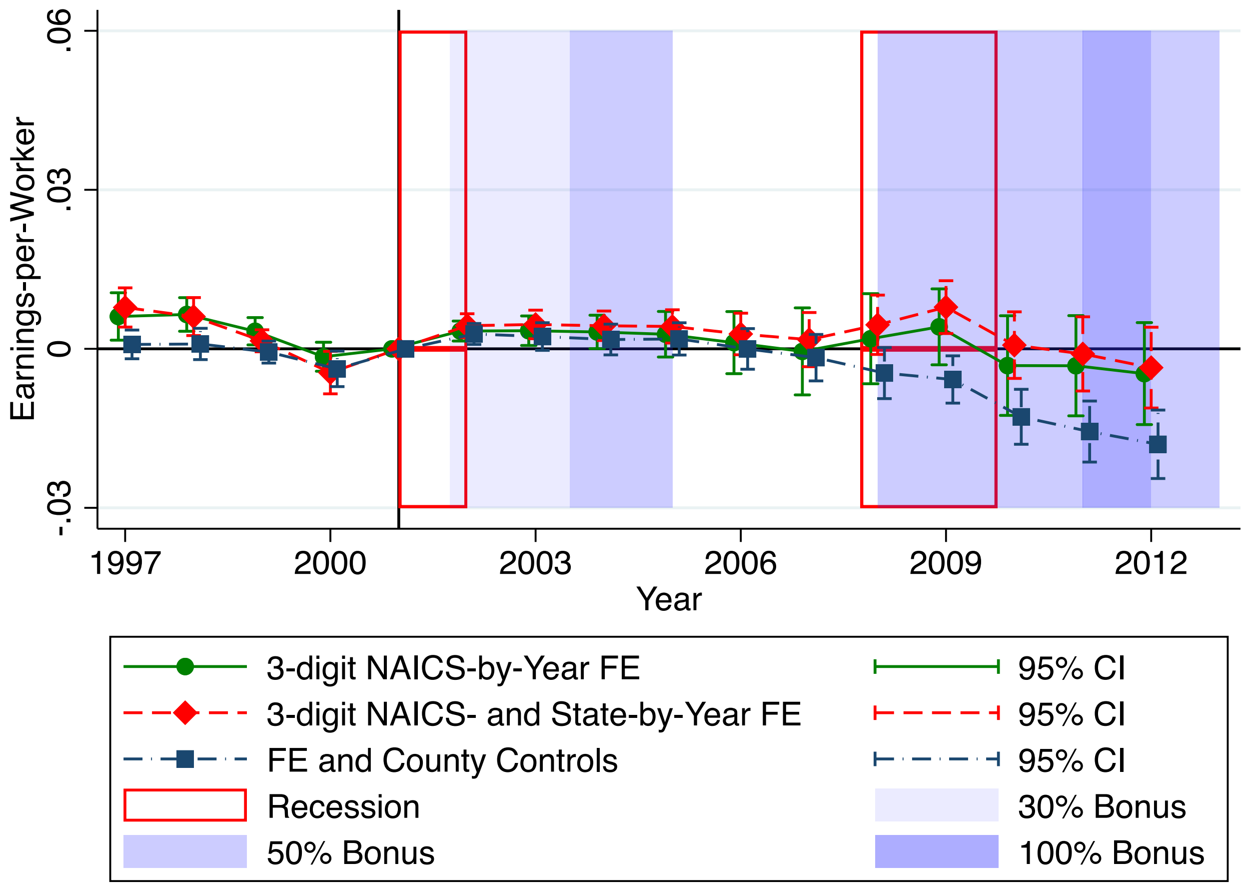
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable in Figure E3 is employment relative to 2001. The covariate of interest is exposure to long duration, as in Figure 2A. The coefficients and additional specifications for Figure E3 are shown in Table E4. See Appendix B for additional discussion about the importance of controls. Standard errors are clustered at the county level.

