Tax Incentives, Small Businesses, and Physical Capital Reallocation*

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Abstract

Using data on a broad range of $298.6 billion worth of equipment purchases spread over 3.32 million equipment transactions by 688,000 small businesses during 1998-2019, we provide the first evidence on the capital reallocation effect of temporary federal tax incentives. We find that accelerated depreciation encourages the utilization of new capital goods. The tax subsidy on new equipment increases the supply of old equipment in the secondary market and lowers the price of the old equipment. The reduced cost of old equipment thus eases the capital constraints for some small businesses and encourages business entry. Our empirical results highlight how investment in new capital goods motivated by tax incentives fosters reallocation of old capital goods to small businesses.

Keywords: Taxes, Bonus Depreciation, Capital Reallocation, Investment, Old Capital

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1 Introduction

Policymakers use tax-based investment incentives as a counter-cyclical fiscal policy to promote investment and foster economic growth. The literature shows that federal tax incentives that accelerate the depreciation of equipment investments increase investment activities and jobs among small businesses.[1] However, these prior studies do not distinguish whether small businesses invest in new or old capital goods. While investment in new capital goods is essential for economic growth (Solow, 1960), the availability of old capital goods can reduce entry barriers for many small businesses.[2] In this paper, we document the first evidence on the effect of favorable tax incentives on the reallocation of old capital goods to small businesses.

Conditional on investment, the effect of tax incentives on firms' propensity to invest in new versus old capital goods is not apparent. Some small businesses may directly benefit from tax incentives by investing in new capital goods. Meanwhile, the higher upfront cost of new capital goods compared to old ones discourages constrained small businesses from investing in new capital goods (Rampini, 2019). However, some of these constrained small businesses can benefit indirectly from tax incentives. With tax subsidy on new capital goods, firms with less binding constraints may replace old capital goods with new capital (Lanteri and Rampini, 2021). This increases the supply of old capital goods and hence lowers their equilibrium price. Thus, small businesses with binding constraints may buy old capital goods and indirectly benefit from tax incentives. For policy design, it is essential to understand the economic magnitude of these direct and indirect benefits from tax incentives.

[1] For example, Zwick and Mahon (2017) show that small businesses in long-duration industries are more likely to increase investment in response to federal tax incentives under Section 168(k) of bonus depreciation that accelerates equipment investments depreciation. In comparison, Tuzel and Zhang (2020) exploit the variation in the state's adoption of Section 179 of federal equipment expensing allowance for eligible firms and documents the distributive effect of tax policy on job growth.

[2] Eisfeldt and Rampini (2007) show firms with binding financial constraints invest in old capital goods. More recently, Ma, Murfin, and Pratt (2021) highlight the importance of the local availability of old capital goods for small business formations.

We test the direct and indirect benefits of tax incentives using data on equipment purchases and three episodes of investment stimulus during 1998-2019. Our data includes 3.32 million purchase transactions by 687,996 small US businesses (with median annual sales of $250,000 and median employment of five workers), covering 31,757 models of new and old machines used across a broad range of industries. Our data source is Uniform Commercial Code (UCC)-1 statements, collected and processed by Equipment Data Associates (EDA). The equipment includes tractors, loaders, excavators, copiers, mowers, trucks, trailers, sprayers, cultivators, etc. In terms of tax policy, we utilize "bonus" depreciation under Section 168(k) of the Internal Revenue Code that accelerates the timing of deductions of investment purchases from taxable income. Tax deductions under Section 168(k) are available only on the purchase of new equipment, allowing firms to accelerate depreciation irrespective of investment size and increase the size of their net NOLs if necessary, which they can claim in the future.[3] The bonus depreciation does not affect the amount of deductions, but it alters the timing. Therefore, future deductions are worth less than current deductions. This will benefit small businesses, especially for those with higher discount rates. Our empirical strategy (similar to Zwick and Mahon (2017)) exploits the technological differences among firms in narrowly defined industries. Firms in industries with most of their investment in *long-duration* categories act as the "treatment group" because bonus depreciation changes their depreciation schedule more significantly than for firms in *short-duration* industries. Most importantly, this federal tax policy was not targeted towards specific industries. However, industry variation emerges because firms with longer-lived assets experience a more significant reduction in the present value cost of investment, caused by bonus depreciation accelerating deductions from further in the future.[4]

[3]When businesses buy equipment, they can choose both Section 179 and Section 168(k) of accelerated depreciation on qualified assets. However, Section 179 must be applied first, and firms may take any amount over the statutory limit to Section 179 under Section 168(k) of bonus depreciation. Section 179 allows business owners to deduct a set dollar amount of investment, and bonus depreciation lets them deduct a percentage of the cost. See Section 2 for details.

[4]In our case, we utilize variation in Section 168(k) of bonus depreciation across industries for three

First, we document our main findings at the equipment purchase transaction level. We find that, conditional on investment, small businesses in treated industries are 5.3% more likely to buy new capital equipment. The impact is almost three times the effect of firm age on probability of buying new equipment previously documented in literature (Ma, Murfin, and Pratt, 2021). At the aggregate firm-level, we find an average increase in equipment investment by 8.3% in response to tax incentives, driven mainly by investment in new equipment.[5] Next, compared to short-duration industries, we find an average decline in prices of old equipment by 2.4% for long-duration (treatment group) industries during the sample period 1998–2019, while no change in the prices of new equipment. Consistent with theory, we find that decline in prices of old equipment leads to an increase in the purchase of old equipment by more constrained small businesses in treated industries. Finally, we find an increase in the business entry of small businesses by 2.3%, especially for industries with the ex-ante higher relative price of old equipment. Our findings suggest that in addition to direct tax benefits, some small businesses may indirectly benefit from lower prices of old capital goods. Thus, we document the unintended positive effect of tax incentives on small businesses.

reasons. First, Section 168(k) of bonus depreciation is available only on new equipment, while Section 179 applies to both new and old qualified assets, except for tax years after Sept. 27, 2017. Thus, in our case, the capital reallocation effect depends on subsidizing the purchase of new capital. Second, the direct benefits of Section 179 are available to only eligible small businesses. In contrast, Section 168(k) allows firms to accelerate depreciation irrespective of investment size, thus affecting all types of firms, especially less constrained firms. This variation is important to test the indirect benefits of tax incentives coming via a decline in prices of old equipment. Finally, the dollar value of claims for Section 168(k) is significantly more than Section 179 claims, thus affecting a large number of businesses in the economy to generate general equilibrium effects. For example, the depreciation claims for Section 168(k) account for $594.49 billion of total $1.13 trillion in 2018, while Section 179 claims were only $33.9 billion.

[5] Consistent with Zwick and Mahon (2017), we find a substantial effect of bonus depreciation on equipment investment. For small businesses with different exposure to bonus depreciation, we find an increase in equipment investment on average by 5.2% between 2001 and 2004 and 14.3% between 2008 and 2010 in response to bonus depreciation. For the Tax Cuts and Jobs Act of 2017 (TCJA), we do not find a statistically significant increase in firm's investment and firm's likelihood to buy new capital equipment during 2018 and 2019. TCJA made an important change to the qualified equipment rules by allowing businesses to claim bonus depreciation on both "new" and "used" capital goods. Lanteri and Rampini (2021) theoretically show that any policy that subsidizes both new and old capital goods generates the demand for old capital by less constrained and unconstrained firms. This may reduce the price effect on old capital goods. Consistently, we find no change on the prices of old equipment in the post TCJA period.

A major challenge with our empirical design is that time-varying industry shocks may overlap with the timing of bonus depreciation. We conduct various tests to alleviate this concern. First, we plot the trends for firms in short- and long-duration industries for each of the three bonus periods. We observe no difference in trends for treatment and control groups for the pre-period and a clear break in trends around the policy change. Second, we control macro-economic trends in the data by including industry-specific linear and quadratic trends in our regressions. Controlling for these macro-economic trends increases our estimates. Finally, since capital goods are used across different industries, we include equipment-level fixed effects and equipment-specific quadratic trends in various regressions to control equipment-level unobservables and movements.

Our data's granularity helps us control time-varying unobservables at the machine level. However, this comes with a disadvantage. We do not observe marginal tax rates for our sample firms, and we may be overestimating our effects. However, this may not be a concern in our case because the tax deductions under Section 168(k) have no business income limitation. Therefore, small businesses can take net operating losses (NOLs) by taking advantage of bonus depreciation. Thus, from a tax perspective, the profit-making and loss-making businesses have equal incentives when investing in bonus depreciation eligible equipment.

