NBER WORKING PAPER SERIES

TAX POLICY AND LOCAL LABOR MARKET BEHAVIOR

Daniel G. Garrett
Eric C. Ohrn
Juan Carlos Suárez Serrato

Working Paper 25546
http://www.nber.org/papers/w25546

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2019

We are very grateful for comments and suggestions from Joe Altonji, Pat Bayer, Allan Collard-Wexler, Mark Curtis, Yuriy Gorodnichenko, Xian Jiang, Matthias Kehrig, Andrea Lanteri, Chad Syverson, Chris Timmins, Daniel Xu, Owen Zidar, and Eric Zwick, as well as for comments from seminar participants at Duke and NTA. All errors remain our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2019 by Daniel G. Garrett, Eric C. Ohrn, and Juan Carlos Suárez Serrato. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Tax Policy and Local Labor Market Behavior
Daniel G. Garrett, Eric C. Ohrn, and Juan Carlos Suárez Serrato
NBER Working Paper No. 25546
February 2019
JEL No. E62,H25,H32,J23,J38

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 differences in policy generosity interacted with county-level variation in industry concentration. Places that experience larger decreases in investment costs see a level increase in employment that implies a $53,000 cost-per-job. We find no positive effects on average earnings. In contrast, we document a persistent growth in capital. These results imply a capital-labor substitution elasticity that grows over time and can exceed unity.

Daniel G. Garrett
Duke University
213 Social Sciences
Durham, NC 27705
daniel.garrett@duke.edu

Eric C. Ohrn
Grinnell College
1226 Park St.
Grinnell IA 50112
ohrneric@grinnell.edu

Juan Carlos Suárez Serrato
Department of Economics
Duke University
213 Social Sciences Building
Box 90097
Durham, NC 27708
and NBER
jc@jcsuarez.com

The Tax Cuts and Jobs Act (TCJA) of 2017 allows firms to immediately deduct or "expense" capital investments from their taxable income, effectively making business investment cheaper. While previous research has shown that similar policies implemented during the previous two decades significantly increased capital investment, the effects of these accelerated depreciation policies on the labor market have not been rigorously evaluated. This empirical void is startling given that job creation and wage growth are central goals of investment tax incentives and that expensing will cost the federal government $119.4 billion over the next five years (JCT, 2017).

This paper provides the first in-depth analysis of the effects of accelerated depreciation policies on employment and earnings by estimating how bonus depreciation affects local labor markets. 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 the benefits of the policy. 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.

Our main result is that, even though bonus depreciation stimulated investment, the ultimate goal of sustained job creation and wage growth proved elusive. While we document that more exposed areas saw a level increase in employment, the number of jobs created was small relative to the cost of the policy. Similarly, we find temporary earnings gains that dissipate by 2012. Comparing the continued growth in capital to the short-lived employment gains implies a growing pattern of substitution from labor to capital. Thus, while bonus depreciation stimulated capital, it is hard to motivate the future use of similar policies on the grounds of helping workers.

We develop these results in four steps. First, we quantify the cumulative effects of our exposure measure on employment growth between 2002–2012. We find that bonus depreciation had a level effect on 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 1.9% on average over our sample period. Relative to the cost of the policy, this employment increase implies a relatively high cost-per-job created of $53,000.

From the perspective of the labor market, bonus depreciation could be an effective stimulus if the stalled employment growth we observe is coupled with increases in productivity and wages. In a second step, we find that bonus depreciation led to a short-lived increase in total earnings that crests in 2005. We then see a retraction of these earnings gains, which all but disappear by 2012. We do not find a positive effect on earnings-per-worker.

One hypothesis that could explain the lackluster effects on the labor market would be that bonus depreciation only had a short-term effect on capital accumulation. As a third step, we explore whether the stock of equipment capital responds to the policy. Juxtaposing the labor market effects, we find significant and persistent increases in the capital stock. These results are in line with Zwick and Mahon (2017, henceforce ZM), who show that bonus has similar effects on investment in the early and late periods of our sample.[1] Together the investment, employment, and earnings responses suggest that instead of generating persistent growth in jobs and wages, capital deepening was followed by a pattern of substitution away from labor.

In our final step, we leverage our unique empirical setting to estimate whether this tax incentive leads firms to substitute labor for capital. Since both capital and labor increase until 2005, we initially find no evidence of substitution between capital and labor. However, by 2010, we find that a one percent decrease in the relative cost of capital caused capital to increase by *more* than 1% relative to labor. These dynamics imply that over time it becomes easier for firms to replace workers with machines.

Our empirical findings 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, our results are robust to including subsector-by-year fixed effects suggesting that differing labor market trends across subsectors are not driving our results. Third, our results are also robust to including state-by-year fixed effects; state-level policies or shocks do not confound our results. 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 equip-

[1] House and Shapiro (2008) also find persistent effects on investment after the early years of bonus depreciation.

ment. Our placebo test shows that our estimates are due to the policy itself and not to trends in industries with longer-lived assets. Finally, any challenge to our identification strategy needs to account for the persistent effects on capital accumulation. 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, 2011; 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 (Kovak et al., 2017; Arulampalam et al., 2012; Fuest et al., 2018; Suárez Serrato and Zidar, 2016; Nallareddy et al., 2018; Yagan, 2015). In particular, this paper shows that national policies, such as a federal tax policy, can have large effects on local labor markets (Autor et al., 2016; Kline and Moretti, 2014; Dix-Carneiro and Kovak, 2017; Suárez Serrato, 2018). Finally, our empirical setting provides a unique opportunity to estimate the elasticity of substitution between labor and capital. In doing so, we provide new estimates that contribute to the literature studying this central elasticity (Caballero et al., 1995; Chirinko et al., 2011; Oberfield and Raval, 2014; Doraszelski and Jaumandreu, 2018; Raval, 2018).

Our results are immediately relevant for policy makers concerned with job creation and wage growth. If the estimated trends in the substitution between capital and labor persist, then incentives for capital accumulation in the TCJA will likely have small effects on employment and wage growth and may induce investment in labor-replacing capital. Policy makers looking to stimulate labor markets with these tax incentives for capital accumulation should proceed with extreme caution.

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% bonus depreciation was first enacted in 2002 as part of the Job Creation and Worker Assistance Act. The policy was initially understood to be temporary, but it was extended to 2003–2004 at a higher, 50% rate. Bonus depreciation was turned off in 2005–2007 before it was re-implemented in response to the 2008 recession. Apart from 2011, when bonus was set at 100% (i.e., immediate expensing), bonus depreciation was available at 50% between 2008–2017. In 2017, TCJA set the bonus rate at 100% for investments made after September 27, 2017, and before January 1, 2023. Overall, the average value of bonus in our sample period of 2002–2012 was 39% and it decreased the after-tax present value cost of new investments by about 2.25% (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 was turned off in 2005. Using financial statement data, Edgerton (2010) found that bonus depreciation created strong investment incentives even for firm 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% bonus depreciation would raise workers' wages

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

[3] Other countries and US states also provide bonus-like policies. Maffini et al. (2016), Criscuolo et al. (2012), and Zhang et al. (2018) find strong investment responses to similar policies in the UK and China, and Ohrn (2018b) finds state-level bonus depreciation increased investment but not employment.

(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, compensation, and wages. 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 subsector-level treatment data from ZM and county-level subsector composition data from the Quarterly Census of Employment and Wages (QCEW).

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.

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

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 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% 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_j^0, which measures the present value of depreciation deductions for the average asset in which industry j invests. It is worth noting that z_j^0'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_j^0'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_j^0's. As shown in Figure 1A, there is considerable within-sector variation in z_j^0'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_j^0 distribution.[6] The sector with the largest share of employment among treated industries is Accommodation and Food Services with 33%. Industries in the Manufacturing, Retail Trade, and Health Care and Social Assistance sectors contribute an additional 40% of the employment in long duration industries.[7]

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

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

[5] Table G1 summarizes z_j^0's by sector.

[6] Since the distribution of z_j^0 is left-skewed, we identify the industries that are most affected by the policy. 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.

[7] Figure G1 shows the fraction of long-duration employment by sector.

the percentage of employees in each county working in treated industries in the year 2001. For example, our county-level Exposure measure would be 0.2 if 20% of employees work in treated industries and the remaining 80% work in untreated industries.[8]

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.[9] For example, only 16% of employment in Hunterdon County, New Jersey, occurs in long-duration industries. Meanwhile, 56% of employment in nearby Atlantic County, New Jersey, occurs 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

$$\Delta Emp_{cjt} = \alpha + \sum_{y=1997}^{2012} \beta_y \left[\mathbf{Exposure}_c \times \mathbb{1}(t = y) \right] + \mathbf{X'}_c \boldsymbol{\gamma}_t + \mu_{st} + \nu_{jt} + \epsilon_{cjt}, \tag{2}$$

where

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

is defined as the county-by-subsector percentage change in employment between year t and 2001. Because county-by-subsectors vary in size, we weight this regression by the national share of employment in each county-subsector in 2001.[10] We estimate similar specifications to quantify the effects of bonus on total compensation, compensation-per-employee, and the stock of equipment capital. We scale Exposure so the coefficients β_y capture the dynamic effects of an increase in Exposure from the 25th to the 75th percentile of the distribution.

The identifying assumption of Equation 2 is that ϵ_{cjt} is not correlated with our measure of Exposure. The differenced county-subsector outcomes eliminate any concerns that permanent

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

[9] Figure 1B plots Exposure relative to the state mean since our empirical analyses include state-by-year fixed effects. Figure G2 plots a raw measure of exposure. Table G2 lists the most and least Exposed counties.

[10] "Subsectors" denote 3-digit NAICS categories. We use a balanced-panel of county-subsectors as our observational unit because QCEW data provide better coverage at this level. Our results are similar when using county-by-4-digit NAICS outcomes.

level differences across county-subsectors can be correlated with Exposure and drive our results.[11] 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, 2017) or state-level adoption of bonus depreciation (Ohrn, 2018b). We also include subsector-by-time fixed effects, ν_{jt}, which rule out the concern that other industry-by-time variation may be responsible for our empirical results.[12]

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 (Hakobyan and McLaren, 2016), China (Autor et al., 2016), and the domestic production activities deduction (Ohrn, 2018a), the share of routine labor (Autor and Dorn, 2013), tangible and intangible capital stock measures, and demographic characteristics from the 2000 Census.[13]

Because Exposure is defined at the county-level, we cluster standard errors within counties (Cameron and Miller, 2015).

By ruling out level differences, state-by-year shocks, subsector-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 effects of bonus depreciation.

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 county-subsectors with a greater Exposure to bonus depreciation were on similar growth paths before the onset of the policy in 2002. Upon implementation, employment in more Exposed county-subsectors experienced additional growth through 2005, relative to other units. The increase in employment tapered slightly during years 2005–2007 before stabilizing during the 2009–2012 period.[14]

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

[12] 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).

[13] 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 Appendices A-B for more detail.

[14] 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. Figure G3A shows we obtain similar results

Table 1 reports the average effect on employment for years 2003–2012. Our main specification in column (2) shows that increasing the Exposure to bonus depreciation from the 25th to the 75th percentile of the exposure distribution increased employment by 1.9%. Column (1) excludes state-by-year fixed effects. Column (3) winsorizes the employment treatment weights at the 1% level and column (4) limits the analysis to county-subsectors 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-subsectors suggests neither very large nor very small units of observation are primarily responsible for our estimates. Overall, bonus depreciation led to persistent differences in employment across county-subsectors during the period 2003-2012.[15]

To better appreciate the magnitude of this effect, we compare the fiscal cost of the policy to the number of jobs it created. Relative to the 109.3 million workers in the US in 2001 (QCEW, 2018), our estimates suggest that the average Exposure level would increase employment by 5.65 million jobs.[16] Compared to estimates from the GAO (2013) that place the 10 year cost of bonus depreciation at \$297.5 billion, the cost-per-job created is approximately \$53,000.[17]

This cost-per-job is greater than estimates from the literature on fiscal multipliers (Suárez Serrato and Wingender, 2016; Chodorow-Reich, 2017), which place the cost-per-job from government spending closer to \$30,000. Zidar (2017) finds a cost-per-job of \$30,000 when personal income tax cuts are directed to earners in the bottom 10% of the income distribution and \$60,000 when tax cuts are equally split between low and high income earners. Closest to our estimate, Suárez Serrato (2018) finds that repealing tax credits for US multinationals resulted in a cost-per-job of \$48,000. Thus, while bonus depreciation had measurable effects on the labor market, our results suggest that tax cuts to corporations are not the most cost-effective forms of stimulus.

One source of the employment gains from Exposure to bonus may be the geographic relocation of workers. Appendix E shows we obtain similar results when we analyze the effects of bonus on

without controls. Appendix C lists additional robustness checks.

[15] 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.

[16] This follows from an average value of Exposure of 2.72 (IQR units), an effect of 1.9%, and base employment of 109.3 million jobs: $5.65 = 109.3 \times 0.019 \times 2.72$. Since our estimates are based on cross-sectional variation that absorbs general equilibrium effects, we can not directly estimate the macroeconomic effects of bonus depreciation. See Fuchs-Schuendeln and Hassan (2016) for related approaches to estimating effects of macroeconomic policies.

[17] The GAO (2013) estimates that 100% bonus depreciation cost \$76.1 billion for one year. Given the average bonus depreciation level during our sample period was 39%, we calculate a 10 year cost of \$297.5 billion.

the employment-to-population ratio, which accounts for this factor. While we find that bonus has very similar dynamic effects on the employment-to-population ratio, these estimates imply a larger cost-per-job holding population constant of $73,000.

A Effects on Compensation and Compensation per Worker

We extend our analysis of bonus depreciation to county-subsector compensation and compensation per worker in Figures 2B-2C. Cumulative compensation patterns do not differ by Exposure in the pre-period. Upon bonus implementation in 2002, compensation in more Exposed county-subsectors increases substantially relative to less Exposed units. In contrast to employment, the effects on compensation 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 compensation by 1.7% from 2003–2012, on average.