Figure E4: Earnings Effects of Bonus Depreciation, Controls Robustness



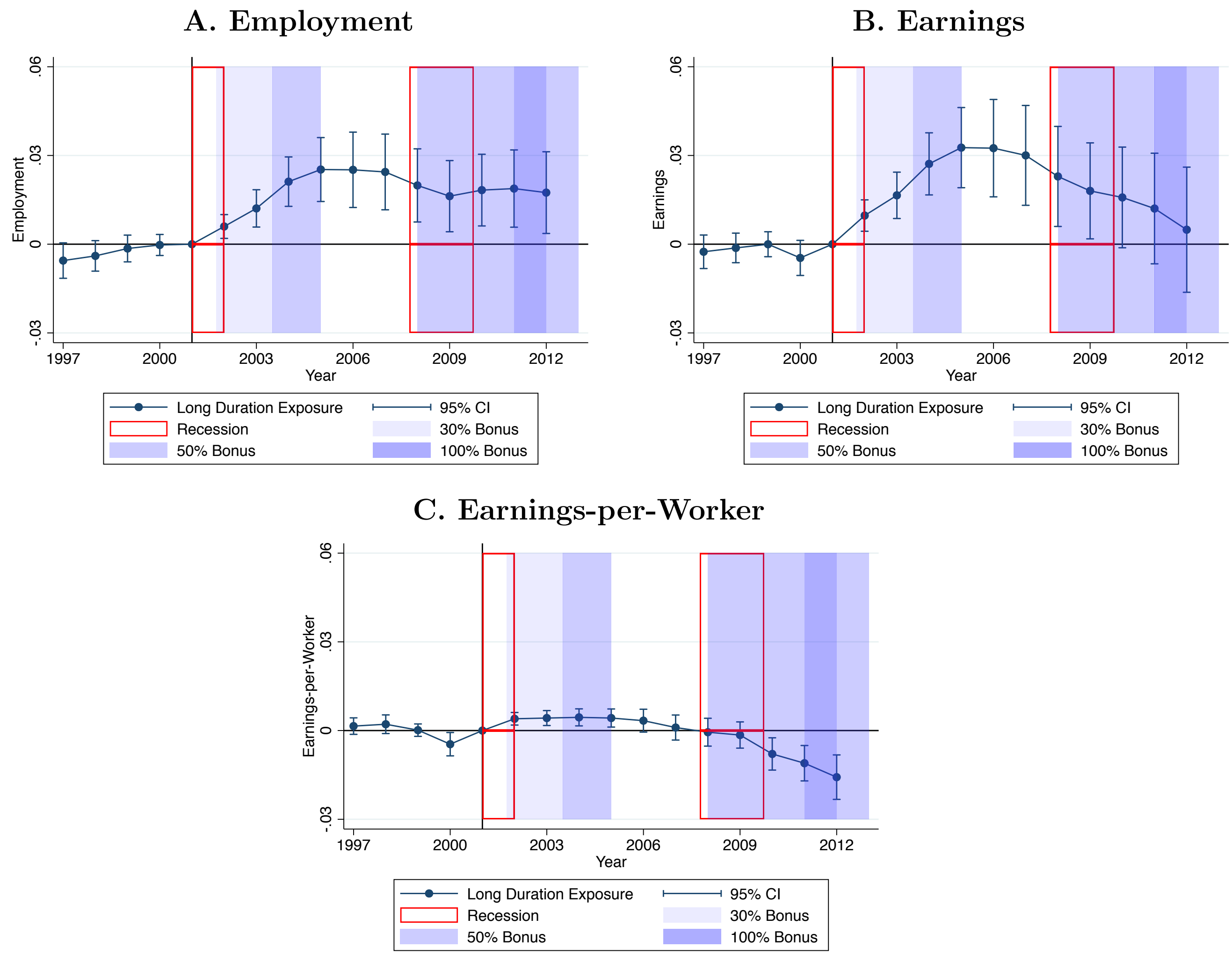
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable in Figure E4 is earnings relative to 2001. The covariate of interest is exposure to long duration, as in Figure 2B. The coefficients and additional specifications for Figure E4 are shown in Table E5. See Appendix B for additional discussion about the importance of controls. Standard errors are clustered at the county level.

Figure E5: Earnings-per-Worker Effects of Bonus Depreciation, Controls Robustness



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable in Figure E5 is earnings-per-worker relative to 2001. The covariate of interest is exposure to long duration, as in Figure 2C. The coefficients and additional specifications for Figure E5 are shown in Table E6. See Appendix B for additional discussion about the importance of controls. Standard errors are clustered at the county level.