In our data, almost 50% of purchase transactions are for old machines. Thus, our results are not affected by type of transactions covered by the data provider. In addition, we use two measures of machine vintage. The first measure of vintage is simply machine age, defined as the time elapsed since the date the machine was placed in service. The second measure of vintage, called "technological age," is calculated as the time elapsed since the machine's model type was first introduced. At the purchase transaction level, for both machine vintage measures, we find a decrease in average machine age and technological age for equipment transacted after tax shocks. We include industry fixed effects to control for industry-specific unobservables, firm controls, and firm fixed effects to control for firm-level heterogeneity in different regression specifications. The absence of differential pre-trends for short- and long-duration industries provides the validity of natural experiment. Overall, these results suggest that firms belonging to the treated industries prefer to buy new capital goods over old capital goods and take the direct tax benefit.

Next, we test whether our results are consistent with the *tax benefit effect* or the *capital allocation effect*. The *tax benefit effect* would suggest that small financially constrained businesses are more likely to respond to tax incentives by increasing their new equipment investment. On the other hand, the *capital reallocation effect* would predict that financially constrained firms would be more likely to buy cheaper old capital instead of new equipment. Lanteri and Rampini (2021) theoretically show that the equilibrium price of old capital is higher than its social value. This implies that some firms may not invest at all because of the higher price of old capital goods. An increase in the tax subsidy for new capital goods implies that less constrained firms are more likely to buy new capital and replace their old equipment. This increases the supply of old capital, in turn lowering its equilibrium price. Therefore, small businesses with binding constraints buy cheaper old capital and less likely to buy new equipment.

Small businesses with a lack of internal finance may rely on bank loans for external finance. We use two measures of access to external finance for small businesses. First, we use Small Business Administration's (SBA) 7 (a) loan data and create ex-ante loan availability measure at 6-digit NAICS level (similar to Erel and Liebersohn (2020)). We find that firms in industries with a lower ex-ante share of SBA loans are less likely to buy new capital goods among the treated firms. Next, we use the geographic variation in access to external finance. Berger, Bouwman, and Kim (2017) show that the prevalence of small banks in an area increases the availability of external financing to small firms. We follow Tuzel and Zhang (2020) and calculate small bank share as the deposit share of small banks (defined as banks with total assets below $50 billion) in each county based on information from quarterly bank Call Reports. We find firms in our sample (i.e., small firms) respond to tax incentives by reducing their likelihood of purchasing new equipment in counties with lower availability of small bank lending. Ma, Murfin, and Pratt (2021) highlight the importance of co-location of potential buyers and sellers of old capital goods for reallocation. Further, not many states conform with federal law on accelerated depreciation (Tuzel and Zhang, 2020). Therefore, we include state-year and industry-state fixed effects to estimate our effects within the same state across industries. Overall, our results are consistent with the *capital reallocation effect*.

Next, we directly test the capital reallocation using size differences between seller and buyers of old capital goods. For each year, we aggregate the data at the industry–buyer state–seller state level. First, we find an increase in the number of old capital goods transactions for treatment industries. These results are robust after including buyer/seller specific state fixed effects. We also find that such transactions are more prominent in industries where the average size of the selling firm is more than the average size of the buying firm. This suggests that large firms are more likely to sell their old equipment to small-sized firms after the tax shock. Finally, we also find an increase in business entry by small firms especially for industries with ex-ante higher relative price of old equipment. Overall, we find that tax incentives encourage less-constrained firms to invest in new capital goods. This increases the supply of old capital goods and results in a decline in the cost of old capital goods. The reduced price of old capital goods encourages constrained firms to invest in old capital goods (*capital reallocation effect*) and enter in the market.

Our paper relates to the large literature on tax incentives, capital reallocation, and vintage capital.[6] To the best of our knowledge, this is the first paper that provides empirical evidence on the *capital reallocation effect* of tax incentives. The previous tax literature exploits cross-sectional variation to study the *tax benefit effect* of tax policy on

[6] See Akcigit and Stantcheva (2020) for survey on tax incentive literature and Boucekkine, de La Croix, and Licandro (2011) for survey on vintage capital.

investment (Desai and Goolsbee, 2004; House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2018)[7] and labor (Gaggl and Wright, 2017; Garrett, Ohrn, and Suárez Serrato, 2020; Tuzel and Zhang, 2020). Our study also complements Zwick and Mahon (2017). They show that financially constrained firms are more likely to increase investments as a response to tax incentives. Our study suggests that the increase in investment could be driven by a decline in the general equilibrium price of old capital goods for very small financially constrained businesses.

We also contribute to the capital reallocation literature. Early work by Eisfeldt and Rampini (2006) show that capital reallocation between firms is pro-cyclical. Eisfeldt and Rampini (2007) show that financially constrained firms tend to acquire older investment goods. Benmelech and Bergman (2011) find that weak creditor rights are associated with both aircraft of older vintage and older technology. Ma, Murfin, and Pratt (2021) use equipment transaction data like our paper and document local capital reallocation from older firms to younger firms. Our paper is closely related to theoretical work by Lanteri and Rampini (2021) and provide empirical evidence for the *capital reallocation effect* of tax incentives. We also contribute to the vintage capital literature. The literature shows that capital of older vintage adversely impacts firm productivity and growth (Benhabib and Rustichini, 1991; Hsieh, 2001), slows technology diffusion (Chari and Hopenhayn, 1991), and increases income inequality across individuals and countries (Jovanovic, 1998). We contribute to this literature by documenting how tax incentives lower the cost of vintage capital and result in investment by constrained firms.

The rest of the paper proceeds as follows. We discuss policy background and conceptual framework in Section 2. Next, we discuss our empirical methodology in Section 3. Section 4 describes our data and summary statistics. Our main empirical results are presented in Section 5, we provide additional results in Section 6 and we conclude in Section 7.

[7] The early work include studies by Summers (1981, 1987); Cummins, Hassett, and Hubbard (1996); Goolsbee (1998); Chirinko, Fazzari, and Meyer (1999).

2 Policy Background and Hypothesis Development

In this section, we first discuss the history of tax incentive policy used in our study, i.e., bonus depreciation (Section 2.1), and then present our main hypothesis (Section 2.2).

2.1 History of Bonus Depreciation

In the United States, firms conventionally depreciate every additional dollar of investment following the standard Modified Accelerated Cost Recovery System (MACRS) schedule. For example, investments in computers and electronic hardware follow a five-year schedule (i.e., they are depreciated by 20% in the year of purchase, and 32%, 19.2%, 11.5%, 11.5%, and 5.8% in the following five years, respectively), while investments in equipment and other office supplies follow a seven or a ten-year schedule.

Section 179 of the Internal Revenue Code, a permanent tax provision, allows firms in all business lines and sizes the option, within certain limits, of expensing the cost of new and used qualified property in the tax year when the assets are placed in service. Business taxpayers who cannot (or choose not to) claim the allowance may recover capital costs over longer using the MACRS schedule. The maximum expensing allowance and investment limits continued to have increased in the last three decades. For example, the maximum expensing allowance was only $10,000 with an investment limitation of $200,000 during 1987-1992. While, for 2018 and after that, the maximum expensing allowance increased to $1,000,000 with an investment limit of $2,500,000.

In 2002, in an effort to help small businesses, Congress introduced bonus depreciation through the Job Creation and Worker Assistance Act under Section 168(k) of IRC. Under the Act, small business owners have been allowed to claim first-year bonus depreciation for qualifying property and equipment used for business purposes. In contrast to Section 179, bonus depreciation has been available only on new equipment. Further, bonus depreciation allows firms to accelerate depreciation irrespective of investment size, thus affecting all types of firms, especially firms not eligible for Section 179. The policy was entirely aimed at lowering the cost of capital for new investments. The bonus depreciation lets companies deduct 30% of the cost of eligible assets before the standard depreciation method is applied.[8]

In general, a company that invests in assets eligible for both the Section 179 and Section 168(k) expensing allowances must recover its cost in a prescribed order. The Section 179 expensing allowance has to be taken first, lowering the company's basis in the asset by that amount. The taxpayer then may apply the bonus depreciation allowance to any remaining basis amount, further reducing the company's basis in the property. Finally, the company can claim a depreciation allowance under the MACRS for any remaining basis, using the double-declining balance method. In the case of Section 179, a company must be profitable to take the Section 179 deduction, it cannot be applied to create a net loss for the business. However, tax deductions under Section 168(k) have no business income limitation. Therefore, small businesses can take net operating losses (NOLs) by taking advantage of bonus depreciation.[9]

The bonus increased to 50% later in 2003. The policy was temporary in nature and set to be expired at the end of 2004. During the financial crisis, the 50% bonus depreciation was reinstated in 2008 as an economic stimulus. The Tax Relief Act increased the

[8] See House and Shapiro (2008) for the legislative history of the first round of bonus depreciation and Kitchen and Knittel (2011) for the second round.