Figure 2C shows that bonus depreciation had no effect on compensation per worker during the pre-period or during the years 2002–2006. Compensation per worker in more exposed county-subsectors then decreases during the 2009–2012 period. Table 1 shows that a one unit of IQR Exposure decreases cumulative compensation per worker by 0.5% during the treatment period. The timing of the decline in compensation per worker coincides with decrease in the compensation effects, suggesting changes in compensation per worker explain some of the later-period decline in total compensation. Overall, the lack of persistent growth in earnings and even slightly negative effects on earnings per worker starkly contradict the prediction that capital deepening would translate into productivity and wage growth.

The compensation 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-subsectors that were most likely to lose jobs to automation (as defined by Autor, 2015) during the 2007–2012 period.[18] Figure 3A presents the results of this exercise and shows that county-subsectors that were most likely to lose jobs to automation were extra responsive in the early years of the policy. These same county-subsectors then saw more rapid declines in cumulative employment after 2006. As many jobs lost to au-

[18]We classify a county-subsector as High Automation if the county-subsector is in the top third of county-subsectors in terms of the percentage of jobs classified by Autor (2015) as the fastest declining industries in 2007–2012. We link occupations to subsectors 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 3A.

tomation were well-paid jobs in production, administration, and sales, the rapid decline in these county-subsectors likely explains some of the later-period declines in compensation and compensation per worker.

B Capital Stock Responses to Bonus Depreciation

We now explore whether the employment and compensation effects we observe are due to response patterns in the policy's primary target: capital accumulation. To apply our methodology to capital, we use BEA data on the Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets to create county-level measures of the stock of equipment capital, K_{ct}. We then calculate the percentage change in capital relative to 2001 for each county to estimate a version of Equation 2.[19]

One limitation of the fact that our capital stock outcome does not vary across subsectors in a given county is that we cannot include subsector-by-year fixed effects in this analysis. Without these fixed effects, we observe that the capital stock declines in counties with greater exposure to bonus depreciation prior to 2002. To correct for these "pre-trends," we employ an estimator proposed by Freyaldenhoven et al. (2018, henceforth FHS). This estimator uses the fact that intellectual property (IP) capital is not eligible for bonus and shares the same pre-trends as equipment capital. The parallel trends in IP allow the estimator to correct for the unobserved confounders behind the equipment pre-trends.[20] Our specification of the effects on capital accumulation then includes the controls mentioned in Section II, state-by-year fixed effects, and the FHS adjustment.

Figure 2D presents the results of our capital stock analysis. A greater exposure to bonus depreciation stimulates growth in the capital stock throughout the treatment period. Accelerations in equipment stock growth are apparent both at policy onset in 2002 and at policy re-implementation in 2008. Notably, House and Shapiro (2008) and ZM also find persistent effects of bonus on capital accumulation. Table 1 shows that, on average, a unit IQR Exposure increases the stock of equipment capital by 3.3% during the period.

The persistent capital effects rule out many potential explanations for the lackluster effects

[19] We focus on percentage changes in the level of capital to match the effects on employment; focusing on investment would capture only the inflows. See Appendix B for details.

[20] Appendix F discusses this estimator and shows that our labor market results are qualitatively unaffected by this correction.

of bonus on the labor market. For instance, these patterns imply our employment results are not the result of long-lived industries being more sensitive to the business cycle.

The capital accumulation effects further contextualize the labor market results. During the first half of the treatment period, capital and employment increased in tandem. Increases in employment led to higher overall compensation but not average wages. In contrast, increases in capital stimulated by bonus depreciation were not matched with additional employment growth during the later half of the treatment period. Instead, the additional capital accumulation in the later years coincided with stagnation in the number of jobs and relative reductions in compensation.

The juxtaposition of persistent increases in capital accumulation with the anemic effects on labor market outcomes casts doubt on the hypothesis that capital deepening may complement the efforts of workers in the modern economy.

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 3B reports the results of this test. Contrasting these flat patterns with Figure 2 suggests that 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 Capital–Labor Substitution in Local Labor Markets

The previous section showed that the bonus-driven capital accumulation had short-lived effects on employment growth and did not translate into wage gains. The data therefore suggest a particular dynamic: capital substitutes for labor and the rate of substitution increases over time. Our empirical setting allows us to directly measure the elasticity of capital-labor substitution and how it changes over time.

Building on Equation 2, we estimate how percent changes in the relative cost of capital, $\Delta\rho_{cjt}$, affect percent changes in the capital-labor ratio, $\Delta\left(\frac{K_{cjt}}{L_{cjt}}\right)$:

$$\Delta\left(\frac{K_{cjt}}{L_{cjt}}\right) = -\sigma\Delta\rho_{cjt} + \mathbf{X'}_c\boldsymbol{\gamma} + \mu_{st} + \nu_{jt} + \epsilon_{cjt}. \quad (3)$$

While Equation 3 can be motivated with a CES production technology (Raval, 2018; Doraszelski and Jaumandreu, 2018), we do not view our estimates of σ as structural parameters. Rather, Equation 3 provides a flexible approach to summarize the substitution patterns in Figure 2. As in Oberfield and Raval (2014), our estimates of σ within local labor markets have a "macro" interpretation that captures substitution across firms with different capital intensities as well as within-firm changes in input use. Relative to prior work, our setting has the advantage of capturing the cumulative effects of a sustained policy experiment on the capital-to-labor ratio.

We construct the capital-labor ratio using QCEW data on employment at the county-subsector and our BEA capital stock measure. We estimate the user-cost for a given year using data on state taxes and investment tax credits, estimates of economic depreciation, and z_j^0.[21] To capture the cumulative effects of bonus on the stock of capital, we define ρ_{cjt} as the cumulative average of yearly cost-of-capital estimates relative to wages using using compensation-per-employee data. All percent changes are relative to 2001 levels and include the FHS adjustment. Equation 3 includes state-by-year and industry-by-year fixed effects and county-level controls.

We identify σ using Exposure as an instrument for $\Delta\rho_{cjt}$. Exposure is a strong instrument for $\Delta\rho_{cjt}$ since bonus depreciation enters directly into ρ_{cjt}. Exposure also has significant effects on employment and capital; intuitively, the reduced-form effect of Exposure on $\Delta\frac{K_{cjt}}{L_{cjt}}$ is the difference between Figures 2A and 2D. Finally, the exclusion restriction — that Exposure is not correlated with other industry-county-level shocks — is supported by the evidence in Section III that Exposure affects local labor markets only through variation in bonus depreciation.

We first estimate Equation 3 on the early years of the policy (2002-2005). Figure 4A shows that, consistent with a Leontief production function, we do not find a statistically significant effect of $\Delta\rho_{cjt}$. In contrast, Figure 4B estimates Equation 3 for years 2006-2010 and shows that $\Delta\rho_{cjt}$ had large effects on the capital-labor ratio. Specifically, a 1% reduction in $\Delta\rho_{cjt}$ would increase the capital-labor ratio by 1.69%, exceeding the substitutability of a Cobb-Douglas production function.[22] This result implies a net-of-depreciation-σ = 1.27 after performing the adjustment of Rognlie (2016).

One way to appreciate the role of capital-labor substitution is to relate σ to the cost-per-job

[21] We construct the cost-of-capital as $(r + \delta_{ct})\frac{1-\tau_{st}(z_{ct}+\text{Inv}_{st})}{1+\tau_{st}}$ using data from Chirinko and Wilson (2008); Bureau of Economic Analysis (2017); Suárez Serrato and Zidar (2017); Zwick and Mahon (2017) where r =7%; see Appendix B for details.

[22] The first-stage implies that an IQR increase in Exposure lowers $\Delta\rho_{cjt}$ by 0.61% (F-stat=13). Since an IQR increase in Exposure increases the capital-labor ratio by 1.03%, $\sigma = \frac{1.03}{0.61} = 1.69$.

calculation. If $\sigma = 0$, as in the early years of the policy, capital and employment would grow in equal proportions. Thus, had employment grown at 3.3% following an IQR of Exposure — the average effect on capital — bonus depreciation would have been a more effective labor market policy with a cost-per-job of \$30,000. Our cost-per-job estimate of \$53,000 in Section III therefore reflects the degree to which capital became a substitute for labor over time.

To capture how σ changes over time, we use a control function approach that includes interactions between $\Delta\rho_{cjt}$ and a cubic trend in Equation 3. Figure 4C reports year-by-year estimates of σ. We estimate $\sigma \approx 0$ in 2003. For 2004-2006, we find $\sigma \in [0.3, 0.7]$, consistent with Chirinko (2008) and Oberfield and Raval (2014). Over the long term, however, we find $\sigma > 1$, as in Karabarbounis and Neiman (2013) and Piketty and Zucman (2014).[23]

Why does the policy-driven capital accumulation turn from being a complement to a substitute for labor? One potential mechanism is that firms are able to substitute between capital and labor more freely over time. That is, in the short-run, firms install capital in the same proportion as before the policy. As the cost of capital remains low, firms substitute to more capital-intensive forms of production, resulting in larger elasticities. This mechanism is consistent with a powerful intuition dating to Samuelson's (1947) *LeChatelier's principle*. More recently, *putty-clay* environments where firms are constrained in their ability to adjust their capital intensity result in larger long-run elasticities (Lambson, 1991; Sorkin, 2015; Bayer et al., 2015).

V Conclusion

This is the first study to provide a detailed analysis of the labor market effects of bonus depreciation. Using a local labor markets approach, we find short-term growth effects on employment and earnings. Bonus depreciation generated one job for every \$53,000 spent on the policy with no positive effects on average earnings for workers. Finally, our results are consistent with a pattern of increased substitution from labor to capital over time.

Theses findings have immediate policy implications as the federal government currently spends \$25 billion per year on accelerated depreciation policies. Overall, our results show incentives for capital accumulation stimulate investment but do not create long-run job or wage growth. It is therefore challenging to justify these expenses on the premise of helping workers.

[23] Figure G8 shows we obtain similar estimates when σ has a linear trend; see Table G14 for estimates.

References

Arulampalam, Wiji, Michael P. Devereux, and Giorgia Maffini, "The direct incidence of corporate income tax on wages," *European Economic Review*, 2012, *56* (6), 1038 – 1054.

Autor, David H., "Why Are There Still So Many Jobs? The History and Future of Workplace Automation," *Journal of Economic Perspectives*, September 2015, *29* (3), 3–30.

_ and David Dorn, "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market," *American Economic Review*, August 2013, *103* (5), 1553–97.

_ , _ , and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, October 2013, *103* (6), 2121–68.

_ , _ , and _ , "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade," WP 21906, NBER 2016.

Barro, Robert J. and Jason Furman, "The Macroeconomic Effects of the 2017 Tax Reform," Brookings Papers on Economic Activity, Brookings Institution 2018.

Bayer, Christian, Ariel M. Mecikovsky, and Matthias Meier, "Productivity Dispersions: Could it simply be technology choice?," 2015.

Bureau of Economic Analysis, "National Data: Private Fixed Assets by Industry," Web Site, Washington, D.C. 2017.

Caballero, Ricardo J., Eduardo M. R. A. Engel, John C. Haltiwanger, Michael Woodford, and Robert E. Hall, "Plant-Level Adjustment and Aggregate Investment Dynamics," *Brookings Papers on Economic Activity*, 1995, *1995* (2), 1–54.

Cameron, Colin A. and Douglas L. Miller, "A Practitioner's Guide to Cluster-Robust Inference," *Journal of Human Resources*, 2015, *50* (2), 317–372.

CEA, "The Growth Effects of Corporate Tax Reform and Implications for Wages," Report (Accessed 2 September 2011), The Council of Economic Advisers 2017.

Chirinko, Robert S., "σ: The long and short of it," *Journal of Macroeconomics*, 2008, *30* (2), 671 – 686. The CES Production Function in the Theory and Empirics of Economic Growth.

_ and Daniel J. Wilson, "State Investment Tax Incentives: A Zero-Sum Game?," *Journal of Public Economics*, 2008, *92* (12), 2362–2384.

_ , Steven M. Fazzari, and Andrew P. Meyer, "A New Approach to Estimating Production Function Parameters: The Elusive Capital–Labor Substitution Elasticity," *Journal of Business & Economic Statistics*, 2011, *29* (4), 587–594.

Chodorow-Reich, Gabriel, "Geographic Cross-Sectional Fiscal Spending Multipliers: What Have We Learned?," Technical Report, National Bureau of Economic Research 2017.

Criscuolo, Chiara, Ralf Martin, Henry Overman, and John Van Reenen, "The causal effects of an industrial policy," Technical Report, National Bureau of Economic Research 2012.

Cummins, Jason G, Kevin A Hassett, R Glenn Hubbard, Robert E Hall, and Ricardo J Caballero, "A reconsideration of investment behavior using tax reforms as natural experiments," *Brookings papers on economic activity*, 1994, *1994* (2), 1–74.

Dix-Carneiro, Rafael and Brian K. Kovak, "Trade Liberalization and Regional Dynamics," *American Economic Review*, October 2017, *107* (10), 2908–46.

Doraszelski, Ulrich and Jordi Jaumandreu, "Measuring the bias of technological change," *Journal of Political Economy*, 2018, *126* (3), 1027–1084.

Edgerton, Jesse, "Investment incentives and corporate tax asymmetries," *Journal of Public Economics*, 2010, *94* (11-12), 936–952.

Freyaldenhoven, Simon, Christian Hansen, and Jesse M Shapiro, "Pre-event trends in the panel event-study design," Technical Report, National Bureau of Economic Research 2018.

Fuchs-Schuendeln, N. and T.A. Hassan, *Natural Experiments in Macroeconomics*, Vol. 2 of *Handbook of Macroeconomics*, Elsevier, August

Fuest, Clemens, Andreas Peichl, and Sebastian Siegloch, "Do Higher Corporate Taxes Reduce Wages? Micro Evidence from Germany.," *American Economic Review*, 2018, *108* (2), 393–418.

GAO, "Corporate Tax Expenditures: Information on Estimated Revenue Losses and Related Federal Spending Programs," Technical Report GAO-13-339, Government Accountability Office March 2013.