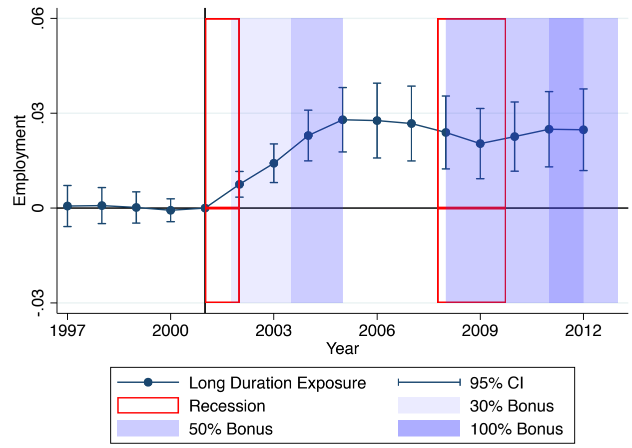
Figure E6: Effects of Bonus Depreciation by Exposure to Long Duration Industries, Long Duration Cutoff at 25%



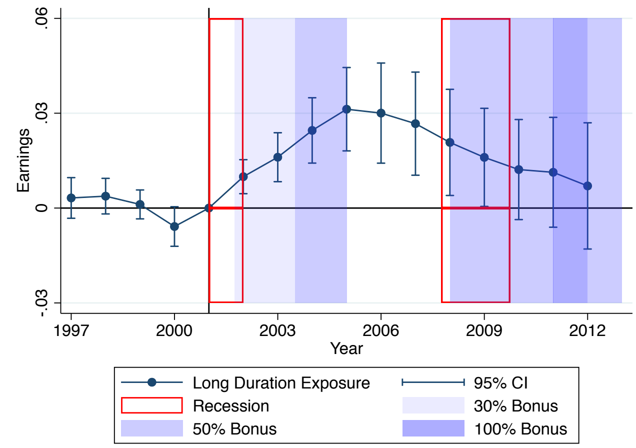
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure E6A, Earnings in Figure E6B and Earnings-per-Worker in Figure E6C. The variable of interest is the percent of employment that is resides in long duration industries normalized to the interquartile range (IQR). These regressions correspond to those displayed in Figure 2 with long duration industries defined at the 25% cutoff instead of 33%.

Figure E7: Effects of Bonus Depreciation by Exposure to Long Duration Industries, Long Duration Cutoff at 40%

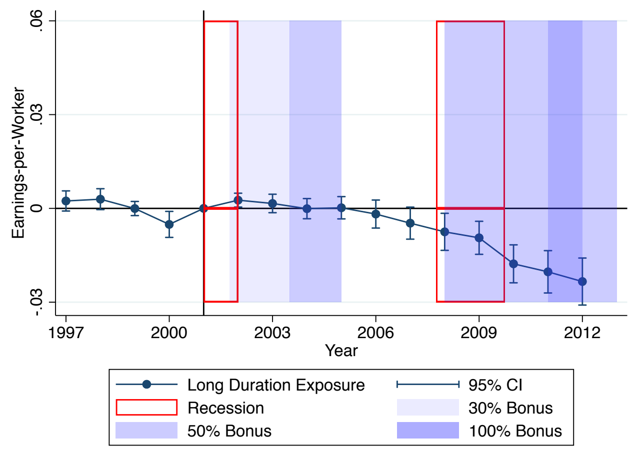
A. Employment



B. Earnings



C. Earnings-per-Worker



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure E7A, Earnings in Figure E7B and Earnings-per-Worker in Figure E7C. The variable of interest is the percent of employment that is resides in long duration industries normalized to the interquartile range (IQR). These regressions correspond to those displayed in Figure 2 with long duration industries defined at the 40% cutoff instead of 33%.