[9] For example, assume that the only investment a company makes in a tax year is the acquisition of 10 new machine tools at a total cost of $700,000. Such a purchase qualifies for both the Section 179 expensing allowance ($500,000) and the 168(k) bonus allowance (50% of acquisition cost) for that year. Therefore, it is required to recover that cost for federal tax purposes in the following order: First, the company claims a Section 179 expensing allowance of $500,000 on its federal tax return for that year, lowering its basis in the property to $200,000 ($700,000-$500,000). Then it claims a bonus depreciation allowance of $100,000 ($200,000 x 0.5), further lowering its basis to $100,000 ($200,000-$100,000). Next, the company claims a deduction for depreciation under the MACRS on the remaining $100,000. Given that the MACRS recovery period for machine tools is five years and five-year property is depreciated using the double-declining-balance method, the company takes an additional depreciation allowance equal to 20% of $100,000, or $20,000, under the half-year convention. The company then recovers the remaining basis of $80,000 ($100,000-$20,000) by taking MACRS depreciation deductions over the next five years at rates of 32%, 19.2%, 11.52%, 11.52%, and 5.76%, respectively. As a result, the company can deduct nearly 89% of the purchase price of the machine tools it buys in the year they are placed in service.

bonus to 100% for tax years ending between September 2010 and December 2011. The Protecting Americans from Tax Hikes (PATH) Act of 2015 extended this program through 2019 for business owners, but included a phase-out of the bonus depreciation rate after 2017. Under the PATH Act, businesses were allowed to deduct their capital expenses by 50% for 2015, 2016, and 2017. The rate was then scheduled to drop to 40% in 2018 and 30% in 2019. However, the TCJA, passed in 2017, introduced significant changes to bonus depreciation rules. Most significantly, the bonus depreciation deduction for qualified property, as defined by the IRS, doubled from 50% to 100%. Further, the TCJA also made an important change to the qualified property rules by allowing businesses to claim bonus depreciation on used assets.[10] Figure 1 plots the maximum first-year deduction for qualified equipment during the bonus and non-bonus deprecation years. Table IA1 provides further details about the depreciation policy. Next, we discuss the conceptual framework and reasons for our choice of particular tax incentive policy.

2.2 Conceptual Framework

According to the investment tax elasticity literature (Hall and Jorgenson, 1967; Summers, Bosworth, Tobin, and White, 1981; Auerbach and Hassett, 1992), the effect of tax policy on investment behavior enters the investment function through the rental value of capital input. Tax incentives reduce the rental value of capital input. This increases the optimal capital stock and net investment level, bringing the capital stock up to its new desired level. The bonus depreciation, a particular tax incentive we use in our study, is available only on new capital goods.[11] However, it is not clear whether firms will buy new or old capital goods. In equilibrium, firms with capital constraints buy used assets due to their lower upfront cost compared to new capital goods and optimal matching of investment

[10] Used equipment is eligible for additional first-year depreciation if the taxpayer or a predecessor did not use the equipment at any time before acquisition. In other words, the use of the equipment has to be new with that taxpayer, although the equipment itself can be used equipment.

[11] TCJA increased the additional first-year depreciation deduction from 50% to 100% for qualified equipment and also allowed a deduction on purchases of old capital goods.

cash flows (Eisfeldt and Rampini, 2007; Rampini, 2019; Ma, Murfin, and Pratt, 2021). Therefore, we predict tax incentives may alleviate financial constraints for such firms, and they are more likely to invest in new capital goods. Since smaller firms are likely to face more significant financial frictions, Zwick and Mahon (2017) also find that small firms are more responsive to investment stimulus (*tax benefit effect*).

H1A: The tax benefit effect predicts firms with financial constraints are more likely to buy new capital goods.

In contrast, Lanteri and Rampini (2021) show that financial frictions can distort the allocation of capital across firms. Typically, older capital goods flow to financially–constrained firms. They show that the equilibrium price of old capital is higher than its social value.[12] This implies that some firms may not invest at all because of the higher price of old capital goods. Tax incentives can *indirectly* benefit some of these firms. A tax subsidy on new investment goods implies firms with less binding constraints may replace old capital goods with new capital. It increases the supply of old capital and hence lowers its equilibrium price. Thus, small businesses with binding constraints may buy old capital goods or be less likely to buy new capital goods (*capital reallocation effect*).

H1B: The capital reallocation effect predicts firms with financial constraints are less likely to buy new capital goods.

In our case, we utilize variation in Section 168(k) of bonus depreciation across industries for three reasons. First, Section 168(k) of bonus depreciation is available only on new equipment, while Section 179 applies to both new and old qualified assets, except for tax years after Sept. 27, 2017. The capital reallocation effect depends on subsidizing

[12] Dávila and Korinek (2018) show that financial frictions may give rise to both distributive externalities (i.e., between sellers and buyers of assets) and collateral externalities (i.e., externalities deriving from the dependence of financial constraints on asset prices). Thus, assets prices could be too high or too low.

the purchase of new capital. Second, the direct benefits of Section 179 are available to only eligible small businesses. In contrast, Section 168(k) allows firms to accelerate depreciation irrespective of investment size, thus affecting all types of firms, especially for firms that are not eligible for Section 179. This variation is important to test the indirect benefits of tax incentives coming via a decline in prices of old equipment. Finally, in 2018, the depreciation claims for Section 168(k) account for $594.49 billion of total $1.13 trillion, while Section 179 claims were only $33.9 billion, thus affecting large number of businesses in the economy to generate general equilibrium effects.[13]

3 Empirical Strategy

In this paper, we utilize the cross-sectional variation in technology in narrowly defined industries. As an illustrative example, consider depreciation benefits that accrue to a firm considering a $500,000 investment in computers and electronic equipment, having a five-year depreciation schedule under MACRS. Table 1 shows the firm's deductions over the asset's economic life. Under the standard half-year MACRS convention, investments in equipment are depreciated by 20% in the year of purchase. While, under the 50% (100%) bonus depreciation rule, 50% (100%) of the total cost is depreciated in the year of purchase. The federal tax policy was not targeted at certain industries. However, industry variation emerges because firms with longer-lived assets experience a larger reduction in the present value cost of investment since bonus depreciation accelerates deductions from farther in the future. We follow Zwick and Mahon (2017) (henceforth, ZM) to calculate z^0.

Letting D_s denote the depreciation rate at period s for an asset with lifespan T, the present value of depreciation deductions associated with $1 of investment in equipment

[13]Refer `https://www.irs.gov/statistics/soi-tax-stats-corporation-tax-statistics`.

can be written as

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

where r denotes the discount rate applied to future cash flows. However, the actual amount of deductions available to firms change over the years depending on the level of tax incentives provided by the government. Under the bonus depreciation schedule $\Theta \in (0, 1)$, the fraction Θ is immediately expensed in the year of purchase, while the residual fraction $(1-\Theta)$ follows the normal MACRS schedule. Thus, under bonus depreciation, the present value of tax benefits with the effective tax rate, τ, is

$$z^\Theta = \tau(\Theta + (1-\Theta)z^0).$$

The effect of bonus depreciation on the deductions schedule is depicted in Table 1. Under the 50% bonus rule, the total deductions in the year of purchase include $250,000, which is expensed immediately and $50,000 from the standard MACRS deductions on the residual balance of $250,000. Long-lived assets 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 less in present value terms.

For example, TCJA allows firms to write off 100% percent of qualifying investments immediately. While the previous regime only allows 50% percent of qualifying investments to be depreciated immediately, the remaining 50% percent is depreciated according to MACRS rules. Bonus depreciation reduces the present value of the cost of investment by $\tau(0.5(1\text{-}z^0))$ if there is no change in the effective tax rate.[14] Therefore, industries with a smaller average z^0 before bonus depreciation, i.e., those with long-lived assets, are more likely to benefit from expensing the full amount. We use ZM's measure z_j^0

[14] We use ZM's measure of z_j^0. They find the lowest value of z_j^0=0.7. For this value, any effective tax rate lower than 24.7% before the shock generates a positive effect for bonus depreciation, i.e., 0.21-$\tau(0.5+0.5\times0.7)\geq 0$. For z_j^0=0.9, maximum in our data, the τ should be 22.1%. TCJA, the top statutory tax rate was reduced from 35% to 21%. Therefore, the bonus increases the marginal tax benefit of investment for the most affected firms only if their effective tax rate is lower than 24.7% before TCJA.

for industry variation.[15] The variation in z_j^0 across industries provides the basis for a difference-in-differences setup with continuous treatment, i.e.,

$$z_{jt}^{\Theta} = \Theta_t + (1 - \Theta_t) z_j^0,$$

where z_{jt}^{Θ} will be less than one and varies across industries before tax changes, and z_{jt}^{Θ} will be equal to 1 for all industries with bonus deprecation of 100%. Thus, industries with lower z_j^0 before the bonus will benefit the most after bonus depreciation. Table 2 provides the list of the most and least effected industries based on z_j^0. For example, we find in our data that the most effected industries at three-digit industry codes include Crop Production (111) and Fabricated Metal Manufacturing (327). The least effected industries include Professional, Scientific, and Technical Services (541) and Administrative and Support Services (561).