Hakobyan, Shushanik and John McLaren, "Looking for Local Labor Market Effects of NAFTA," *The Review of Economics and Statistics*, 2016, *98* (4), 728–741.

Hall, Robert E and Dale W Jorgenson, "Tax Policy and Investment Behavior," *The American Economic Review*, 1967, *57* (3), 391–414.

House, Christopher L and Matthew D Shapiro, "Temporary investment tax incentives: Theory with evidence from bonus depreciation," *American Economic Review*, 2008, *98* (3), 737–68.

IRS, "SOI Tax Stats - Corporation Complete Report," Web Site https://www.irs.gov/statistics/soi-tax-stats-corporation-complete-report (Accessed: December 1, 2017), U.S. Internal Revenue Service 2017.

JCT, "Estimated Budget Effects of the Conference Agreement for H.R. 1, the "Tax Cuts and Jobs Act"," JCX-67-17, The Joint Committee on Taxation August 2017.

Karabarbounis, Loukas and Brent Neiman, "The Global Decline of the Labor Share," NBER Working Papers 19136, National Bureau of Economic Research, Inc June 2013.

Kitchen, John and Matthew Knittel, "Business Use of Special Provisions for Accelerated Deprecition: Section 179 Expensing and Bonus Deprecition, 2002-2009," 2011.

Kline, Patrick and Enrico Moretti, "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority *," *The Quarterly Journal of Economics*, 2014, *129* (1), 275–331.

Kovak, Brian K., Lindsay Oldenski, and Nicholas Sly, "The Labor Market Effects of Offshoring by U.S. Multinational Firms: Evidence from Changes in Global Tax Policies," Working Paper 23947, National Bureau of Economic Research October 2017.

Lambson, Val Eugene, "Industry evolution with sunk costs and uncertain market conditions," *International Journal of Industrial Organization*, 1991, *9* (2), 171 – 196.

Maffini, Giorgia, Jing Xing, Michael P Devereux et al., "The impact of investment incentives: evidence from UK corporation tax returns," Technical Report 2016.

Nallareddy, Suresh, Ethan Rouen, and Juan Carlos Suárez Serrato, "Corporate Tax Cuts Increase Income Inequality," Technical Report, National Bureau of Economic Research 2018.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," Technical Report, working paper, Federal Trade Commission 2014.

Ohrn, Eric, "The Effect of Corporate Taxation on Investment and Financial Policy: Evidence from the DPAD," *American Economic Journal: Economic Policy*, May 2018, *10* (2), 272–301.

_ , "The Effect of Tax Incentives on U.S. Manufacturing: Evidence from State Accelerated Depreciation Policies," February 2018. Mimeo.

Piketty, Thomas and Gabriel Zucman, "Capital is Back: Wealth-Income Ratios in Rich Countries 1700–2010 *," *The Quarterly Journal of Economics*, 2014, *129* (3), 1255–1310.

QCEW, "Bureau of Labor Statistics: Quarterly Census of Employment and Wages," Web Site (Accessed: December 1, 2017), https://www.bls.gov/cew/ 2017.

_ , "Employment and Wages, Annual Averages 2001," December 2018.

Raval, Devesh, "The micro elasticity of substitution and non-neutral technology," Technical Report, working paper, Federal Trade Commission 2018.

Rognlie, Matthew, "Deciphering the fall and rise in the net capital share: accumulation or scarcity?," *Brookings papers on economic activity*, 2016, *2015* (1), 1–69.

Samuelson, Paul Anthony, "Foundations of economic analysis," 1947.

Sorkin, Isaac, "Are there long-run effects of the minimum wage?," *Review of economic dynamics*, 2015, *18* (2), 306–333.

Suárez Serrato, Juan Carlos, "Unintended Consequences of Eliminating Tax Havens," Working Paper, Duke University April 2018.

_ **and Owen Zidar**, "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms," *American Economic Review*, 2016.

_ **and** _ , "The Structure of State Corporate Taxation and its Impact on State Tax Revenues and Economic Activity," Working Paper, Duke University May 2017.

_ **and Philippe Wingender**, "Estimating Local Fiscal Multipliers," Working Paper 22425, National Bureau of Economic Research July 2016.

Yagan, Danny, "Capital Tax Reform and the Real Economy: The Effects of the 2003 Dividend Tax Cut," *The American Economic Review*, 2015, *105* (12), 3531–3563.

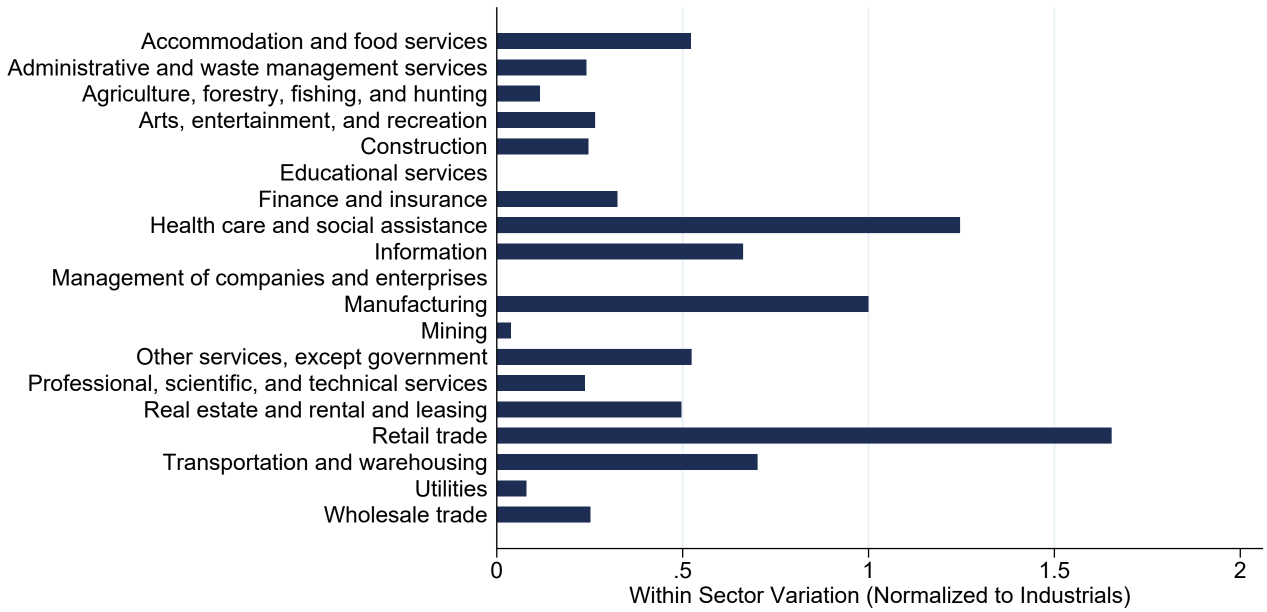
Zhang, Lei, Yuyu Chen, and Zongyan He, "The effect of investment tax incentives: evidence from China's value-added tax reform," *International Tax and Public Finance*, 2018, *25* (4), 913–945.

Zidar, Owen M, "Tax cuts for whom? Heterogeneous effects of income tax changes on growth and employment," Technical Report, National Bureau of Economic Research 2017.

Zwick, Eric and James Mahon, "Tax Policy and Heterogeneous Investment Behavior," *American Economic Review*, January 2017, *107* (1), 217–48.

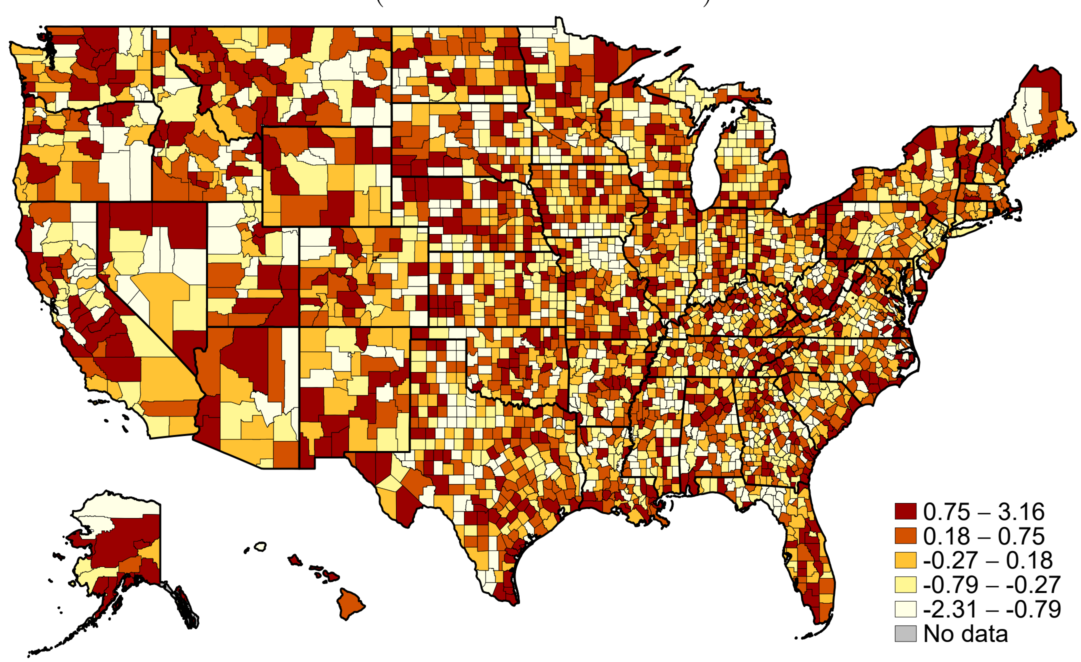
Figure 1: Exposure to Long Duration Industries

A. Within Sector Variation in Duration



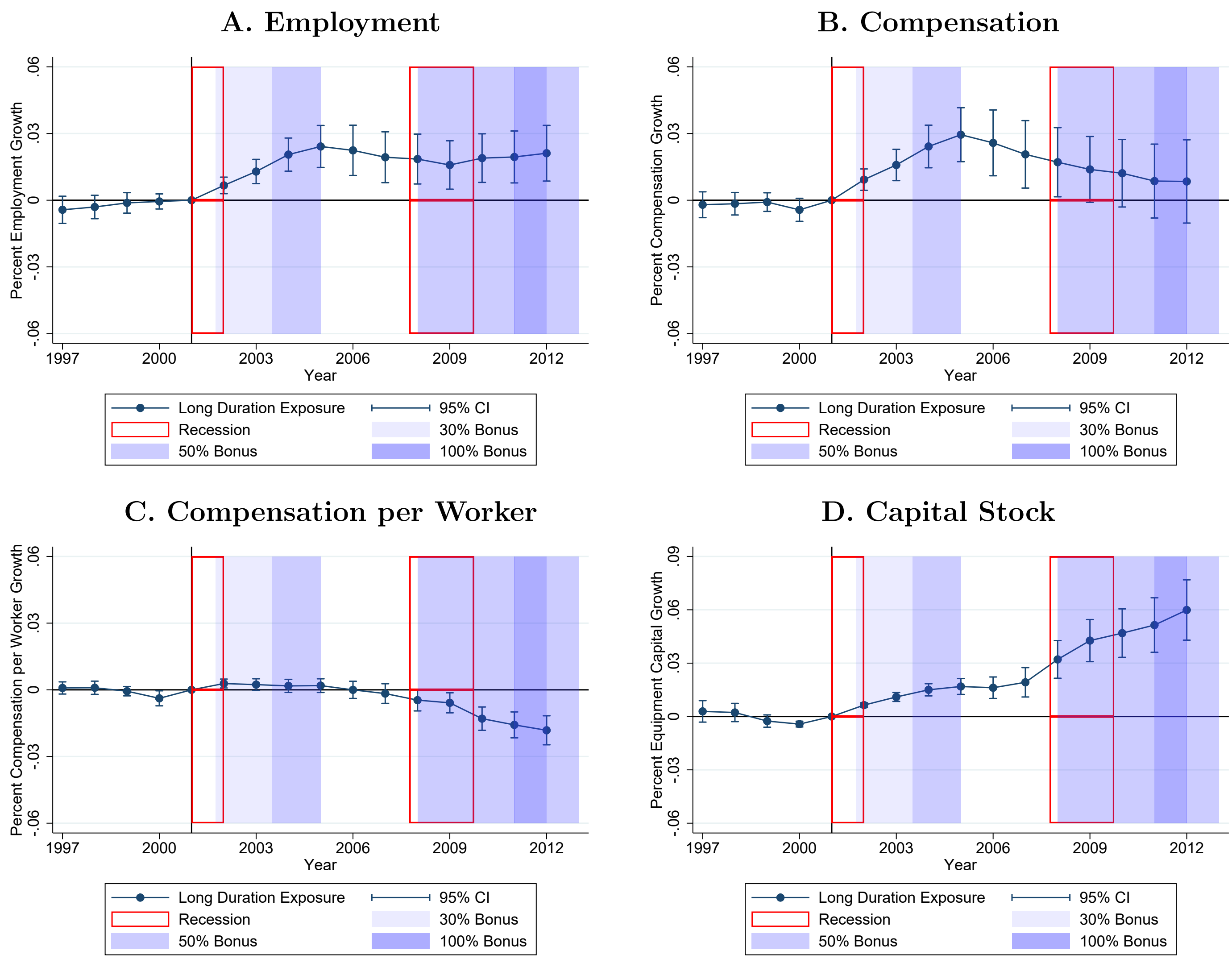
B. Percent of Employment in Long Duration Industries

(Relative to State Mean)



Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). Figure 1A shows the within-sector variation in duration of industries relative to manufacturing. For each sector, we calculate the within-sector coefficient of variation of the measure of duration from Zwick and Mahon (2017) and multiply that by the share of sector capital and sector 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 G2 without adjusting for state means.