Table E1: Characteristics of Investment Duration by Sector

NAICS	Industry	Average	SD	CV	Employment	Capital	Variation
11	Agriculture, forestry, fishing, and hunting	0.862	0.010	1.160	0.945	3.658	0.116
21	Mining	0.881	0.008	0.940	0.382	2.353	0.038
22	Utilities	0.767	0.032	4.110	0.183	6.613	0.079
23	Construction	0.894	0.003	0.320	7.300	3.183	0.247
31-33	Manufacturing	0.880	0.008	0.870	10.892	24.917	1.000
42	Wholesale trade	0.888	0.004	0.450	5.295	4.875	0.251
44-45	Retail trade	0.881	0.009	1.010	15.518	3.929	1.654
48-49	Transportation and warehousing	0.890	0.016	1.830	3.633	9.191	0.702
51	Information	0.879	0.018	2.070	3.033	10.031	0.663
52	Finance and insurance	0.887	0.006	0.700	4.387	8.860	0.324
53	Real estate and rental and leasing	0.878	0.019	2.180	2.157	7.638	0.496
54	Professional, scientific, and technical services	0.893	0.003	0.300	7.489	2.527	0.237
55	Management of companies and enterprises	0.880	.	.	1.811	0.928	.
56	Administrative and waste management services	0.892	0.003	0.280	8.157	1.639	0.241
61	Educational services	0.885	.	0.000	1.663	0.559	0.000
62	Health care and social assistance	0.880	0.009	1.070	11.038	4.794	1.246
71	Arts, entertainment, and recreation	0.858	0.015	1.800	1.393	0.767	0.265
72	Accommodation and food services	0.870	0.004	0.460	10.750	2.148	0.522
81	Other services, except government	0.876	0.011	1.250	3.974	1.389	0.524

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This table shows the average duration characteristics of each 2-digit NAICS sector. The Variation column shows within-sector variation, defined as the coefficient of variation multiplied by the employment weight, relative to manufacturing in 2001. Sector variables are calculated by aggregating data at the industry level using employment shares from QCEW.

Table E2: List of Counties by Exposure to Long Duration Industries

Rank	County	Long Duration Employment Exposure
1	Kent County, Delaware	.1132373
2	Durham County, North Carolina	.1204463
3	Forsyth County, Georgia	.1347249
4	Sullivan County, Tennessee	.1513936
5	Olmsted County, Minnesota	.1519782
6	Catawba County, North Carolina	.1568298
7	Rankin County, Mississippi	.1573195
8	Sarpy County, Nebraska	.1583619
9	New Castle County, Delaware	.1604007
10	Clayton County, Georgia	.161008
508	Clark County, Nevada	.4558978
509	Cape May County, New Jersey	.4573346
510	Merced County, California	.4581397
511	Napa County, California	.4653518
512	Fresno County, California	.471666
513	Yuma County, Arizona	.4897471
514	Monterey County, California	.4994023
515	Yakima County, Washington	.5202556
516	Tulare County, California	.5315269
517	Atlantic County, New Jersey	.5559594

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This table lists the top ten and bottom ten major counties based on their exposure to long duration industries. This list only includes counties with more than 100,000 in population in 2000.

Table E3: County Level Descriptive Statistics

	Mean	SD	25^{th}	50^{th}	75^{th}
Total Population, 2001	92217.745	298364.878	11596.000	25449.000	63130.000
Total Employment	34587.489	126911.918	2338.000	6426.000	19019.000
Employment Growth, 2001-2007	0.053	0.185	-0.040	0.038	0.122
Employment Growth, 2001-2012	0.025	0.269	-0.101	-0.005	0.107
Number of 3-Digit NAICS Industries	36.540	20.004	20.000	35.000	50.000
County Capital					
Equipment Stock, 2001	1226.515	5151.298	43.399	165.312	576.610
Intellectual Property Stock, 2001	430.718	2053.905	4.027	22.121	133.989
Exposure to Bonus Depreciation					
Average NPV of Depreciation (No Bonus)	0.879	0.005	0.877	0.879	0.882
Long Duration Exposure	0.206	0.096	0.142	0.203	0.259
Long Duration Exposure, 25%	0.168	0.087	0.111	0.160	0.210
Long Duration Exposure, 40%	0.256	0.113	0.178	0.257	0.331
Exposure to Non-Eligible Long Duration	0.021	0.036	0.003	0.012	0.026

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This table displays descriptive characteristics of the county level exposure to long duration industries. The Mean column displays the mean across counties and the SD column displays the standard deviation. The following three columns display the 25^{th}, 50^{th}, and 75^{th} percentile of the distribution, respectively.