We use transaction-level capital investments data in the baseline case. We discuss them in detail in Section 4. The regression framework implements the following difference-in-differences (DD) specification,

$$y_{i,m,t} = \alpha + \beta z_{j,t}^{\Theta} + \gamma X_{i,t} + \delta_j + \omega_t + \kappa_m + \epsilon_{i,m,t}, \tag{1}$$

where index i refers to firm, m refers to machine, j denotes the four-digit NAICS industry and t indicates the year. $z_{j,t}^{\Theta}$ is measured at the four-digit NAICS industry level and increases during bonus years. We use an indicator variable equal to one if the machine is new, machine age and model age as different dependent variables for $y_{i,m,t}$ (described in Table A1). The coefficient of interest is β. The baseline specification also includes two sets of fixed effects: industry fixed effects (δ_j) to control for industry-specific unobservables and ω_t denotes year fixed effects to control for time trends. In some specifications, we include machine fixed effects (κ_m) to control for technological differences in machines.

[15] ZM calculate z^0 for each asset-class defined by MACRS, assuming a 7 percent discount rate. Next, 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.

We include firm/establishment-level controls such as logged sales and logged employees, which are collectively represented as $(X_{i,t})$. We also include linear and quadratic trends at two-digit NAICS level to control for macro-economic shocks. In some specifications we include buyer/firm fixed effects. Following Zwick and Mahon (2017), we cluster at the four-digit NAICS level.

4 Data and Descriptive Statistics

4.1 Data Sources and Sample Selection

The main source of data that we use for empirical analysis is from Equipment Data Associates (EDA), which collects and processes Uniform Commercial Code (UCC)-1. A UCC-1 statement is filed by the lender to the according state to claim collateral in case debtors default on a business loan. Consequently, UCC-1 statements include details of the creditor and the debtor, and descriptions of the underlying collateral. While the UCC-1 filings are publicly available, all states, except California and Texas, do not allow for bulk downloads. Thus, a large sample of UCC-1 statements are only availabe through EDA, which has a contract with all states that allows for bulk downloads. While all the UCC-1 statements are collected, only those with collateral on equipment in the agriculture, aircraft, construction, copier, lift trucks, logging, machine tools, printing, trucking, and woodworking industries are processed.

The greatest strength of the EDA data is that we are able to observe capital investments at the transaction level. EDA first classifies the UCC-1 filings based on the nature of the transaction: leases, rentals, sales, wholesales, and refinances. For our purpose, we restrict the sample to sales and wholesale transactions [16]. In addition to the nature of the

[16] In our baseline results, we drop lease transactions for two reasons. First, in our data, we can not distinguish capital leases from operating leases. As per the IRS tax code, only capital leases are eligible for bonus depreciation. Second, since most leases are on new transactions, which removes variation in the machine age.

transaction, EDA also provides machine-level characteristics such as the manufacturer, manufacturing year, model, serial number, equipment value, and whether the equipment is new or used. For each equipment transaction, we construct the log value of equipment price, the machine age from the manufacturing year, and the model age. The model age proxies for the "technological age" and is calculated as the number of years passed since the model was first introduced.

In addition to the machine characteristics, EDA supplements firm characteristics such as annual sales, number of employees, and year of establishment of the acquiring firm from Dun & Bradstreet. However, many of the firm characteristics are missing. We augment this with firm-level data from Mergent Intellect, which provides the same firm-level variables as those EDA obtains from Dun & Bradstreet, but is more comprehensive. Various other papers also used UCC financing statements data. Edgerton (2012) documents the effect of credit supply on business investment during great recession. Murfin and Pratt (2019) use EDA data and show that how equipment manufacturers use captive finance to maintain higher resale price for their products. Ma, Murfin, and Pratt (2021) use EDA data to document importance of the local availability of old capital goods for business formations and capital reallocation. Gopal and Schnabl (2021) utilize a comprehensive set of UCC filings data and document the gap left by contraction in small business lending by banks has been filled by finance companies and fintech lenders.[17]

4.2 Summary Statistics

Table 3 displays summary statistics of the equipment and firm characteristics for our sample period from 1998 to 2019. There is a total of $3,332,000$ equipment transactions, with an average (median) price and age of \$$87,718$ (\$$60,752$) and 4.125 (1), respectively. The average (median) model age of a machine is 6.901 (5) years, and approximately 54.5% of the equipment in our sample is new. The firms that acquire the equipment have

[17]Further description of the data can be found in Edgerton (2012); Gopal (2019).

an average (median) of approximately \$430 (0.605) million in sales and 35 (5) employees. The average (median) value of z^{Θ}, which is the present discounted value of a dollar of depreciation deductions and our main variable of interest, is 0.940 (1).

We plot the distribution of equipment transactions, *New* indicator, *Machine Age*, *Model Age* respectively in Figure 2. Since EDA processes UCC-1 statements of certain equipment industries, we have a high proportion of firms (buyers) in the construction, agriculture, and manufacturing. However, the firms (buyers) acquiring equipment are still distributed across all two-digit NAICS industry levels. The figure suggests that certain industries like health care, utilities, finance, information, etc. have the highest proportion of new equipment with the lowest machine age and technological age respectively. On the other side, industries with the oldest machines and technology include agriculture, mining, retail, construction, etc. As noted before, the distribution of buyers suggests that we have a high proportion of firms (buyers) in construction, agriculture, wholesale and manufacturing.

5 Results

5.1 Impact of tax incentives on New Equipment Investment

In this subsection, we first discuss the graphical evidence on the effect of bonus depreciation on new equipment purchases (Section 5.1.1). Next, we provide baseline results for Equation (1) (Section 5.1.2). Finally, we test the impact of bonus depreciation on machine vintage and model age (Section 5.1.3).

5.1.1 Graphical Evidence using Treatment Indicator

As discussed in Section 3, we follow an empirical strategy similar to Zwick and Mahon (2017) that exploits the technological differences among firms in narrowly defined industries. Firms in industries with most of their investment in long-duration categories act as the "treatment group" because bonus depreciation incentives significantly change their depreciation schedule compared to short-duration categories (control group). The industries with a smaller average z^0 before bonus depreciation, i.e., those with long-lived assets, are more likely to benefit from expensing the full amount. We use ZM's measure z^0_j- based on four-digit NACIS, for industry variation. We define the treatment indicator variable (*Treat*) based on the bottom three deciles of z^0_j. The control group involves the four-digit industries in the top three deciles of z^0_j.

We start with this simplified set-up to give an intuition on the main result and its economic significance. However, dropping the middle group will result in a smaller sample size of 1.96 million transactions. Our variable of interest is *New*, which takes the value 1 for new equipment purchases and 0 otherwise. We implement a difference-in-differences model according to specification (1) to test whether the treated firms invest in new capital equipment when there is an increase in bonus depreciation rates. In this analysis (and in future analysis), we combine the three episodes of bonus depreciation changes into a single analysis between 1998-2019. As shown in Figure 1, we define 1998-2000, 2005-2007, and 2016-2017 as the pre-shock window when the bonus depreciation levels were low (*Post=0*). We further define Sep 2001- 2004, July 2008-2011, and 2018-2019 as the post-shock window when there is an increase in bonus depreciation levels. The variable of interest for this design is *Treat*$\times$ *Post*. The results are documented in Table 4 *Panel A*. In column (1), we start with industry and year fixed effects. The coefficient of 0.055 on *Treat*$\times$ *Post* indicates that firms in treated industries increase their purchase of new equipment by 5.5%. Columns (2) and (3) control for time-variant omitted industry-level factors using linear and quadratic industry trends with two-digit NAICS industry dummies. The effect on new equipment purchases increase to 5.8% for the treated firms. Finally, in column (4), we control for the effect of size using the natural logarithm value of sales and employees. The coefficient size decreases marginally to 5.3%.