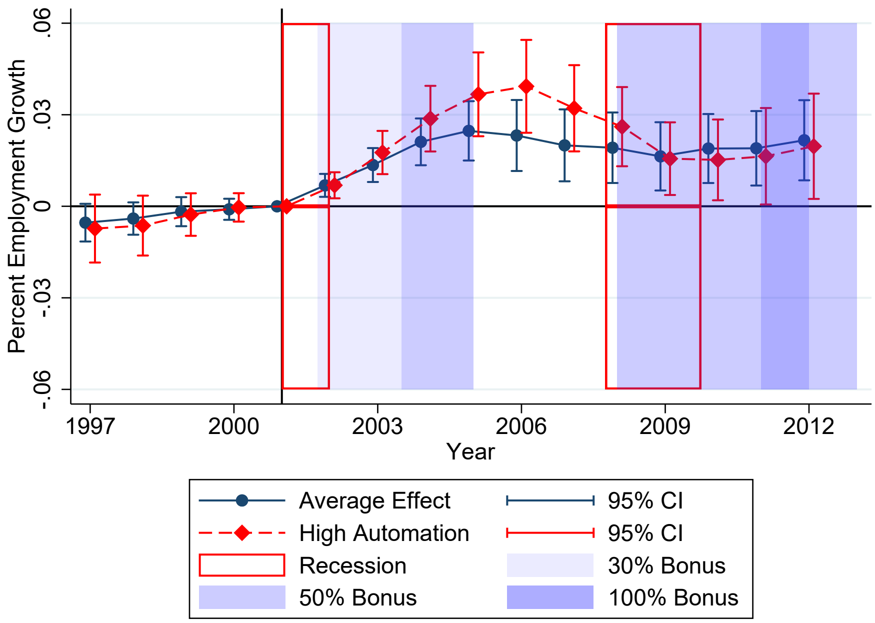
Figure 2: Effects of Bonus Depreciation by Exposure to Long Duration Industries



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, Compensation in Figure 2B, Compensation per Worker in Figure 2C, and Capital Stock 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. These results are robust to the exclusion of the local controls as shown in Figure G3, the FHS estimator as shown in Figure G4, and the definition of a long-duration industry exposure as shown in Figures G5, G6, and G7. Tables G6, G7, G8, and G9 show the annual coefficients for employment, compensation, compensation per worker, and equipment, respectively, with additional specifications. Standard errors are clustered at the county level.

Figure 3: Effects of Bonus Depreciation: Automation and Placebo Tests

A. Heterogeneity by Automation Likelihood

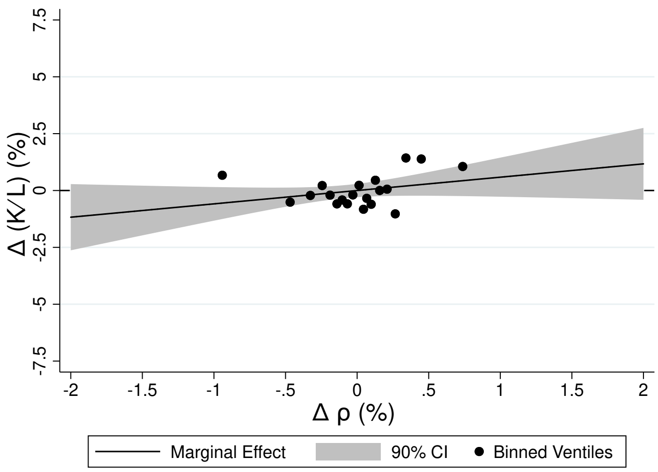


B. Placebo Test: Exposure to Long Duration Industries that Rely on Ineligible Capital

Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). Figure 3A shows the heterogeneous effect of exposure to bonus depreciation on local employment growth. 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. Figure 3B 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 3B give evidence that structures and land investment are not driving the results. Standard errors are clustered at the county level.

Figure 4: Estimates of the Capital-Labor Elasticity of Substitution

A. For Years 2002-2005

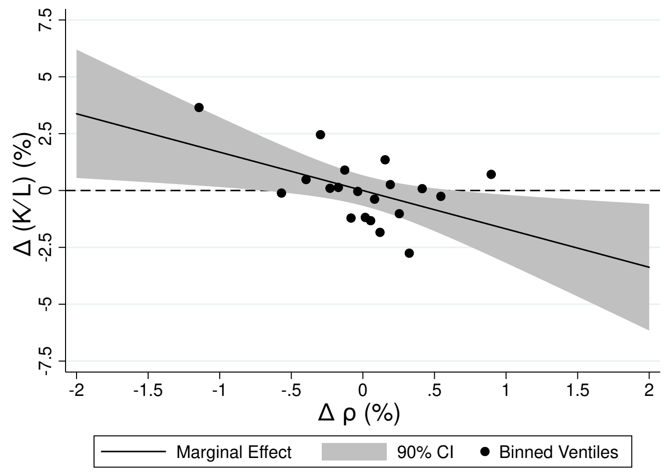


Notes: Estimating equation:

$$\Delta\widehat{\left(\frac{K_{cjt}}{L_{cjt}}\right)} = \underset{(0.453)}{0.586}\,\Delta\rho_{cjt} + \mathbf{X'}_c\hat{\gamma} + \hat{\mu}_{st} + \hat{\nu}_{jt}$$

1^{st}-stage F-stat = 39.58, σ p-value = 0.196.

B. For Years 2006-2010

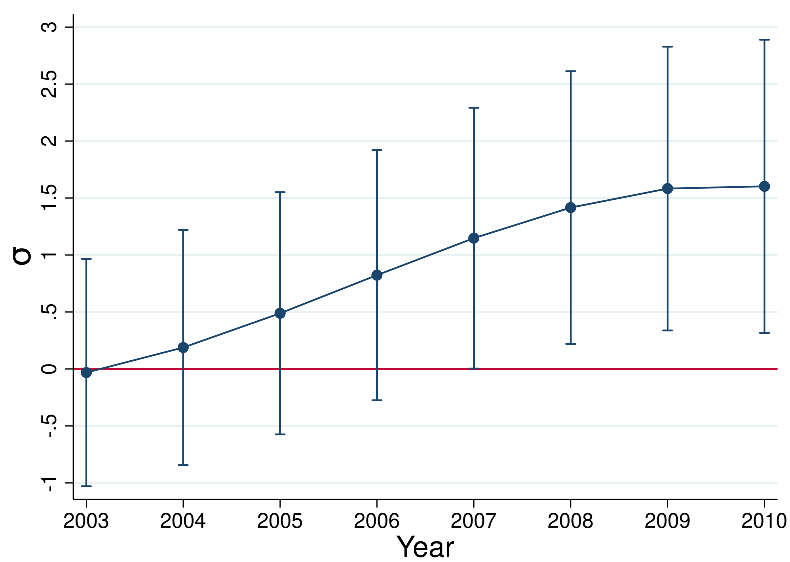


Notes: Estimating equation:

$$\Delta\widehat{\left(\frac{K_{cjt}}{L_{cjt}}\right)} = -\underset{(0.828)}{1.687}\,\Delta\rho_{cjt} + \mathbf{X'}_c\hat{\gamma} + \hat{\mu}_{st} + \hat{\nu}_{jt}$$

1^{st}-stage F-stat = 13.10, σ p-value = 0.042.

C. Year-by-year Estimates



Notes: Author's calculations using data from QCEW, Zwick and Mahon (2017), the Census Bureau, and the Bureau of Economic Analysis. Figures 4A and 4B display instrumental variables estimates of σ for the early and late years of the policy. Data are residualized from state-by-year and industry-by-year fixed effects and controls. We instrument $\Delta\rho_{jct}$ with Exposure and present the 1^{st}-stage F-statistics below each graph. In 2002-2005, we estimate an average elasticity of -0.59 and fail to reject the null hypothesis of a Leontief production function. In 2006-2010, we estimate an average elasticity of 1.69, which is larger than substitution implied by a Cobb-Douglass model. In Figure 4C, we use a control function approach that allows for σ to vary by year according to interactions between $\Delta\rho_{jct}$ and a cubic trend. The plot also includes 90% confidence intervals. The estimated elasticities increase from zero in 2003 to over 1.5 by 2010. See Figure G8 for estimates from a linear trend and Table G14 for point estimates. See Section IV for more discussion and information about the regressions.

Table 1: **Local Labor Market Effects of Bonus Depreciation (2003-2012)**

	(1)	(2)	(3)	(4)
Employment Growth				
Long Duration Exposure	0.013**	0.019***	0.016***	0.021***
	(0.006)	(0.005)	(0.005)	(0.007)
Compensation Growth				
Long Duration Exposure	0.006	0.017***	0.015**	0.021**
	(0.009)	(0.006)	(0.006)	(0.009)
Compensation per Worker Growth				
Long Duration Exposure	-0.009***	-0.005***	-0.003**	-0.004*
	(0.003)	(0.002)	(0.002)	(0.003)
Equipment Stock Growth				
Long Duration Exposure	0.039***	0.033***	0.034***	0.033***
	(0.006)	(0.005)	(0.005)	(0.005)
Year-by-Subsector Fixed Effects†	Yes	Yes	Yes	Yes
Year-by-State Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Dropping Small County-Subsectors				Yes

Notes: This table shows estimates from Equation 2 where β is not allowed to vary by year and all controls discussed in Section III are included. The sample for this table includes years 2003 to 2012. The outcomes are employment in the first row, compensation in the second, compensation per worker in the third, and equipment stock in the final row. Column (1) shows estimates with subsector-by-year fixed effects while column (2), the main specification, adds state-by-year fixed effects. The following two columns show robustness of the results to winsorizing the weights at the 5% level and to dropping county-subsectors with less than 1,000 workers in 2001. Standard errors are clustered at the county level. The same regressions for the pre-period, 1997 to 2000, are shown in Table G5 and fail to reject parallel trends. The regressions without county level controls are displayed in Table G4 to show robustness.

†The regressions of equipment capital stock combine all subsectors together, so the subsector-by-year fixed effects are only year fixed effects for the equipment outcome.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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 contains additional details on the construction of our county-level measures of capital and the user cost of capital. Appendix C lists results from robustness checks that are mentioned in the body of the paper. Appendix D discusses the role of tax losses and Section 179 expensing rules in the interpretation of our results. Appendix E shows that we obtain similar results when we analyze the effects of bonus depreciation on the employment-to-population ratio. Appendix F presents details on the implementation of the estimator of Freyaldenhoven et al. (2018). Finally, additional tables and figures are included in Appendix G.

A Variable Definitions

Variable name	Definition
	Accelerated Depreciation Variables
Industry	We define the industry as the 4-digit NAICS category.
Subsector	We define the subsector as the 3-digit NAICS category.
Sector	We define the sector as the 2-digit NAICS category .
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
Compensation	Total payments made to workers in a geographic area and industrial grouping in a given year according to QCEW (2017), *total_annual_wages*.
Compensation 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*.
Equipment	Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets, Equipment at the subsector-national level from Bureau of Economic Analysis (2017). Subsector level capital is applied to counties based on subsector employment shares of national employment.
Intellectual Property	Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets, Intellectual Property Products at the subsector-national level from Bureau of Economic Analysis (2017). Subsector level capital is applied to counties based on subsector employment shares of national employment.
	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 subsector level.
IP Stock	Total intellectual property products in 2001 from Bureau of Economic Analysis (2017) allocated to counties using employment shares at the subsector 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 (2017).
Investment Tax Credit	State level investment tax credits from Chirinko and Wilson (2008) are used in the calculation of user cost of capital.

B Data Construction Details

In this appendix we provide additional details on the construction of specific variables.

In Section III.B, we use a county-level measure of the equipment capital stock. To construct this measure, we use BEA data on the Current-Cost Net Capital Stock of Private Nonresidential Fixed Assets are available at the subsector-national level. We use these data to create county-level measures of capital stock, K_{ic}. To do so, we allocate the national equipment capital in each subsector in each year, K_{it}, to counties by the share of national employment in the subsector in each county in each year, s_{ict}, so that:

$$K_{ct} = \sum_i s_{ict} \times K_{it}.$$

Since K_{ct} does not vary within counties, we assign our measures of the change in capital to all subsectors in a county.

In Section IV, we use an estimate of the relative cost of capital to estimate Equation 3. To construct the cumulative user cost of capital that is relevant for the capital stock, we first compute the instantaneous use cost of capital

$$\widetilde{ucc_{ct}} = (r + \delta_{ct}) \frac{1 - \tau_{st}(z_{ct} + \text{Inv}_{st})}{1 + \tau_{st}}.$$

We assume the return on capital r is 7%. We derive county-level measures of the economic depreciation rate δ_{ct} based on BEA investment data, county-industry mixes from QCEW, and the law of motion for capital. Corporate tax rates, τ_{st}, vary at the state level and are taken from Suárez Serrato and Zidar (2017). We compute a county-level average of the discounted present value of depreciation deductions, z_{ct}, using data from Zwick and Mahon (2017) and the QCEW. Finally, state investment tax credits, Inv_{st} are taken from Chirinko and Wilson (2008). Since the adoption of bonus depreciation persistently decreased the cost of investment, we calculate the relevant user cost ucc_{ct} as the cumulative average $\widetilde{ucc_{ct}}$ between 2001 and a given year t. Finally, the relative user cost of capital $\rho_{jct} = \frac{ucc_{ct}}{w_{jct}}$, where we use employee compensation per worker from the QCEW in place of w_{jct}.

C 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 G1 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 G2.

  - 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 G2.

  - Table G1 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.

  - Table G3 shows additional county descriptive statistics associated with exposure to long duration, population, and local capital stock.

- **Robustness to Controls and FHS Estimator.** We show the robustness of the county-level regressions of employment, compensation, compensation per worker, and equipment in a series of expanded results with different controls and different definitions of key variables. The results are robust to the inclusion or exclusion of the controls.

  - Figure G3 shows the robustness of the specifications in Figure 2 to not including the baseline county-level controls. The controls for trade exposure, demographics, routine jobs, and capital stocks in 2001 are not included in the robustness figure.

  - Table G4 shows the analogue to Table 1 that does not include the controls for other county level variables.

  - Table G5 shows the pre-period regression results associated with the regressions in Table 1 to show that there were no pre-trends going into the sample period.