Table E4: Event Study Regression of Total Employment on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)	(5)
X 1997	-0.003	0.003	-0.004	-0.003	0.000
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
X 1998	-0.004	0.001	-0.003	-0.004	0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
X 1999	-0.004	0.001	-0.001	-0.003	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
X 2000	-0.002	-0.001	-0.001	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
X 2002	0.010***	0.010***	0.007***	0.004***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
X 2003	0.015***	0.017***	0.013***	0.010***	0.013***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)
X 2004	0.023***	0.024***	0.020***	0.016***	0.020***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.005)
X 2005	0.028***	0.027***	0.024***	0.020***	0.026***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.006)
X 2006	0.028***	0.027***	0.022***	0.018***	0.024***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.008)
X 2007	0.024***	0.024***	0.019***	0.016***	0.021***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
X 2008	0.019**	0.020***	0.018***	0.016***	0.019**
	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
X 2009	0.012	0.017***	0.016***	0.013**	0.017**
	(0.008)	(0.006)	(0.005)	(0.005)	(0.008)
X 2010	0.011	0.017***	0.019***	0.016***	0.021***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.008)
X 2011	0.010	0.014**	0.019***	0.017***	0.021**
	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
X 2012	0.011	0.012*	0.021***	0.019***	0.025***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.009)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of total employment. The dependent variable is the percent change in total Earnings relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (3) is corresponds to Figure 2A.

Table E5: Event Study Regression of Total Earnings on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)	(5)
X 1997	0.004	0.010***	-0.002	-0.002	0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
X 1998	0.003	0.007**	-0.002	-0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
X 1999	0.000	0.003*	-0.001	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
X 2000	-0.004	-0.005	-0.004	-0.003	-0.005
	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
X 2002	0.013***	0.015***	0.009***	0.007***	0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
X 2003	0.019***	0.022***	0.016***	0.012***	0.016***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)
X 2004	0.028***	0.031***	0.024***	0.019***	0.024***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.006)
X 2005	0.035***	0.035***	0.029***	0.025***	0.033***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.008)
X 2006	0.035***	0.034***	0.026***	0.022***	0.029***
	(0.011)	(0.009)	(0.007)	(0.007)	(0.010)
X 2007	0.030**	0.030***	0.020***	0.018**	0.026**
	(0.013)	(0.009)	(0.008)	(0.007)	(0.010)
X 2008	0.026**	0.029***	0.017**	0.015**	0.021*
	(0.013)	(0.009)	(0.008)	(0.007)	(0.011)
X 2009	0.020*	0.028***	0.014*	0.011	0.017
	(0.012)	(0.008)	(0.007)	(0.007)	(0.011)
X 2010	0.013	0.023***	0.012	0.012	0.016
	(0.012)	(0.008)	(0.008)	(0.007)	(0.011)
X 2011	0.011	0.017*	0.009	0.009	0.013
	(0.013)	(0.009)	(0.008)	(0.008)	(0.012)
X 2012	0.011	0.011	0.008	0.010	0.017
	(0.014)	(0.011)	(0.009)	(0.009)	(0.013)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of total Earnings. The dependent variable is the percent change in total earnings relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. Column (3) is shown as Figure 2B.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E6: Event Study Regression of Earnings-per-Worker on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)	(5)
X 1997	0.006***	0.008***	0.001	0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
X 1998	0.006***	0.006***	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
X 1999	0.003**	0.002	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	-0.001	-0.004**	-0.004**	-0.002*	-0.006**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
X 2002	0.003***	0.004***	0.003***	0.002***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	0.003**	0.005***	0.002*	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
X 2004	0.003**	0.004***	0.002	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
X 2005	0.003	0.004***	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
X 2006	0.001	0.003	-0.000	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
X 2007	-0.000	0.002	-0.002	0.000	0.000
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
X 2008	0.002	0.005	-0.005*	-0.003	-0.003
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
X 2009	0.004	0.008***	-0.006**	-0.005**	-0.004
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
X 2010	-0.003	0.001	-0.013***	-0.009***	-0.012***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.004)
X 2011	-0.003	-0.001	-0.016***	-0.012***	-0.016***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
X 2012	-0.005	-0.004	-0.018***	-0.013***	-0.017***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of earnings-per-worker. The dependent variable is the percent change in earnings-per-worker relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. Column (3) is shown as Figure 2C.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E7: Event Study Regression of Employment on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Placebo Industries	(1)	(2)	(3)	(4)	(5)
X 1997	-0.009***	-0.002	-0.002	-0.002	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
X 1998	-0.007**	-0.001	-0.001	-0.001	-0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
X 1999	-0.005***	-0.001	-0.000	-0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	-0.002*	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2002	0.001	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	0.004*	0.000	0.001	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
X 2004	0.009**	0.001	0.002	0.002	0.001
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
X 2005	0.013**	0.001	0.002	0.002	0.001
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
X 2006	0.016**	0.001	0.001	0.001	0.000
	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
X 2007	0.016**	0.001	-0.001	0.000	-0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
X 2008	0.015**	0.000	-0.001	-0.000	-0.002
	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
X 2009	0.011**	-0.001	-0.002	-0.002	-0.003
	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)
X 2010	0.010*	-0.001	-0.002	-0.001	-0.003
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
X 2011	0.010*	-0.002	-0.002	-0.001	-0.003
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
X 2012	0.010*	-0.001	-0.002	-0.000	-0.003
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of employment. The dependent variable is the percent change in employment relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries with more than five times more structures and intellectual property than equipment normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. Column (3) is shown in Figure 2D. * $p < 0.1$,
** $p < 0.05$, *** $p < 0.01$.