Next, we re-do our analysis by graphically plotting the regression results above in Figure 3. We plot the % *New* equipment for firms in treatment and control groups around the years before and after the bonus depreciation changes. For these plots, we subdivide the sample into three time periods depending on the changes in bonus depreciation schedule: 1998-2004, 2005-2011, and 2016-2019. For each bonus event, we use the previous year as the benchmark period. For example, for the 1998-2004 event, we use the year 2000 as a benchmark and estimate the regression for treatment and control groups for the data period 1998-2004. Figure 3 plots the regression coefficients with its 95% confidence intervals. The solid line plots the difference-in-differences coefficients with its 95% confidence intervals. The bold dashed line indicates the period immediately before the bonus depreciation schedule change. As can be seen, the %New for the treatment and control industries followed parallel trends before the bonus depreciation schedule change in each of the three-time periods. The differences between the treatment and control group are statistically insignificant. This increases our confidence that the results we present can be interpreted as causal. Second, within one year of the bonus depreciation schedule, there is an increase in the proportion of new equipment investments for firms in the treatment industries compared to control group. For example, in the year 2001, we find 9% more new machine purchases for the treatment industries than the control industries. This is consistent with our baseline results reported earlier. For Bonus II, we notice an temporary shift in purchase behavior of treated industries and highlights the temporary nature of incentive policies. However, we do not find any differential response of treated firms with TCJA. One possible reason could tax treatment of old capital goods under new law. TCJA made an important change to the qualified equipment rules by allowing businesses to claim bonus depreciation on both "new" and "used" capital goods. The bonus depreciation equally effects the firm's likelihood of buying new verus old capital.

5.1.2 Using Continuous Treatment variable

Note that the treatment dummy and the figures do not differentiate in the magnitude of bonus deprecation schedules over the years. Also, it ignores the industry-level variation in present value factors by combining all treatment industries into a single group. Finally, many firm-specific and times-specific unobserved heterogeneity that may lead to higher investment in new equipment for firms located in treatment industries are ignored. So we implement the difference-in-differences model according to specification (1) using a continuous measure of the present value of depreciation deductions (z). The continuous treatment variable also enables us to use the complete sample of 3.32 million transactions for 1998-2019. The coefficient of interest is β. The results are documented in Table 4, *Panel B*.

In column (1), we include industry and year fixed effects with clustering at the industry level. This will remove the effect of the time trends and industry-level variation. The first column reports an economically positive and statistically significant (at the 1% level) increase in the new equipment transactions for the treatment group. The average change in z for the entire sample period is 3.9 cents (0.039). This means a one SD increase in z would increase the likelihood of buying new equipment by 3.4% ($0.039 \times 0.871 = 0.034$). To address the issue that time-varying industry shocks may overlap with the timing of bonus depreciation, we include industry-specific linear and quadratic trends in our regression. In Columns (2) and (3), we include linear industry trends and quadratic industry trends, respectively, and find a similar effect to column (1). The corresponding coefficients are very similar to the baseline specification. Next, we control for firm size because prior literature suggests that bigger firms are more likely to purchase new equipment. In column (4), we find that size as measured by the natural logarithm value of sales and employees is positively associated with the likelihood of buying new equipment. z continues to have a similar effect on *New* after we control for the effect of size. In column (5), we include Size $\times$ Year fixed effects and Employee $\times$ Year fixed effects to control for the non-linear time trends in buyer size and the number of employees that could drive the relation between z and *New*. The results are the same as before, with an increase in the likelihood of buying new equipment by about 3.4%.

Next, we control for the effect of firm age, given the prior literature that documents that mature firms are more likely to buy new equipment. Hence we use the natural logarithm of one plus the firm age defined as the difference between the year of formation and the transaction year. However, this process reduces the number of observations to 2.11 million due to missing firm age information. The coefficient on β indicates an increase in the likelihood of buying new equipment by about 4.2% (0.039 $\times$ 1.067). In column (7), we include equipment type fixed effects to control for the scenario where the *New* indicator is matched to different types of equipment that have different depreciation dynamics. The results continue to be positive and economically significant.

Next, in column (8), we control the effect of geographical variation in the purchase of new equipment by including *Industry* $\times$ *State* fixed effects and *Year* $\times$ *State* fixed effects. Finally, we control for firm-specific heterogeneity and include buyer fixed effects in column (8). We notice that the effect continues to be positive and economically significant. Overall, we find a 3.4% - 4.3% increase in the probability of investing in new capital for the treatment group. The results imply that the tax incentives encourage firms to invest in new capital goods instead of old or vintage capital goods.

5.1.3 Do tax incentives affect machine vintage?

In column (1) of Table (5) Panel A, we include industry and year fixed effects with clustering at the industry level. The first column reports that there is a decrease in the *Log(Machine Age)* of equipment purchased by the treatment group. The average change in z for the entire sample period is 3.9 cents (0.039). So a one SD change in z would decrease the machine age by 14.2 log points (-3.637 $\times$ 0.039). In terms of years, this translates to a reduction in machine age by $e^{-0.142} = 0.87$ years or roughly 10.5 months.

In columns (2) and (3), we include linear industry trends and quadratic industry trends, respectively, and find a similar effect to column (1). The corresponding coefficients are similar to the baseline specification with an average reduction in the machine age by $e^{-3.7\times0.039} = 0.87$ years. The results continue to be negative and significant for column (4) and column (5), where we control the size effect. Next, in column (6), we control the effect of firm age, defined natural logarithm of the difference between the year of formation and the transaction year. There is a 0.85 year decrease in machine age for the treatment group compared to the control sample.

In column (7), we include equipment type fixed effects to control for the scenario where machine age is matched to different types of equipment that have different depreciation dynamics. The results continue to be negative and economically significant. As before, we also control for the effect of geographical variation in the machine age by including Iindustry $\times$ State fixed effects. The resulting coefficient shows a decrease in machine age by 10.5 months for the treatment group. These results collectively suggest that bonus deprecation lowers the average age of machines transacted in the treatment industries.

In Table 5 Panel B we document the effect of tax incentives on our second measure of vintage, viz., technological age (*Log(Model Age)*). In column (1) of Panel B, we include industry and year fixed effects with clustering at the industry level. The first column reports that there is an economically negative and significant effect on the *Log(Model Age)* for firms in the treatment industries. In terms of economic effect a one SD change in z would decrease the model age by 0.94 years ($e^{-1.631\times0.039}$). The results continue to be negative and significant for columns (2)-(3), where we control linear and quadratic industry trends. We find similar results in columns (4)–(9). As before, we also control for the effect of geographical variation in the machine age by including Industry $\times$ State fixed effects. In terms of economic magnitude, there is an approximate 11 months decrease in *Log(Model Age)* across all specifications for the treatment group. The results in Table 5 collectively suggest that there is an decrease in the average *Log(Model Age)* (technological age) transacted with bonus depreciation for the long-duration industries compared to the short-duration industries.

5.2 Heterogeneous response to tax incentives

In this section we test the heterogeneous response to tax incentives based on firm's financial constraints. We use three measures of financial constraints using firm size (Section 5.2.1), SBA lending (Section 5.2.2) and small bank lending (Section 5.2.3).

5.2.1 Tax Incentives and Financial Constraints: Effect of Firm Size

In the last section, we provided evidence that treatment firms are more likely to respond to the bonus deprecation incentives by buying new equipment. This is consistent with the objective of bonus deprecation, as businesses are more likely to increase new equipment purchases. However, the results don't necessarily suggest evidence in favor of capital reallocation. So, we explore the heterogeneity of our results based on financial constraints. The *tax benefit effect* (Zwick and Mahon, 2017) would suggest that small financially constrained businesses are more likely to respond to tax incentives by increasing their new equipment investment. On the other side, the *capital reallocation effect* (Lanteri and Rampini, 2021) would predict that financially constrained firms would buy cheaper old capital due to a reallocation from less constrained firms that purchase newer capital.

In this test, we use total sales as a proxy for financial constraints. We define *Low_Sales* as an indicator variable that takes value 1 for firms with below-median sales during the pre-bonus depreciation years (Figure 1). The main variable of interest is *Low_Sales* $\times$ *z*. A negative coefficient on *Low_Sales* $\times$ *z* would be consistent with *capital reallocation effect*, while a positive or zero coefficient would be consistent with the *tax benefit effect.* The results are documented in columns (1)-(3) of Table 6. We include both linear and quadratic industry fixed effects and year fixed effects with clustering at the industry level. We also control for the geographical variation in the availability of old capital (Ma et al., 2021) by including *Industry* $\times$ *State* $\times$ *Sales* fixed effects and *Year* $\times$ *State* $\times$ *High_Sales* fixed effects. We document that the coefficient on *Low_Sales* $\times$ z is negative and significant. This means smaller firms are approximately 1.05% less likely to buy newer equipment than larger firms in the treatment industries. We find similar results for the two vintage measures. In other words, small financially constrained firms are less likely to buy new capital which is consistent with the *capital reallocation effect* hypothesis.