- We also include several results that show the robustness of the baseline results on employment, compensation, and compensation per worker to the FHS estimator. Figure G4 shows the effects of bonus depreciation on county level outcomes with the FHS estimator corresponding to Figure 2.
- Tables G6, G7, G8, and G9 show the annual coefficients from Figure 2 for employment, compensation, compensation per worker, and equipment, respectively. The labor market outcomes tables all include four specifications where column (2) is the preferred specification with state-by-year and subsector-by-year fixed effects. The equipment table combines all subsectors and so column (1) is the preferred specification.

- **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 analogue of Figure 2 is shown using exposure to the top 25% of long duration firms in Figure G5. The equipment robustness is shown separately in Figure G7.
  - The analogue of Figure 2 is shown using exposure to the top 40% of long duration firms in Figure G6. The equipment robustness is shown separately in Figure G7.
  - Tables G10, G11, G12, and G13 show the annual coefficients from Figure 3B for employment, compensation, compensation per worker, and equipment, respectively. The labor market outcomes tables each include four specifications where column (2) is the preferred specification with state-by-year and subsector-by-year fixed effects. The equipment table combines all subsectors and so column (1) is the preferred specification.

- **Robustness of σ Estimates.** Finally, we show robustness of our results in Section IV of the capital-labor elasticity of substitution.
  - In Figure G8 we show that year-by-year estimates of σ following a linear trend are qualitatively similar to the estimates presented in Figure 4C with a cubic trend.
  - We present point estimates and further results in Table G14.

D 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 four 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. Third, these adjustments have no effect on the estimation of rates of substitution between capital and labor in Section IV. The adjustments to the reduced-form effects apply equally to the dependent and endogenous variables in this estimation and they cancel out as part of the instrumental variables strategy.

4. 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 (2011), 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 D1A 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 D1B reports data from Kitchen and Knittel (2011) 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 D1C 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:

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

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

To understand the role of Share 179_t, assume that $\text{Share Gains}_t = 1$ 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 growth 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 $1.52 = \frac{50\%}{75\%\times[39\%+(1-39\%)\times 8\%]}$.

Finally, we note that these adjustments have no bearing on our estimates of substitution patterns in Section IV. This is because this adjustment affects both the dependent variable (changes in the capital-to-labor ratio) and the endogenous variable (changes in the input cost ratio).

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 D.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 D1A-D1C 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 D1D plots the value of the adjustment factor Share Gains$_t \times [b + (1-b)\text{Share } 179_t]$ 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$_t \times [b + (1-b)\text{Share } 179_t]$ from 2001 until a given year t. Figure D1E plots this cumulative average relative to the average value of Share Gains$_t \times [b + (1-b)\text{Share } 179_t]$ over the time period. We can then divide our estimates in Figure 2 by the values of Figure D1E 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 D1D 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 D1F 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 D1: 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 (2011). 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 D 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 D1A shows the bonus rate b for each year. Figure D1B shows the fraction of total investment that is eligible for Section 179 deductions. Figure D1C shows the percent of assets and revenues in firms that do not have losses. Figures D1A, D1B, and D1C combine into Figure D1D, the adjustment factor, and Figure D1E, 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 D1F.

E 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).

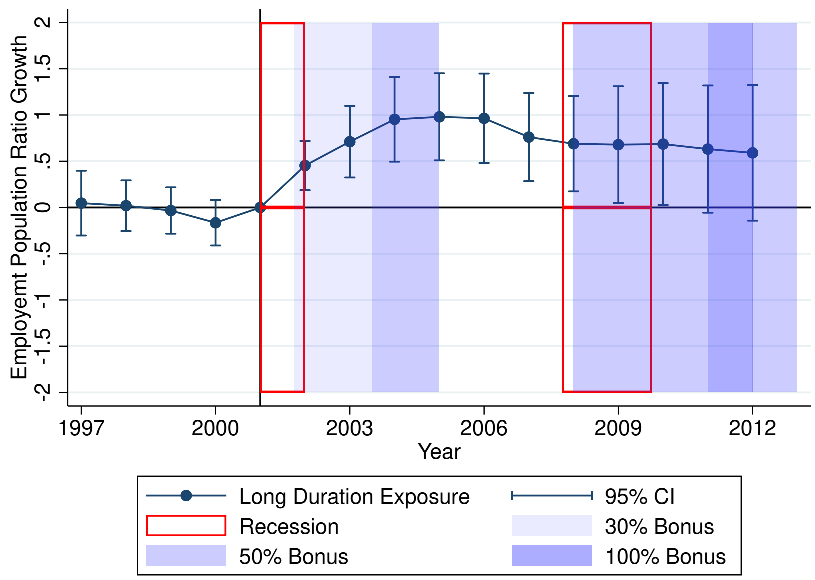
Figure E1 plots the results of this analysis and shows that, similar to Figure 2, the effects of bonus depreciation on employment crest in 2006. This figure shows that, by 2006, a unit IQR increase in Exposure increases the employment-to-population ratio by 1 percentage point.

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 and since it allows us to study how changes in the stock of employment relate to the stock of capital in Section IV.

Finally, it is worth noting that the dynamics of the effects of bonus depreciation in Figure E1 are very similar those of our main result in Figure 2A. Specifically, bonus depreciation has temporary effects on the growth of employment. While these level effects are persistent, bonus depreciation does not lead to sustained increases in the rate of employment growth.

Figure E1: 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). This estimating equation for this figure matches that of Figure G4.

F Details on the use of the Freyaldenhoven et al. (2018) Estimator

As we discuss in Section III.B and Appendix B, our measure of capital stock does not vary across subsectors in a given county. This prevents us from including subsector-by-year fixed effects when estimating the effects of bonus depreciation on capital accumulation using the specification in Equation 2. Moreover, when we estimate a model without subsector-by-year fixed effects, we find that counties that were more exposed to bonus depreciation experience relative patterns of decline prior to the implementation of the policy in 2002–see Figure F1A.

The concern raised by these pre-trends is that there is a confounder η_{ct} that could bias our results. That is, the true data generating process may be as follows:

$$\Delta K_{ct} = \alpha + \sum_{y=1997}^{2012} \beta_y \Big[\textbf{Exposure}_c \times \mathbb{1}(t = y)\Big] + \delta\eta_{ct} + \mu_{st} + \epsilon_{ct}. \qquad \text{(F.1)}$$

Our estimates of the effects of bonus depreciation could then be biased if $\delta \neq 0$ and η_{ct} is correlated with Exposure.

To deal with this concern, Freyaldenhoven et al. (2018) propose an estimator to correct for the role of the confound η_{ct}. The estimator makes use of a covariate x_{ct} that is related to the confound η_{ct} but that is not affected by Exposure. The second requirement for this covariate is that the dynamic behavior between x_{ct} and Exposure mirrors that between η_{ct} and Exposure.

As we show in Figure F1B, the stock of intellectual property has a similar pre-trend with respect to Exposure as the stock of equipment capital. Moreover, since bonus depreciation only applies to capital equipment, the stock of intellectual property should not be affected by bonus depreciation. We therefore use the stock of intellectual property in the role of the auxiliary covariate x_{ct}.

The equation we aim to estimate is then:

$$\Delta K_{ct} = \alpha + \sum_{y=1997}^{2012} \beta_y \Big[\textbf{Exposure}_c \times \mathbb{1}(t = y)\Big] + \lambda x_{ct} + \mu_{st} + \epsilon_{ct}. \qquad \text{(F.2)}$$

Note, however, that even though x_{ct} is related to η_{ct}, controlling for x_{ct} in Equation F.2 would only correct for the confounder if $x_{ct} = \delta\eta_{ct}$; that is, if the effects of η_{ct} on x_{ct} and ΔK_{ct} are exactly parallel. To get around this problem, Freyaldenhoven et al. (2018) propose to use leads of the Exposure variable as an instrument to identify the coefficient λ that scales the auxiliary covariate x_{ct} in order to properly account for $\delta\eta_{jt}$ in Equation F.1. In practice, we use leads of Exposure to instrument for the average effect of IP capital in the pre-period.

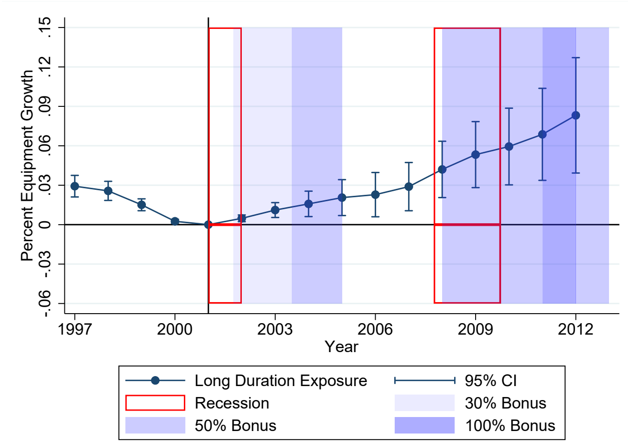
The intuition for this adjustment can be visualized in Figure F1. By using leads of Exposure as instruments for x_{ct}, we rescale the coefficients in Figure F1B to have the same scale as those in Figure

F1A The result of this process is Figure F1C, which shows a lack of meaningful pre-trends. Comparing Figure F1A and Figure F1C, we find a slightly larger effect of Exposure on the stock of equipment capital. This follows from the idea that, absent bonus depreciation, η_{ct} would have put downward pressure on both equipment and IP capital.

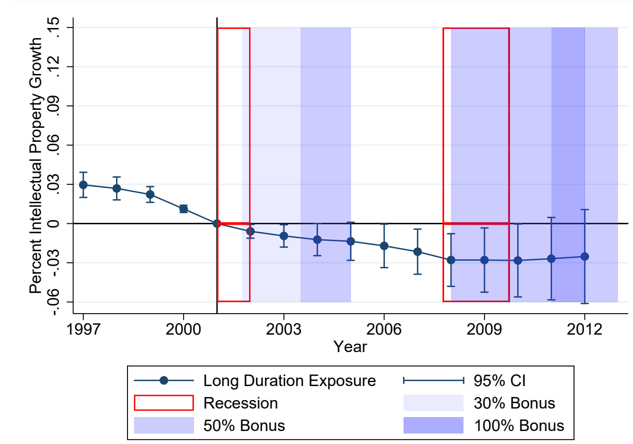
Finally, note that this adjustment does not affect our estimates of the effects of bonus depreciation on employment, compensation, and compensation per worker, as shown in Figure G4. This result follows from the graphical intuition behind this procedure. By rescaling Figure F1B to the scale of the pre-trends in Figures 2A, 2B, and 2C, the variation in the post-period in x_{ct} is rescaled to have a very small magnitude. This follows since the lack of pre-trends in Figures 2A, 2B, and 2C imply that the effects of η_{ct} on employment, compensation, and compensation-per-worker are very small (i.e., the corresponding δ's for these outcomes are close to zero).

Figure F1: Event Study of Capital Stock on County Bonus Exposure, FHS Estimator

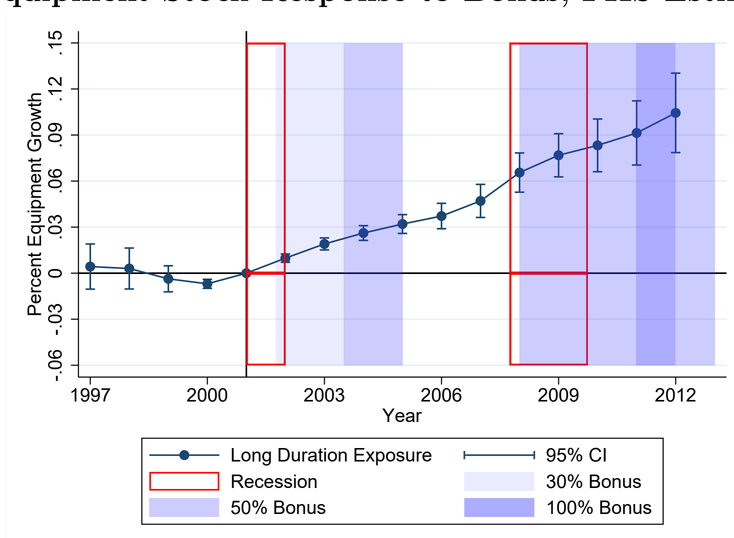
A. Raw Equipment Stock Response to Bonus



B. Raw Intellectual Property Stock Response to Bonus



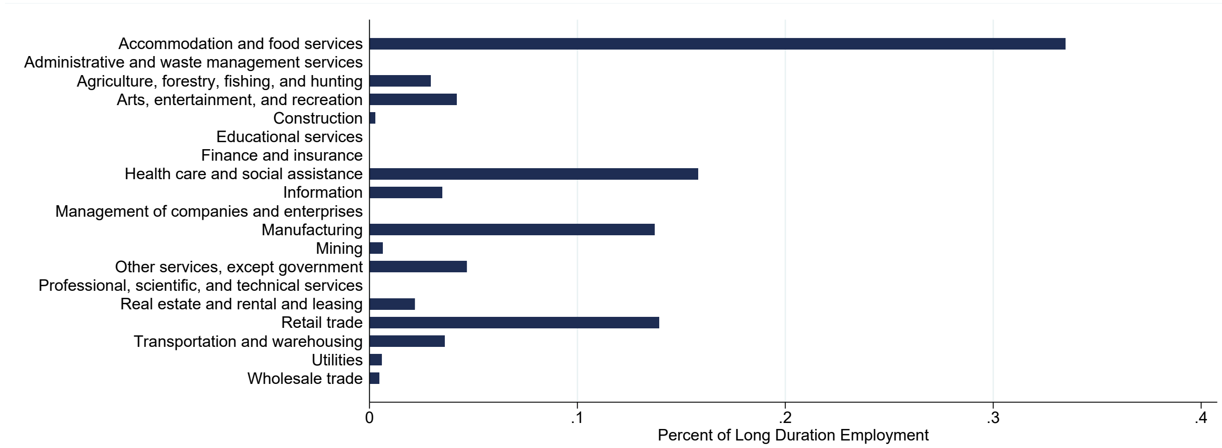
C. Equipment Stock Response to Bonus, FHS Estimator



Notes: Author's calculations using data from QCEW, Zwick and Mahon (2017), and the Bureau for Economic Analysis. This figure shows the implementation of the FHS estimator that uses correction for unobservables. Figure F1A shows the yearly estimates from the raw event study of equipment investment without using the FHS estimator. Equipment stock was growing more slowly in counties more exposed to bonus depreciation from 1997 to 2001, but the exposed counties grew more quickly from 2002-2012. The presence of a pre-trend hints that there is an unobservable confound that is affecting equipment capital stock formation in counties with more bonus exposure. Figure F1B shows that the pre-trends are shared with IP capital stock, which is not eligible for bonus depreciation. We estimate the FHS estimator using IP capital stock as the variable that is not affected by the policy but is correlated with county unobservables and show the results of the corrected regression in Figure F1C. See Appendix F for the full discussion.