Table E8: Event Study Regression of Total Earnings on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Placebo Industries	(1)	(2)	(3)	(4)	(5)
X 1997	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 1998	0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 1999	0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
X 2000	0.000	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
X 2002	0.001	0.000	0.001	0.001*	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
X 2003	0.001	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2004	0.002**	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2005	0.004***	0.002**	0.002*	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2006	0.005***	0.003**	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
X 2007	0.006***	0.004**	0.002	0.001	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
X 2008	0.006***	0.004**	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
X 2009	0.006***	0.003**	-0.000	-0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
X 2010	0.005***	0.004**	-0.001	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
X 2011	0.005**	0.004*	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
X 2012	0.003	0.002	-0.003*	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of total earnings. The dependent variable is the percent change in total earnings relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries with more than five times more structures and intellectual property than equipment normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. Column (3) is shown in Figure 2D.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E9: Event Study Regression of Earnings Divided by Employment on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Placebo Industries	(1)	(2)	(3)	(4)	(5)
X 1997	-0.006**	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
X 1998	-0.006***	-0.001	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
X 1999	-0.004***	-0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	-0.001	0.001	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2002	0.002*	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	0.005**	0.000	0.000	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
X 2004	0.012***	0.002	0.002	0.003	0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
X 2005	0.019***	0.004	0.003	0.004	0.003
	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
X 2006	0.024***	0.004	0.002	0.003	0.002
	(0.008)	(0.005)	(0.004)	(0.005)	(0.005)
X 2007	0.027***	0.005	0.001	0.002	0.000
	(0.009)	(0.005)	(0.005)	(0.005)	(0.006)
X 2008	0.026***	0.005	0.000	0.001	-0.001
	(0.009)	(0.005)	(0.005)	(0.006)	(0.006)
X 2009	0.020***	0.002	-0.003	-0.003	-0.004
	(0.008)	(0.005)	(0.005)	(0.006)	(0.006)
X 2010	0.019***	0.003	-0.004	-0.003	-0.003
	(0.007)	(0.005)	(0.005)	(0.006)	(0.006)
X 2011	0.019***	0.002	-0.005	-0.003	-0.005
	(0.007)	(0.005)	(0.006)	(0.007)	(0.007)
X 2012	0.019**	0.002	-0.005	-0.002	-0.006
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
3-digit Industry-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed Effects		Yes	Yes	Yes	Yes
County Characteristics			Yes	Yes	Yes
Winsorized Weights				Yes	
Drops Small County-Industries (<1000)					Yes

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). The coefficients displayed in this table come from an event study regression of total earnings divided by employment. The dependent variable is the percent change in total earnings divided by employment relative to 2001. The variable of interest is the percent of employment that is derived from long duration industries with more than five times more structures and intellectual property than equipment normalized to the interquartile range (IQR). Standard errors clustered at the county level are shown in parentheses. Column (3) is shown in Figure 2D.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.