5.2.2 Tax Incentives and Financial Constraints: SBA Lending

In this subsection we proxy for financial constraint based on SBA lending. SBA lending provides us with an alternative proxy of financial constraint which is independent of firm fundamentals. We use Small Business Administration's (SBA) 7 (a) loan data and create ex-ante loan availability measure at 6-digit NAICS level. Firms in industries with higher ex-ante loan availability are less likely to be financially constrained. We define *Low_Loan_Share* as an indicator variable that takes value 1 for firms which are in industries with below median share of SBA loans during the pre bonus depreciation years (1). The main variable of interest is *Low_Loan_Share* $\times$ z. We include both linear and quadratic industry fixed effects and year fixed effects with clustering at the industry level. Ma, Murfin, and Pratt (2021) highlight the importance of co-location of potential buyers and sellers of old capital goods for reallocation. Therefore, we include state-year and state-industry-fixed effects to estimate our effects within the same state across industries. The results are documented in Table 6. In columns (4)-(6) of Table 6, we find that those transactions in industries with a lower ex-ante share of SBA loans are less likely to buy new capital goods among the treated firms. In other words more financially constrained firms are less likely to buy new equipments

5.2.3 Tax Incentives and Financial Constraints: Effect of Small Bank Lending

In this subsection, we explore geographic variation in access to small business lending. For small businesses, availability of external finance is important to alleviate financial constraints. Prior literature (Berger, Bouwman, and Kim, 2017) show that the prevalence of small banks in an area increases the availability of external financing to small firms. Consistent with Tuzel and Zhang (2020), we calculate small bank share as the deposit share of small banks (defined as banks with total assets below $50 billion) in each county based on information from quarterly bank Call Reports. Low_Small_Bank_Share is an indicator that is equal to 1 for below-median availability of small business lending (or more financial constraint) during the pre-bonus depreciation years. The measure captures the local firms' access to small banks. The main variable of interest is *Low_Small_Bank_Share* $\times$ *z*. A negative coefficient on *Low_Small_Bank_Share* $\times$ *z* would be consistent with *capital reallocation effect*, while a positive or zero coefficient would be consistent with the *tax benefit effect*. The results are documented in columns (7)-(9) of Table 6. We document that the coefficient on *Low_Small_Bank_Share* $\times$ *z* is negative and significant. This means that firms respond to tax incentives by reducing their likelihood of purchasing new equipment in counties with lower availability of small bank lending.

Overall, the results from Section 5.2.1, 5.2.2, and 5.2.3 suggest that small businesses with financial constraints are less likely to buy equipment, consistent with *capital reallocation effect* hypothesis. Next, we test if tax incentives lowers the price of old capital and also directly test the capital reallocation using size differences in buyers and sellers.

5.3 Mechanism

In this section we provide results for the main mechanism. Firstly, we provide the results for regression estimates where we test the impact of tax incentives on the relative price of old capital goods (Section 5.3.1). Then we directly test the capital reallocation using size differences in buyers and sellers after the tax incentives (Section 5.3.2).

5.3.1 Tax incentives and Equipment Price effects

Next, we test for the presence of *capital allocation effect*. While the heterogeneity tests provide consistent evidence with capital reallocation, they don't show the underlying mechanism. The capital reallocation model (Lanteri and Rampini (2021)) suggests that the competitive-equilibrium price of old capital is higher than its socially optimal level because of financial frictions. Bonus depreciation on new investment leads to a more efficient allocation by increasing the supply of old capital. This will reduce the price of the old capital and allow the financially constrained firms to produce at a larger scale and grow their net worth faster. Empirically, we start by calculating the average price of the old and new equipment's for a given equipment manufacturer within a four-digit industry NAICS code. First, we calculate the average price of old and new equipment by aggregating all the transactions in a four-digit NAICS code for a given equipment type and equipment manufacturer-model during each year. For example, let's consider a Wind-rower (EDA Equipment Code: 8850) sold by John Deere in the oilseed and grain farming industry (four-digit NAICS code:1111). The average equipment price of the model number W-235 Wind-rower sold brand *new* by John Deere for the year 2019 is \$61,079. The corresponding average price for the older version of the same equipment in the same industry is \$34,935. This is done to ensure that we precisely capture the price of an equipment model by the same manufacturer within the four-digit NAICS code. We define *Log(New_Price)* and *Log(Old_Price)* as the logarithm of the average price of new and old equipment respectively. This aggregation at the year-equipment type-equipment manufacturer-model-industry level results in a fewer number of observations for old and new equipment prices compared to our transaction level data . Next, we calculate the ratio of the average price of old equipment to the average price of new equipment (*Old_to_New_Price*), which is our other variable of interest. In the above example, the average price ratio for Wind-rower model W-235 in the particular industry by John Deere would be 0.572. Since we calculate the price ratio within year-equipment type-equipment manufacturer-model-industry, we loose many observations due to the unavailability of both old and new equipment transactions within our aggregation group. Our main objective is to compare this price of used capital to the new capital in the treatment group after bonus depreciation.

The regression framework implements the following difference-in-differences (DD) specification,

$$price_{j,m,t} = \alpha + \beta z^{\Theta}_{j,t} + \gamma X_{j,m,t} + \delta_j + \omega_t + \kappa_m + \epsilon_{j,m,t} \tag{2}$$

where, price refers to *Log(New_Price)*, *Log(Old_Price)* or (*Old_to_New_Price*) respectively. The index m refers to machine type-model-manufacturer, j denotes the four-digit NAICS industry and t indicates the year. $z^{\Theta}_{j,t}$ is measured at the four-digit NAICS industry level and increases during bonus years. $Old\_to\_New\_Price_{j,m,t}$ (described in Table A1) is measured as the ratio of the average price of old equipment to average price of new equipment within four digit NAICS code for a given equipment type and equipment manufacturer-model during each year. The coefficient of interest is β. The baseline specification includes a wide array of fixed effects: industry fixed effects (δ_j) to control for industry-specific unobservables, ω_t denotes year fixed effects to control for time trends. We include machine fixed effects (κ_m) to control for technological differences in machines. We include industry average of firm/buyer-level controls such as logged sales and logged employees, which are collectively represented as ($X_{i,t}$). We also include linear and quadratic trends at two-digit NAICS level to control for macro-economic shocks. Following Zwick and Mahon (2017), we cluster at the four-digit NAICS level.

The results are documented in Table 7. In column (1) of Table 7, we include industry and year fixed effects with clustering at the industry level. The first column reports an economically significant decrease in the price of old equipment for the treatment group after bonus depreciation. For one standard deviation increase in z, the average price of old equipment decreases by approximately 2.4%. In column (2) we find that the coefficient on average price of new equipment is negative but insignificant. In Column (3) we find that the coefficient on the ratio of old to new equipment price is negative and significant. For one standard deviation increase in z, the average ratio of $Old\_to\_New\_Price$ decreases by approximately 0.5%. Consistent with the capital reallocation theory, the results collectively document a significant reduction in the used to new equipment price ratio after bonus depreciation.

5.3.2 Capital reallocation between buyer and seller

Next, we directly test the capital reallocation using size differences between seller and buyers of old capital goods. For capital reallocation to work we expect relatively bigger sellers to transact with smaller buyers. Ma, Murfin, and Pratt (2021) highlight the importance of co-location of potential buyers and sellers of old capital goods for reallocation. Hence, for each year, we aggregate the data at industry-buyer state-seller state level. This will ensure that transactions between buyer and seller occur within close vicinity of each other. To identify the buyer-seller pair for each transaction, we drop those transactions with missing seller information. We also focus exclusively on old capital transactions. Capital reallocation would suggest that bigger sellers in treatment industries are more likely to sell older equipment to smaller buyers. Our main variable of interest is the number of old equipment transactions (Old_Count) within each industry-buyer state-seller state. The regression framework implements the following difference- in-differences (DD) specification,

$$Log(Old\_Count)_{i,j,s,t} = \alpha + \beta z^{\Theta}_{j,t} \times size\_diff + \delta_j + \omega_t + \kappa_s + \epsilon_{i,s,t} \tag{3}$$

index i refers to buyer state, s refers to the seller state, j denotes the four-digit NAICS industry, and t indicates the year. $z^{\Theta}_{j,t}$ is measured at the four-digit NAICS industry level and increases during bonus years. $Log(Old\_Count)_{i,j,s,t}$ (described in Table A1) is measured as the log of the number of old equipment transactions (Old_Count) within each four-digit industry-buyer state-seller state. *Size_Diff* is and indicator variable that takes value of 1 when the difference in size between sellers and buyer is above median, 0 otherwise. The coefficient of interest is β. The baseline specification also includes two sets of fixed effects: industry fixed effects (δ_j) to control for industry-specific unobservables, and ω_t denotes year fixed effects to control for time trends. In some specifications, we include machine fixed effects (κ_m) to control for technological differences in machines. We include the industry average of firm/buyer-level controls such as logged sales and logged employees, which are collectively represented as ($X_{i,t}$). We also include linear and quadratic trends at the two-digit NAICS level to control for macroeconomic shocks. Following Zwick and Mahon (2017), we cluster at the four-digit NAICS level.