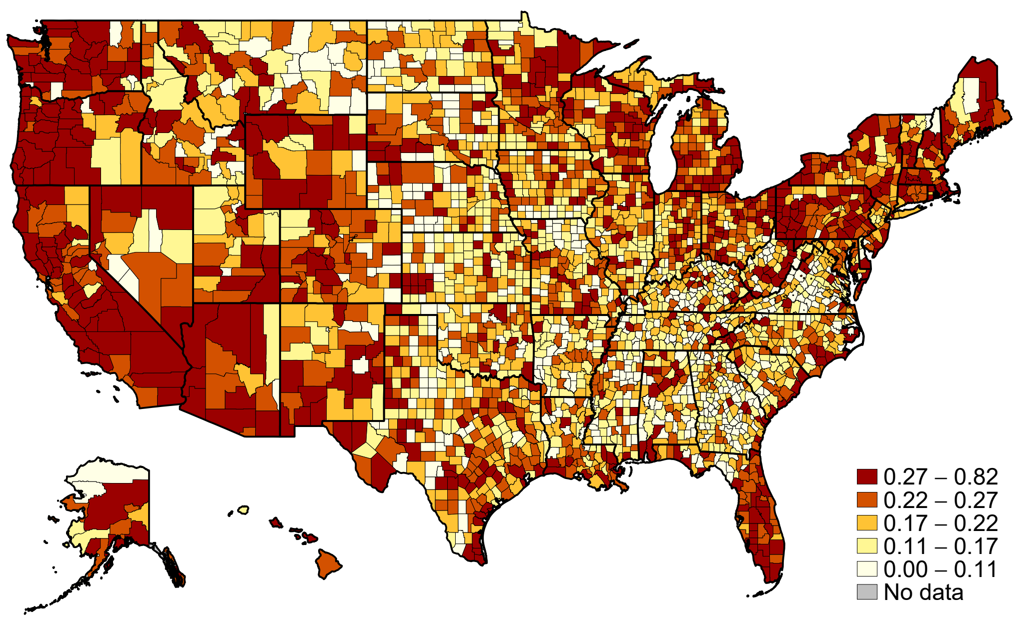
G Additional Figures and Tables

Figure G1: Percent of Long Duration Employment Derived from Each Sector



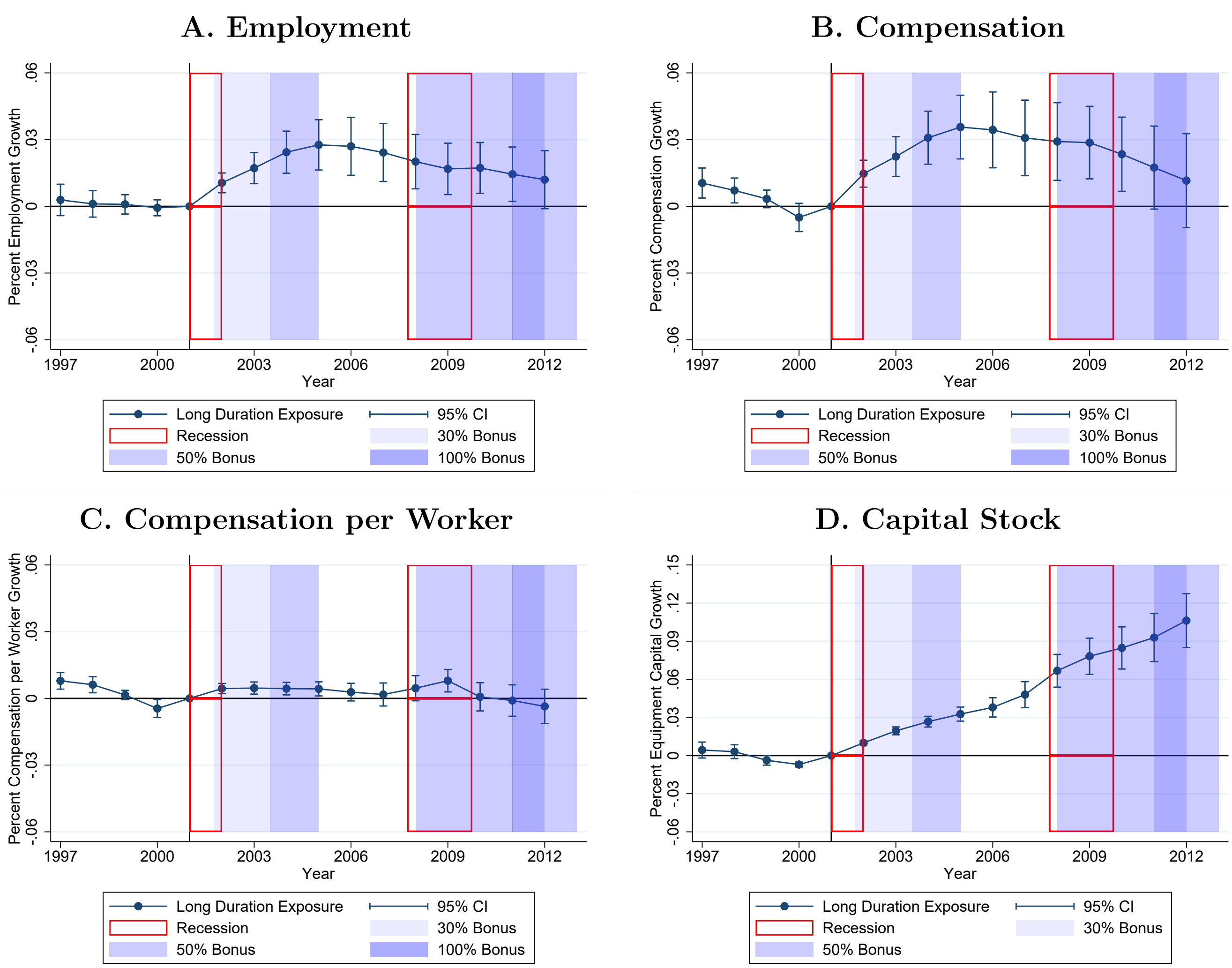
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the percent of long duration employment coming from each sector as defined by 2-digit NAICS in 2001. Data are at the national level.

Figure G2: Exposure to Long Duration Industries in 2001, Raw



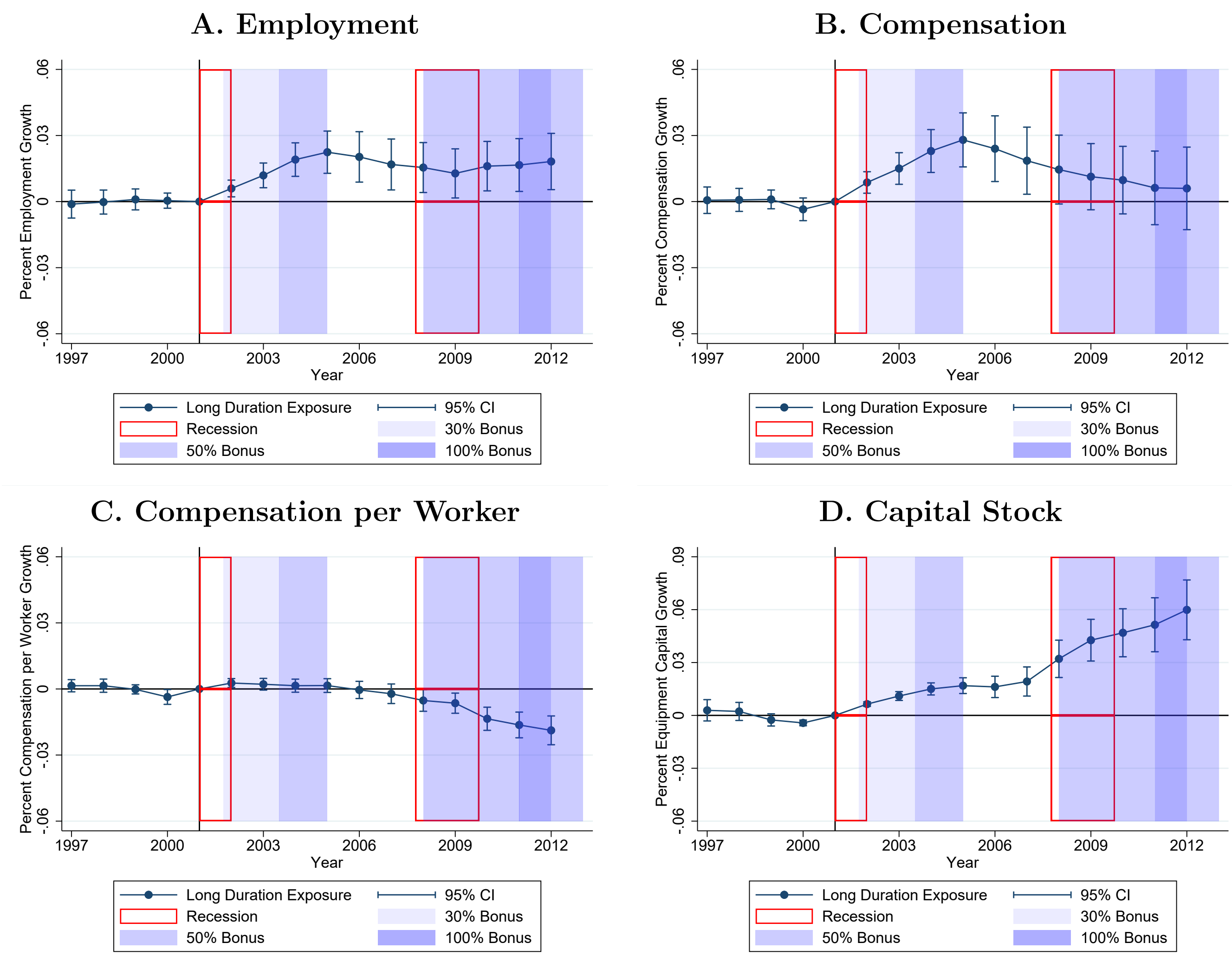
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the percent of employment in each county that comes from the top three deciles of employment-weighted industries by average duration of investment. Industries are defined by 4-digit NAICS codes. A version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

Figure G3: Effects of Bonus Depreciation by Exposure to Long Duration Industries, No County Economic or Demographic Controls



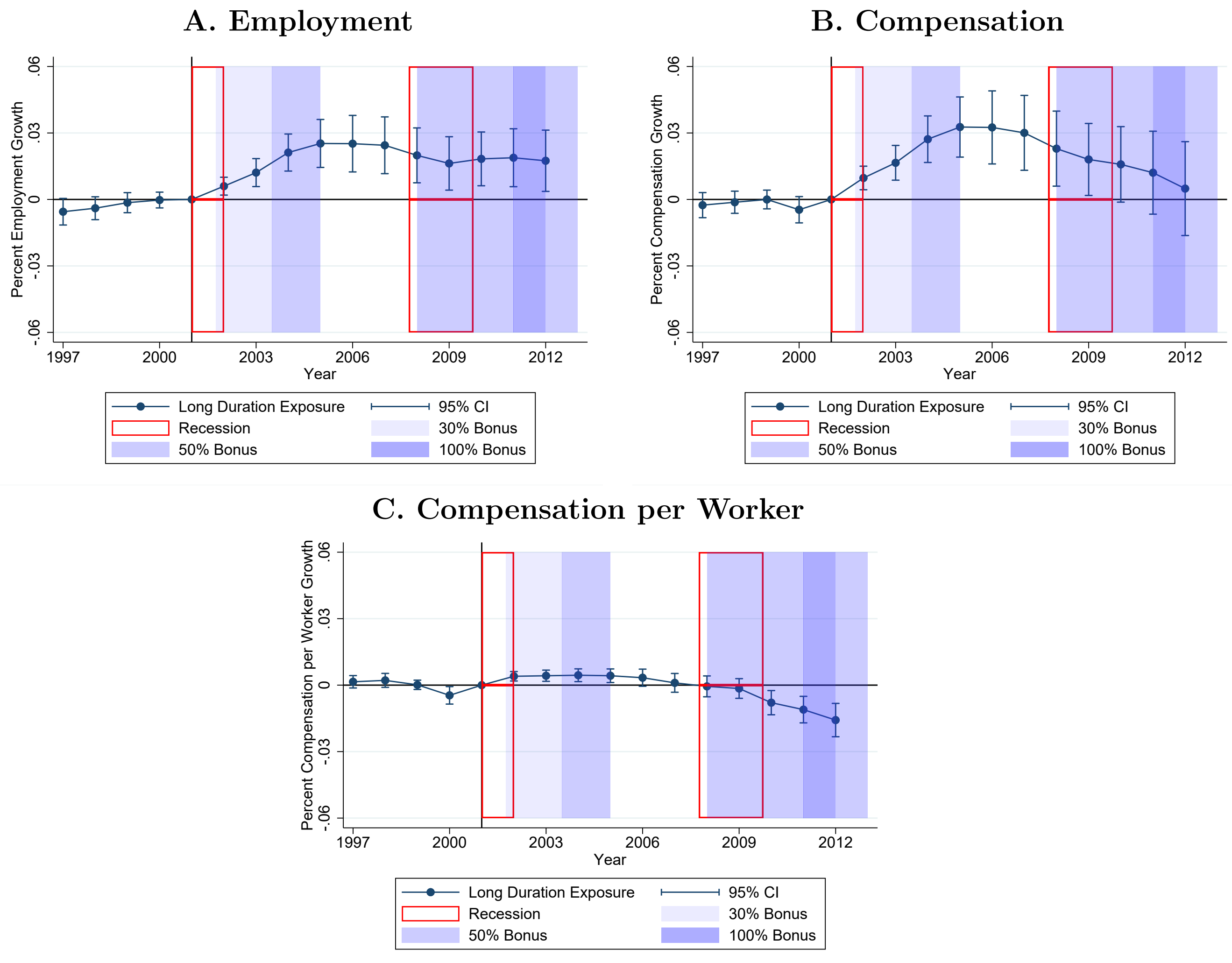
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure G3A, Compensation in Figure G3B, Compensation per Worker in Figure G3C, and Equipment Capital Stock in Figure G3D. 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 the FHS estimator for all outcomes. Standard errors are clustered at the county level.