Table 8 provides the regression results. First, we find an increase in the number of old capital goods purchase in the treatment industries. In terms of economic effect, a one SD increase in z would increase the number of old equipment sold by 1.12 units ($e^{3.991*0.039}$). This means that treatment group of firms are more likely to sell their old equipment's to buyers in the nearby vicinity within the same industry. Next, we find that such transactions are more in industries where the average size of the selling firm is more than the average size of buying firm. These results are robust after including buyer by seller state fixed effects. This suggests that large less constrained firms are more likely to sell their old equipment to small-sized constrained firms when they are located in the same state after the tax shock. Overall, we find that tax incentives encourage less constrained firms to invest in new capital goods (*tax benefit effect*). This increases the supply of old capital goods and results in a decline in the cost of old capital goods. The reduced price of old capital goods encourages constrained firms to invest in old capital goods (*capital reallocation effect*).

5.4 New Business Creation

In the following analysis we examine whether reallocation of old capital via bonus depreciation would encourage entry of small businesses. One implication of the inefficiently high price of old capital is that some firms may not enter the market. With tax incentives, the relative price of old capital goes down due to increased supply from new equipment buyers. Thus, we expect a more small business entry after tax incentives, especially in industries with a higher ex-ante relative price of old equipment. We use the County Business Patterns (CBP) database from the U.S. Census Bureau to obtain state- and county-level statistics on business establishments. This dataset reports the number of net firms (new business formations less old business retirements) by industry, size category, and year. We use the county-level business establishments data by four-digit NAICS code between 1998-2019. This will allow us to identify the treatment group of industries controlling for the geographical variations in business formation. The CBP defines firm size using the following categories: one to four employees, five to nine employees, 10 to 19 employees, 20 or more employees, etc. The median group of employees in the EDA database is 5. Hence we focus our analysis on establishments with 5-9 employees. Our dependent variable is the log of the number of establishments with 5-9 employees (est5_9). Table 9 report the regression results. In Column (1), we report the effect of z on *est5_9*. We document that there is a positive and significant effect on the count of small businesses. In other words, a one SD increase in z would increase the entry of small businesses by approximately 2.3 %. In Column (2), we test the incremental effect of z on *est5_9* with respect to the ex-ante old to new equipment prices. To calculate the old to new price ratio, we carefully consider the ratio of equipment prices within the industry, machine type, manufacturer-model group as before. Since the small business data is at the geography level, we also consider the old to new price ratio variation within the state.

However, this results in a significant observation loss due to the granularity in computing old to new prices. In the final sample, we have 428,293 county–industry (NAICS4)-year observation with non-missing old to new prices (*oldtonewprice_withinstate*). The results of this cross-section are reported in Columns (2) and (3) of Table 9. We document a positive and significant effect of z on *est5_9* when ex-ante old to new equipment prices (*oldtonewprice_withinstate*) are above median. This is consistent with our expectations that tax incentives result in more new businesses, especially in industries and locations with higher ex-ante relative price of old equipment.

5.5 Aggregate Results at Buyer level

The main results documented in this paper are at the yearly machine transaction level. The unique feature of the machine transaction data allows us to track machine reallocation as a response to tax incentives. However, we cannot distinguish between extensive and intensive margin. In other words, whether the reallocation between old and new equipment happens between existing firms or they primarily involve first-time buyers or a combination of both. To test for the intensive margin, we aggregate our data at the buyer-year level combined with buyer fixed effects. The other reason to perform aggregate analysis is to calculate investment elasticity and provide a comparison of the same with existing literature. In this test, we aggregate the individual transactions for a given firm year to calculate the total dollar equipment investment (*EQTVALUE*) for a firm-year. We further sub-classify the total investment into total dollar value of new (*EQTVALUE_New*) and old (*EQTVALUE_Old*) equipment investment respectively. We also calculate the percentage of total investment spent in new equipment (*percent_new_dollar*) As before, we implement the difference in difference model according to specification (1). In addition, we use an array of fixed effects to allow for the most restricted specification from our main model. The main results are documented in Table IA2. In column (1), we document the effect of z on *Log(EQTVALUE)*. The coefficient suggests that a one SD increase in z would increase the equipment purchase by the firm by 9.56 log points (0.039×2.452). In column (2), we document the effect on new equipment purchase. The results are positive and significant, with a one SD increase in z would increase the new equipment purchase by the firm by 9.35 log points (0.039×2.398). In Columns (3) we document that there is no significant direct impact of bonus depreciation on old equipment investment. This is expected given that bonus deprecation applies to only new equipment for majority of our sample window. In col (4) we document that there is a significant increase in the overall percentage of dollar investment in new equipment. Overall, the results suggest that we cannot rule out the within buyer intensive margin effect of bonus depreciation. We also document that the investment elasticity effect is comparable to Zwick and Mahon (2017), and most of this is driven by new equipment purchase.

6 Additional Results

In Table IA3 we report results from equation (1) addressing the issue of sample selection in the EDA data. For example, Agriculture firms comprise almost 23% of the EDA sample, while they consist of less than 1% of the BEA population. Hence we re-weight the EDA data to match the distribution of machine purchases across two-digit NAICS industries with the distribution of GDP in the 2019 BEA data. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size $\times$ year fixed effects and Employee $\times$ year fixed effects. The results suggests that the effect of tax incentives on new equipment purchase is negative and significant. However there is a reduction in the economic magnitude from the unweighted sample.

In Table IA4 we report results from equation (1) we transform the machine and model age variables using the inverse hyperbolic sine operator. The results on equipment vintage remains qualitatively and quantitatively similar.

Next we identify transactions that happened in states that conform to the federal bonus deprecation vs those in states that do not conform to federal bonus deprecation. For example, California disallows a deduction for bonus depreciation. Cal. Rev. Tax. Code § 24349. Hence, we predict that it is easier for firms to take advantage of tax deductions in conformed states compared to non-conformed states. In Table IA5 we document that the main results remain similar to before. The cross-section effect of conformity has an even more stronger effect on equipment vintage.

In our main tests we eliminate leases because they may or not be part of federal tax deductions depending on whether they are capital leases or operating leases. Also another concern is that leases may be biased towards new equipment transactions, in which case we are less likely to observe the capital reallocation. However we rerun our main tests restricting to lease only transactions in table IA6. We find that the results are qualitatively and quantitatively very similar to those transactions based on sales and wholesales.

One concern about our sample is that we have many small firms in our study such that the bonus depreciation limits don't apply as they will all be subject to Section 179. In that case we won't observe the reallocation from comparatively bigger firms to smaller firms. In order to alleviate such concern we conduct our analysis by removing equipment purchases from firms that are subject to yearly section 179 limits. The results are documented in table IA7. We document that the main results are significant as before, but the magnitudes are higher than our full sample. This is because this subsample includes relatively larger firms who are more likely to be affected by bonus deprecation.

Next we examine the price effect around the TCJA period. TCJA made an important change to the qualified equipment rules by allowing businesses to claim bonus depreciation on both "new" and "used" capital goods. Lanteri and Rampini (2021) theoretically show that any policy that subsidizes both new and old capital goods generates the demand for old capital by less constrained and unconstrained firms. This may reduce the price effect on old capital goods. The results are documented in Table IA8. Consistent to theory, we find no change on the prices of old equipment in the post TCJA period.

7 Conclusion

This paper uses 3.32 million purchase transactions covering 31,757 models of new and old machines used across a broad range of industries to address an important policy question: Do tax incentives on new capital goods foster reallocation of old capital goods to more financially constrained firms? For three waves of bonus depreciation during 1998-2019, we find that temporary federal tax incentives in the form of accelerated depreciation encourage the utilization of new capital goods (*tax benefit effect*). Next, we find that firms with less binding constraints replace their old capital with new capital. This increases the supply of old capital and hence lowers its equilibrium price (*capital reallocation effect*). Our results suggest that small businesses with binding constraints may buy old capital goods and indirectly benefit from tax incentives. These findings are important for policy design. For example, TCJA made an important change to the qualified equipment rules by allowing businesses to claim bonus depreciation on both "new" and "used" capital goods. Our results suggest that such policies may reduce the indirect benefit of tax incentives.