Figure G4: Effects of Bonus Depreciation by Exposure to Long Duration Industries, FHS Estimator



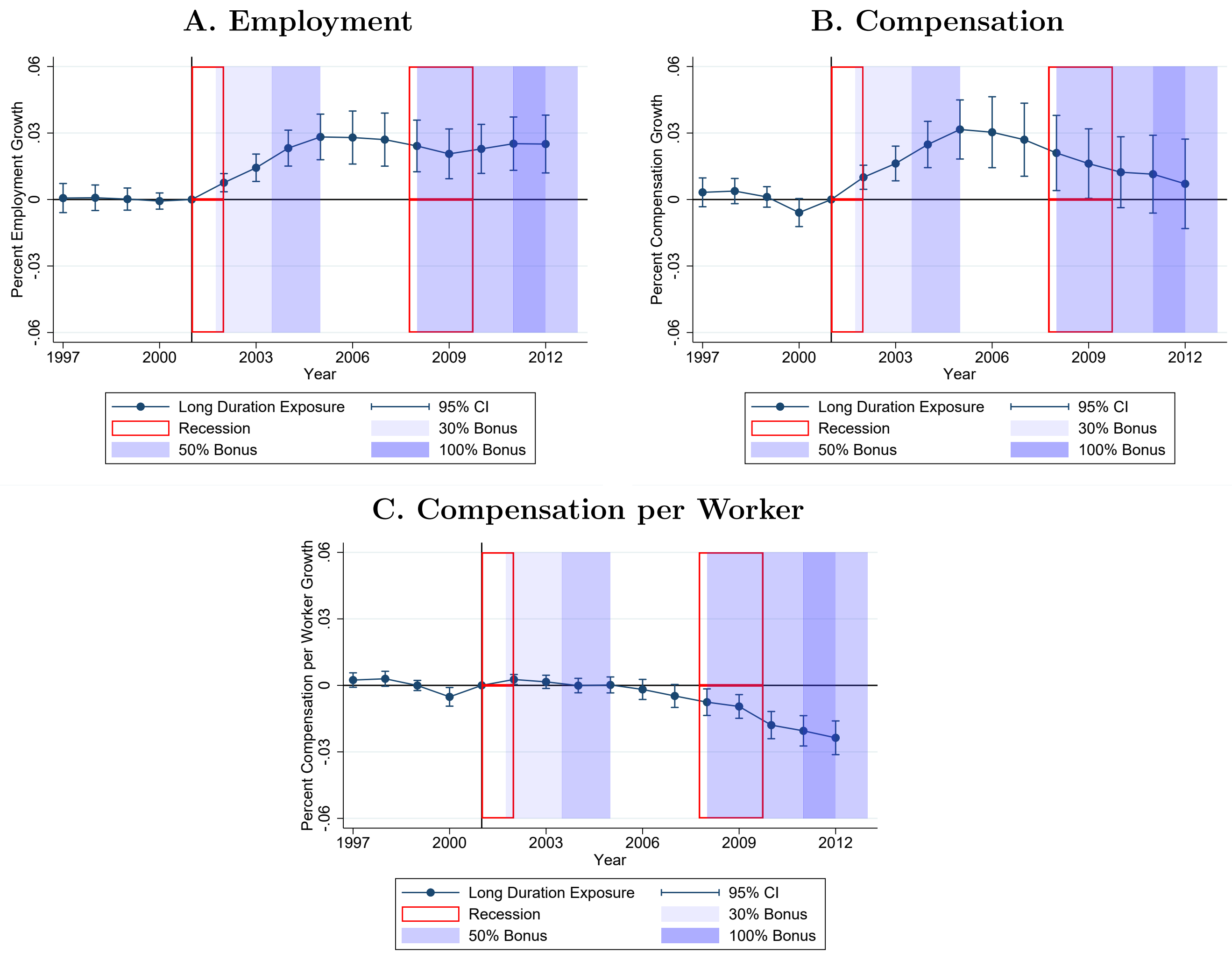
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure G4A, Compensation in Figure G4B, Compensation per Worker in Figure G4C, and Equipment Capital Stock in Figure G4D. 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 the FHS estimator correction using intellectual property products capital stock as described in Appendix F.

Figure G5: Effects of Bonus Depreciation by Exposure to Long Duration Industries, Long Duration Cutoff at 25%



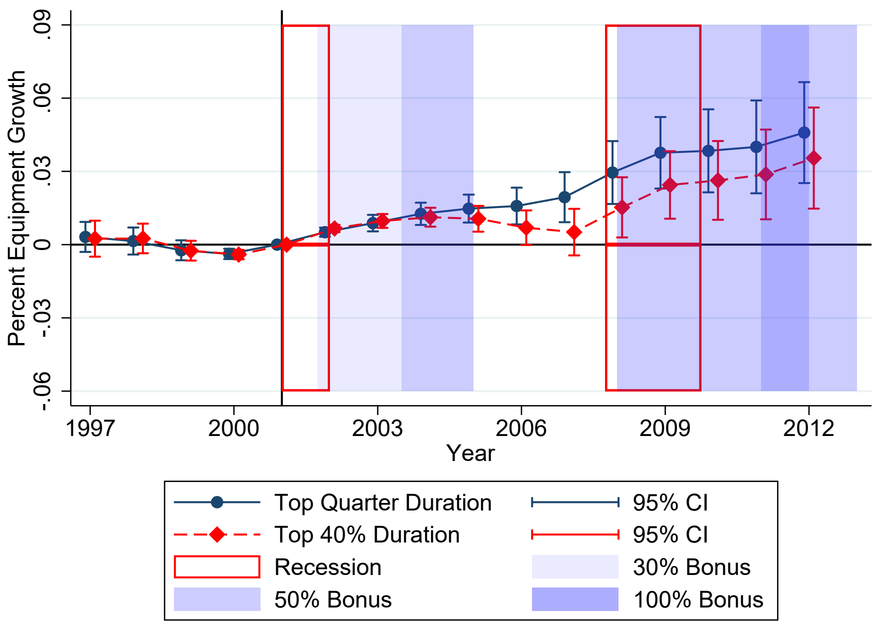
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure G5A, Compensation in Figure G5B and Compensation per Worker in Figure G5C. 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 30%.

Figure G6: Effects of Bonus Depreciation by Exposure to Long Duration Industries, Long Duration Cutoff at 40%



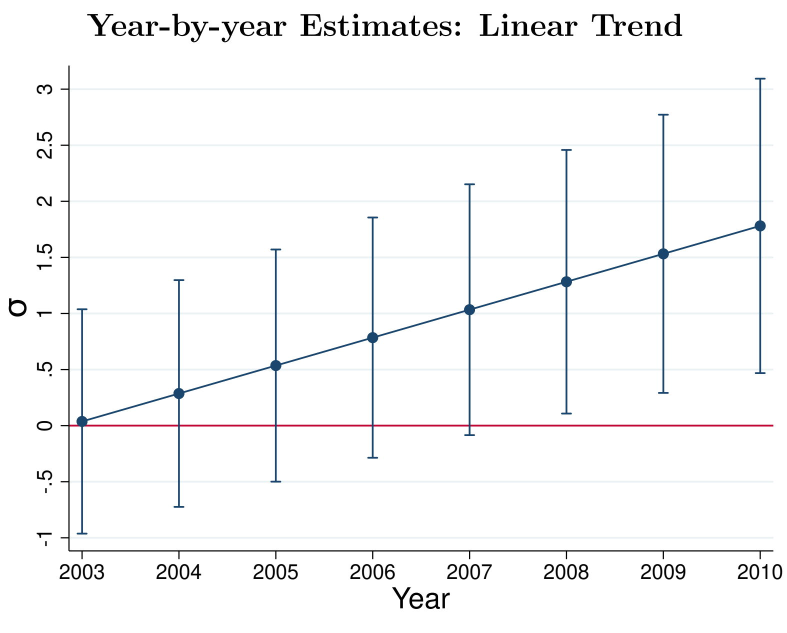
Notes: Author's calculations using data from QCEW and Zwick and Mahon (2017). This figure shows the annual coefficients from an event study around the implementation of bonus depreciation. The dependent variable is Employment in Figure G6A, Compensation in Figure G6B and Compensation per Worker in Figure G6C. 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 30%.

Figure G7: Effect of Bonus Depreciation by Exposure to Long Duration Industries, Long Duration Cutoff 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 is Equipment Capital Stock. 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 cutoffs other than the top tercile.

Figure G8: Alternative Estimates of the Capital-Labor Elasticity of Substitution



Notes: Author's calculations using data from QCEW, Zwick and Mahon (2017), the Census Bureau, and the Bureau of Economic Analysis. This figures reports the estimates of σ by year from an estimation where we use a control function approach that allows σ to vary by year according to interactions between $\Delta\rho_{jct}$ and a linear trend. The plot also includes 90% confidence intervals. The estimated elasticities increase from zero in 2003 to over 1.5 by 2010. See Figure 4C for estimates from a cubic trend and Table G14 for point estimates. See Section IV for more discussion.

Table G1: Characteristics of Investment Duration by Sector

NAICS	Industry	Average	SD	CV	Employment	Capital	Variation
11	Agriculture, forestry, fishing, and hunting	.8617	.01	1.16%	.94%	3.7%	.2
21	Mining	.881	.0083	.94%	.38%	2.4%	.1
22	Utilities	.7673	.0316	4.11%	.18%	6.6%	1.3
23	Construction	.8941	.0028	.32%	7.3%	3.2%	.047
31-33	Manufacturing	.8799	.0077	.87%	11%	25%	1
42	Wholesale trade	.8882	.004	.45%	5.3%	4.9%	.1
44-45	Retail trade	.8811	.0089	1.01%	16%	3.9%	.18
48-49	Transportation and warehousing	.8898	.0163	1.83%	3.6%	9.2%	.78
51	Information	.8794	.0182	2.07%	3%	10%	.96
52	Finance and insurance	.8872	.0062	.7%	4.4%	8.9%	.29
53	Real estate and rental and leasing	.8782	.0191	2.18%	2.2%	7.6%	.77
54	Professional, scientific, and technical services	.8934	.0027	.3%	7.5%	2.5%	.035
55	Management of companies and enterprises	.8805	.	.%	1.8%	.93%	.
56	Administrative and waste management services	.8924	.0025	.28%	8.2%	1.6%	.021
61	Educational services	.8854	.	0%	1.7%	.56%	0
62	Health care and social assistance	.88	.0094	1.07%	11%	4.8%	.24
71	Arts, entertainment, and recreation	.8576	.0154	1.8%	1.4%	.77%	.064
72	Accommodation and food services	.8695	.004	.46%	11%	2.1%	.046
81	Other services, except government	.8762	.0109	1.25%	4%	1.4%	.08

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 G2: 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	Sullivan County, Tennessee	.1513936
4	Olmsted County, Minnesota	.1519782
5	Newport News city, Virginia	.1536248
6	Catawba County, North Carolina	.1568298
7	Sarpy County, Nebraska	.1583619
8	New Castle County, Delaware	.1604007
9	Clayton County, Georgia	.161008
10	Hunterdon County, New Jersey	.1623814
448	Kern County, California	.4485655
449	Clark County, Nevada	.4558978
450	Merced County, California	.4581397
451	Napa County, California	.4653518
452	Fresno County, California	.471666
453	Yuma County, Arizona	.4897471
454	Monterey County, California	.4994023
455	Yakima County, Washington	.5202556
456	Tulare County, California	.5315269
457	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 G3: County Level Descriptive Statistics

	Mean	SD	25^{th}	50^{th}	75^{th}
County Characteristics					
Total Population, 2001	79688.726	263687.930	10669.000	22722.000	55882.000
Total Employment	34189.283	125898.817	2337.000	6402.500	18957.000
Employment Growth, 2001-2007	0.053	0.185	-0.040	0.037	0.122
Employment Growth, 2001-2012	0.026	0.269	-0.101	-0.005	0.107
Number of 3-Digit NAICS Industries	36.517	19.977	20.000	35.000	50.000
County Capital					
Equipment Stock, 2001	1211.563	5107.248	43.399	165.088	576.027
Intellectual Property Stock, 2001	425.889	2045.456	4.027	22.048	133.150
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 Real Estate	0.005	0.007	0.000	0.003	0.007

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 G4: Local Labor Market Effects of Bonus Depreciation (2003-2012, No County Controls)

	(1)	(2)	(3)	(4)
Employment Growth				
Long Duration Exposure	0.018***	0.020***	0.013***	0.020***
	(0.006)	(0.005)	(0.004)	(0.007)
Compensation Growth				
Long Duration Exposure	0.023**	0.026***	0.019***	0.027***
	(0.009)	(0.007)	(0.006)	(0.010)
Compensation per Worker Growth				
Long Duration Exposure	0.001	0.003	0.005***	0.003
	(0.003)	(0.002)	(0.002)	(0.002)
Equipment Stock Growth				
Long Duration Exposure	0.069***	0.059***	0.058***	0.060***
	(0.005)	(0.006)	(0.006)	(0.006)
Year-by-Subsector Fixed Effects†	Yes	Yes	Yes	Yes
Year-by-State Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Dropping Small County-Subsectors				Yes

Notes: This table shows the estimates from a pooled regression of equation 2 where β is not allowed to vary by year and the DPAD variable is the only other included control. The sample for this table includes only years 2003 to 2012 to highlight the long run change in outcomes due to exposure to long duration industries. The outcomes are employment in the first row, compensation in the second, compensation per worker in the third, and equipment stock in the final row. Column (1) shows estimates with subsector-by-year fixed effects while column (2), the main specification, adds state-by-year fixed effects. The following two columns show robustness of the results to winsorizing the weights at the 5% level and to dropping county-subsectors with less than 1,000 workers in 2001. Standard errors are clustered at the county level. The primary specifications with all controls are shown in Table 1.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

† The regressions of equipment capital stock combine all subsectors together, so the subsector-by-year fixed effects are only year fixed effects for the equipment outcome.

Table G5: Local Labor Market Effects of Bonus Depreciation (1997-2000, No Pre-Trends)

	(1)	(2)	(3)	(4)
Employment Growth				
Long Duration Exposure	-0.005*	-0.002	-0.003	0.001
	(0.003)	(0.002)	(0.002)	(0.003)
Compensation Growth				
Long Duration Exposure	-0.004	-0.002	-0.002	-0.000
	(0.003)	(0.002)	(0.002)	(0.003)
Compensation Per Worker Growth				
Long Duration Exposure	-0.000	-0.001	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Equipment Stock Growth				
Long Duration Exposure	-0.004*	-0.002	-0.003	-0.002
	(0.003)	(0.002)	(0.002)	(0.002)
Year-by-Subsector Fixed Effects†	Yes	Yes	Yes	Yes
Year-by-State Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Dropping Small County-Subsectors				Yes

Notes: This table shows the estimates from a pooled regression of equation 2 where β is not allowed to vary by year and all controls discussed in Appendix A are included. The sample for this table includes only years 1997 to 2000 to test the parallel trends assumption in the preperiod, which we fail to reject. The outcomes are employment in the first row, compensation in the second, compensation per worker in the third, and equipment stock in the final row. Column (1) shows estimates with subsector-by-year fixed effects while column (2), the main specification, adds state-by-year fixed effects. The following two columns show robustness of the results to winsorizing the weights at the 5% level and to dropping county-subsectors with less than 1,000 workers in 2001. Standard errors are clustered at the county level. The primary specifications for the post-implementation effects are shown in Table 1.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

† The regressions of equipment capital stock combine all subsectors together, so the subsector-by-year fixed effects are only year fixed effects for the equipment outcome.

Table G6: Event Study Regression of Total Employment Growth on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	0.002	-0.004	-0.003	0.000
	(0.003)	(0.003)	(0.003)	(0.004)
X 1998	0.002	-0.003	-0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.004)
X 1999	0.003	-0.001	-0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.003)
X 2000	0.002	-0.001	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
X 2002	0.005**	0.007***	0.004***	0.008***
	(0.002)	(0.002)	(0.002)	(0.003)
X 2003	0.011***	0.013***	0.010***	0.013***
	(0.003)	(0.003)	(0.002)	(0.004)
X 2004	0.016***	0.021***	0.017***	0.020***
	(0.004)	(0.004)	(0.003)	(0.005)
X 2005	0.019***	0.024***	0.020***	0.026***
	(0.005)	(0.005)	(0.004)	(0.006)
X 2006	0.015**	0.022***	0.019***	0.024***
	(0.006)	(0.006)	(0.005)	(0.008)
X 2007	0.012*	0.019***	0.016***	0.022***
	(0.006)	(0.006)	(0.006)	(0.008)
X 2008	0.011*	0.019***	0.016***	0.019**
	(0.006)	(0.006)	(0.006)	(0.008)
X 2009	0.009	0.016***	0.013**	0.017**
	(0.006)	(0.006)	(0.005)	(0.008)
X 2010	0.013**	0.019***	0.017***	0.021***
	(0.006)	(0.006)	(0.006)	(0.008)
X 2011	0.013**	0.019***	0.017***	0.022**
	(0.006)	(0.006)	(0.006)	(0.009)
X 2012	0.015**	0.021***	0.019***	0.025***
	(0.006)	(0.006)	(0.006)	(0.009)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 growth. The dependent variable is the percent change in total compensation 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (2) is corresponds to Figure 2A.

Table G7: Event Study Regression of Total Compensation Growth on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	0.005	-0.002	-0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.004)
X 1998	0.005	-0.002	-0.002	0.002
	(0.003)	(0.003)	(0.002)	(0.003)
X 1999	0.004*	-0.001	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.003)
X 2000	-0.002	-0.004	-0.003	-0.005
	(0.003)	(0.003)	(0.002)	(0.004)
X 2002	0.009***	0.009***	0.007***	0.011***
	(0.003)	(0.002)	(0.002)	(0.003)
X 2003	0.014***	0.016***	0.012***	0.017***
	(0.004)	(0.004)	(0.003)	(0.005)
X 2004	0.019***	0.024***	0.019***	0.025***
	(0.005)	(0.005)	(0.004)	(0.006)
X 2005	0.022***	0.029***	0.025***	0.033***
	(0.006)	(0.006)	(0.006)	(0.008)
X 2006	0.016**	0.026***	0.022***	0.030***
	(0.008)	(0.008)	(0.007)	(0.010)
X 2007	0.009	0.021***	0.018**	0.027**
	(0.008)	(0.008)	(0.007)	(0.011)
X 2008	0.006	0.017**	0.016**	0.021*
	(0.008)	(0.008)	(0.007)	(0.011)
X 2009	0.004	0.014*	0.011	0.017
	(0.008)	(0.008)	(0.007)	(0.011)
X 2010	0.002	0.012	0.012	0.016
	(0.008)	(0.008)	(0.008)	(0.011)
X 2011	-0.002	0.009	0.009	0.013
	(0.009)	(0.008)	(0.008)	(0.012)
X 2012	-0.002	0.008	0.010	0.017
	(0.010)	(0.010)	(0.009)	(0.013)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 compensation growth. The dependent variable is the percent change in total compensation 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (2) is shown as Figure 2B.

Table G8: Event Study Regression of Compensation per Worker Growth on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	0.003*	0.001	0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.002)
X 1998	0.003	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.002)
X 1999	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	-0.004	-0.004**	-0.002*	-0.006**
	(0.002)	(0.002)	(0.001)	(0.002)
X 2002	0.004***	0.003***	0.002***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	0.003*	0.002*	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)
X 2004	0.002	0.002	0.002	0.002
	(0.002)	(0.001)	(0.001)	(0.002)
X 2005	0.001	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
X 2006	-0.001	-0.000	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
X 2007	-0.004	-0.002	0.000	0.000
	(0.003)	(0.002)	(0.002)	(0.003)
X 2008	-0.006**	-0.005*	-0.003	-0.003
	(0.003)	(0.002)	(0.002)	(0.003)
X 2009	-0.007***	-0.006**	-0.005**	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)
X 2010	-0.014***	-0.013***	-0.010***	-0.013***
	(0.003)	(0.003)	(0.002)	(0.004)
X 2011	-0.017***	-0.016***	-0.012***	-0.016***
	(0.003)	(0.003)	(0.003)	(0.004)
X 2012	-0.019***	-0.018***	-0.014***	-0.017***
	(0.004)	(0.003)	(0.003)	(0.004)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 compensation per employee growth. The dependent variable is the percent change in compensation 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (2) is shown as Figure 2C.

Table G9: Event Study Regression of Equipment Growth on Exposure to Long Duration Industries

Exposure to Long Duration Industries	(1)	(2)	(3)
X 1997	0.003	0.001	0.003
	(0.003)	(0.003)	(0.003)
X 1998	0.002	0.001	0.002
	(0.003)	(0.003)	(0.003)
X 1999	-0.003	-0.003*	-0.002
	(0.002)	(0.002)	(0.002)
X 2000	-0.004***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)
X 2002	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
X 2003	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)
X 2004	0.015***	0.015***	0.015***
	(0.002)	(0.002)	(0.002)
X 2005	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)
X 2006	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)
X 2007	0.019***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)
X 2008	0.032***	0.032***	0.032***
	(0.005)	(0.005)	(0.005)
X 2009	0.043***	0.043***	0.043***
	(0.006)	(0.006)	(0.006)
X 2010	0.047***	0.048***	0.047***
	(0.007)	(0.007)	(0.007)
X 2011	0.051***	0.052***	0.051***
	(0.008)	(0.008)	(0.008)
X 2012	0.060***	0.061***	0.060***
	(0.009)	(0.009)	(0.009)
State-by-Year Fixed Effects	Yes	Yes	Yes
Winsorized Weights		Yes	
Drops Small Counties (<1000)			Yes
Controls for County Characteristics	Yes	Yes	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 g total compensation divided by employment. The dependent variable is the percent change in total compensation divided by employment 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Column (2) is shown as Figure 2D.

Table G10: Event Study Regression of Employment Growth on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
X 1998	-0.000	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
X 1999	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	0.002*	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
X 2002	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2004	0.001	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
X 2005	0.000	0.002	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
X 2006	-0.001	0.001	0.001	0.000
	(0.004)	(0.004)	(0.004)	(0.005)
X 2007	-0.002	-0.001	0.000	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)
X 2008	-0.002	-0.001	-0.000	-0.002
	(0.004)	(0.004)	(0.004)	(0.005)
X 2009	-0.004	-0.002	-0.002	-0.003
	(0.004)	(0.004)	(0.004)	(0.005)
X 2010	-0.004	-0.002	-0.001	-0.003
	(0.004)	(0.004)	(0.004)	(0.005)
X 2011	-0.004	-0.002	-0.001	-0.003
	(0.004)	(0.004)	(0.005)	(0.005)
X 2012	-0.003	-0.002	-0.000	-0.003
	(0.004)	(0.004)	(0.005)	(0.005)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 growth. 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G11: Event Study Regression of Total Compensation Growth on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	-0.000	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
X 1998	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
X 1999	0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
X 2000	0.002	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2002	-0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
X 2003	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
X 2004	0.001	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.003)
X 2005	0.001	0.003	0.004	0.003
	(0.003)	(0.003)	(0.003)	(0.004)
X 2006	-0.001	0.002	0.003	0.002
	(0.004)	(0.004)	(0.005)	(0.005)
X 2007	-0.003	0.001	0.002	0.000
	(0.005)	(0.005)	(0.005)	(0.006)
X 2008	-0.004	0.000	0.001	-0.001
	(0.005)	(0.005)	(0.006)	(0.006)
X 2009	-0.008	-0.003	-0.003	-0.004
	(0.005)	(0.005)	(0.006)	(0.006)
X 2010	-0.008	-0.004	-0.003	-0.003
	(0.005)	(0.005)	(0.006)	(0.006)
X 2011	-0.010*	-0.005	-0.003	-0.005
	(0.006)	(0.006)	(0.007)	(0.007)
X 2012	-0.010	-0.005	-0.002	-0.006
	(0.007)	(0.006)	(0.007)	(0.007)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 compensation growth. The dependent variable is the percent change in total compensation 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G12: Event Study Regression of Compensation Divided by Employment Growth on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Long Duration Industries	(1)	(2)	(3)	(4)
X 1997	0.000	0.000	0.000	0.000
	(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)
X 1999	-0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
X 2000	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
X 2002	0.000	0.001	0.001*	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
X 2003	-0.001	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2004	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
X 2005	0.000	0.002*	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
X 2006	0.001	0.002	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.002)
X 2007	0.000	0.002	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
X 2008	-0.000	0.001	0.001	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
X 2009	-0.003*	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
X 2010	-0.003**	-0.001	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
X 2011	-0.004**	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)
X 2012	-0.006***	-0.003*	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.003)
State-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Subsector-by-Year Fixed Effects		Yes	Yes	Yes
Winsorized Weights			Yes	
Drops Small County-Sectors (<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 compensation divided by employment growth. The dependent variable is the percent change in total compensation 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G13: Event Study Regression of Equipment Capital Stock Growth on Exposure to Structures Intensive Long Duration Industries (Placebo Test)

Exposure to Long Duration Industries	(1)	(2)	(3)
X 1997	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
X 1998	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
X 1999	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
X 2000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
X 2002	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
X 2003	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)
X 2004	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
X 2005	0.004***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
X 2006	0.007***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)
X 2007	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)
X 2008	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
X 2009	0.006**	0.005**	0.006**
	(0.003)	(0.002)	(0.003)
X 2010	0.004	0.003	0.004
	(0.003)	(0.003)	(0.003)
X 2011	0.002	0.001	0.002
	(0.003)	(0.003)	(0.003)
X 2012	0.001	-0.000	0.001
	(0.004)	(0.004)	(0.004)
State-by-Year Fixed Effects	Yes	Yes	Yes
Winsorized Weights		Yes	
Drops Small Counties (<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 equipment capital stock growth. The dependent variable is the percent change in equipment capital stock 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 state and sector levels are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table G14: Estimate of the Capital-Labor Elasticity of Substitution

	OLS	IV			Control Function	
			2002-2005	2006-2010	Linear	Cubic
$\Delta\rho$	-0.371***	0.785	-0.586	1.687**	1.034	1.148*
	(0.015)	(0.651)	(0.453)	(0.828)	(0.680)	(0.696)
$\Delta\rho \times (year - 2007)$					0.249***	0.304***
					(0.071)	(0.095)
$\Delta\rho \times (year - 2007)^2$						-0.028**
						(0.013)
$\Delta\rho \times (year - 2007)^3$						-0.008**
						(0.003)
First Stage F-stat		21.970	39.580	13.100	21.970	21.970

Notes: Author's calculations using data from QCEW, Zwick and Mahon (2017), the Census Bureau, and the Bureau of Economic Analysis. This table shows estimates of Equation 3 where the coefficient on $\Delta\rho_{jct}$ can be interpreted as the capital-labor elasticity of substitution, σ. See Figure G8 for the year-by-year values of σ from the model with a linear trend and Figure 4C for the year-by-year values of σ from the model with a cubic trend. Standard errors are clustered at the county level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.