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Table A1: Description of Key Variables

This table reports variable definitions. Data sources include the Equipment Data Associates (EDA), which collects and processes Uniform Commercial Code (UCC)-1. We augment this data with firm-level data from Mergent Intellect, which provides the same firm-level variables as those EDA obtains from Dun & Bradstreet, but is more comprehensive.

Variable	Description	Source
z_{jt}^{Θ}	Present value of depreciation deductions for the average asset in which industry j invests at time t.	Zwick and Mahon (2017)
Post	Dummy that is assigned a value of one between (Sep 2001- Dec 2004), (July 2008- Dec 2011), & (2018-2019), zero otherwise.	Constructed
EQTVALUE	$ value of equipment purchased by the establishment.	EDA
Log(EQTVALUE)	Natural log of EQTVALUE.	Constructed
New	Dummy that is assigned a value of one for new equipment purchased, 0 otherwise	EDA
Machine Age	Age (in years) of machines purchased by the establishment as defined in the UCC transaction data .	EDA
Model Age	Age (in years) of the particular model calculated as the difference between the transaction year and the starting year of the model.	EDA
Sales	$ value of sales by the establishment.	EDA, Mergent
Employees	Number of employees in an establishment.	EDA, Mergent
Log(Employees)	Natural log of *Employees*.	EDA, Mergent
old_to_new_price	Average ratio of old to new equipment price, averaged over a given equipment and model type in a given year.	EDA

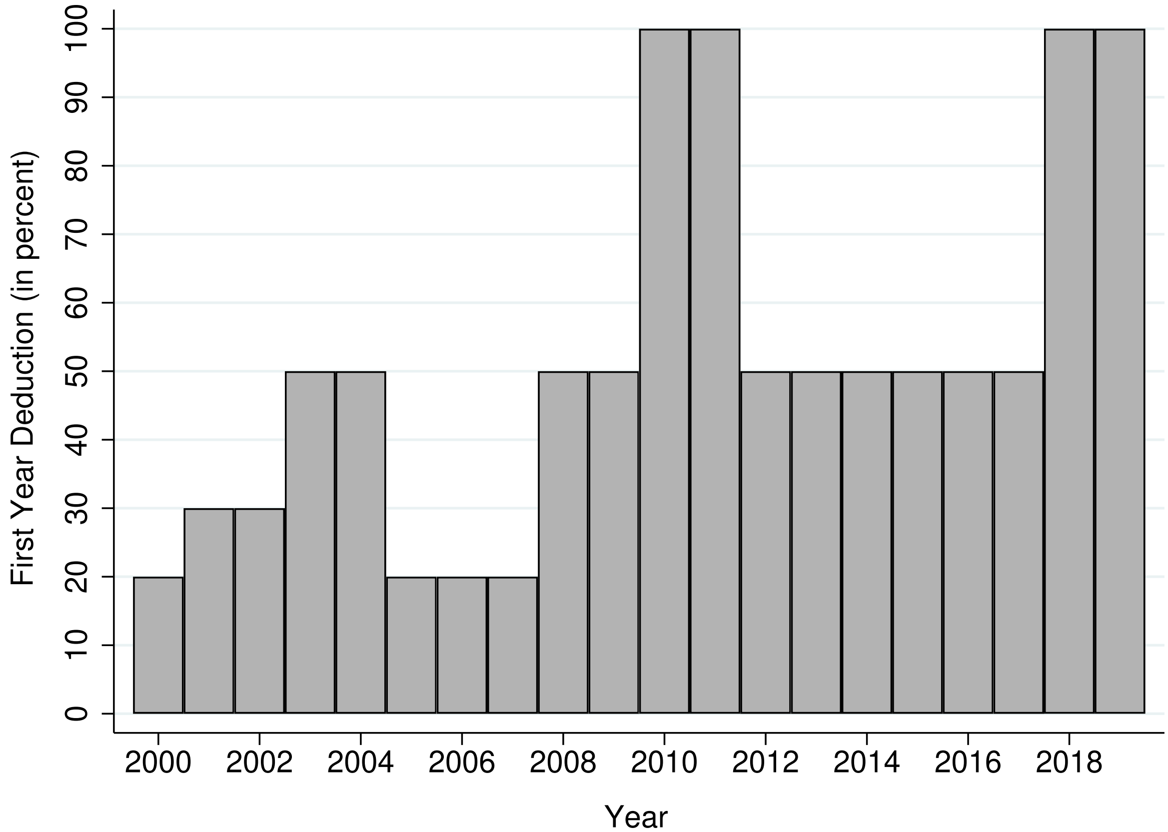

Figure 1: This figure plots maximum first year deduction for qualified equipment during bonus and non-bonus deprecation years. Under Modified Accelerated Cost Recovery System (MACRS), in non-bonus years firms can deduct 20% in the year of purchase.

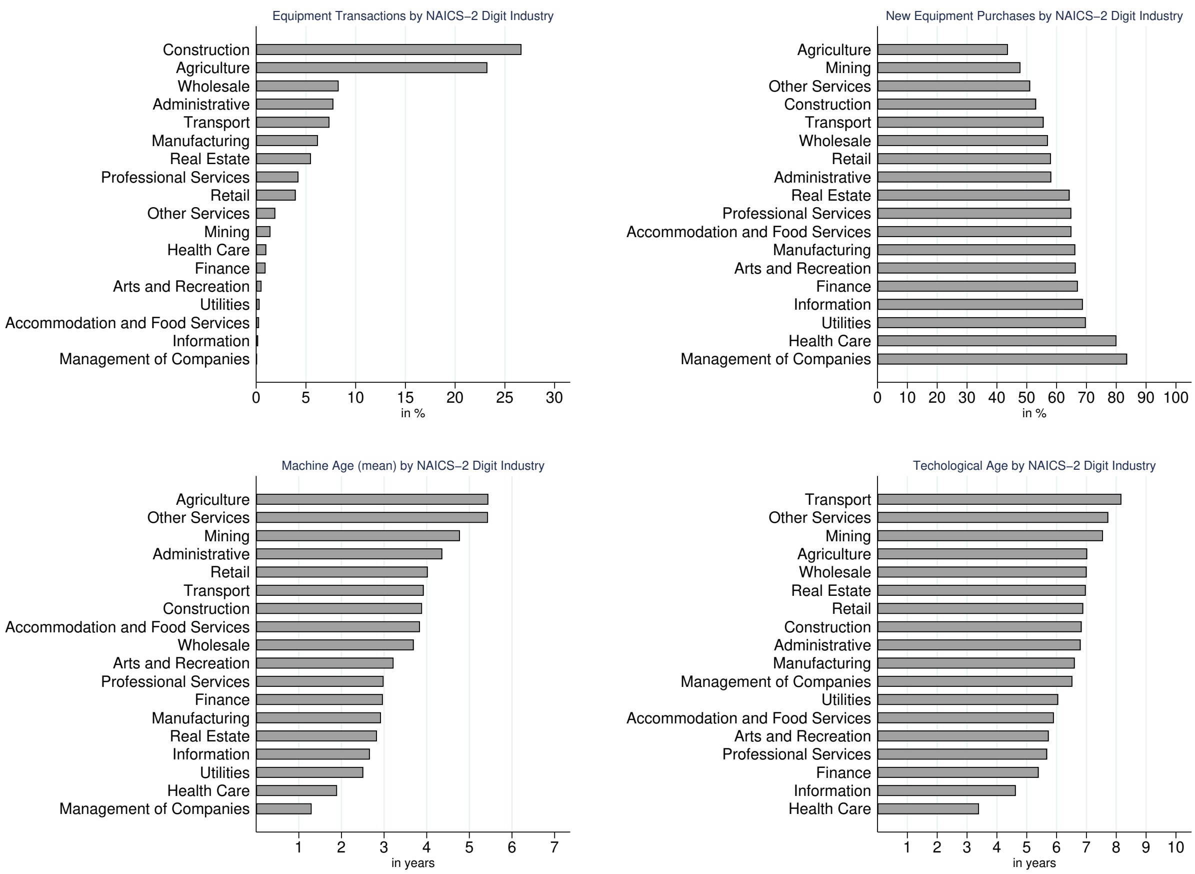

Figure 2: This figure plots the distribution of key dependent variables by 2-digit NAICS codes

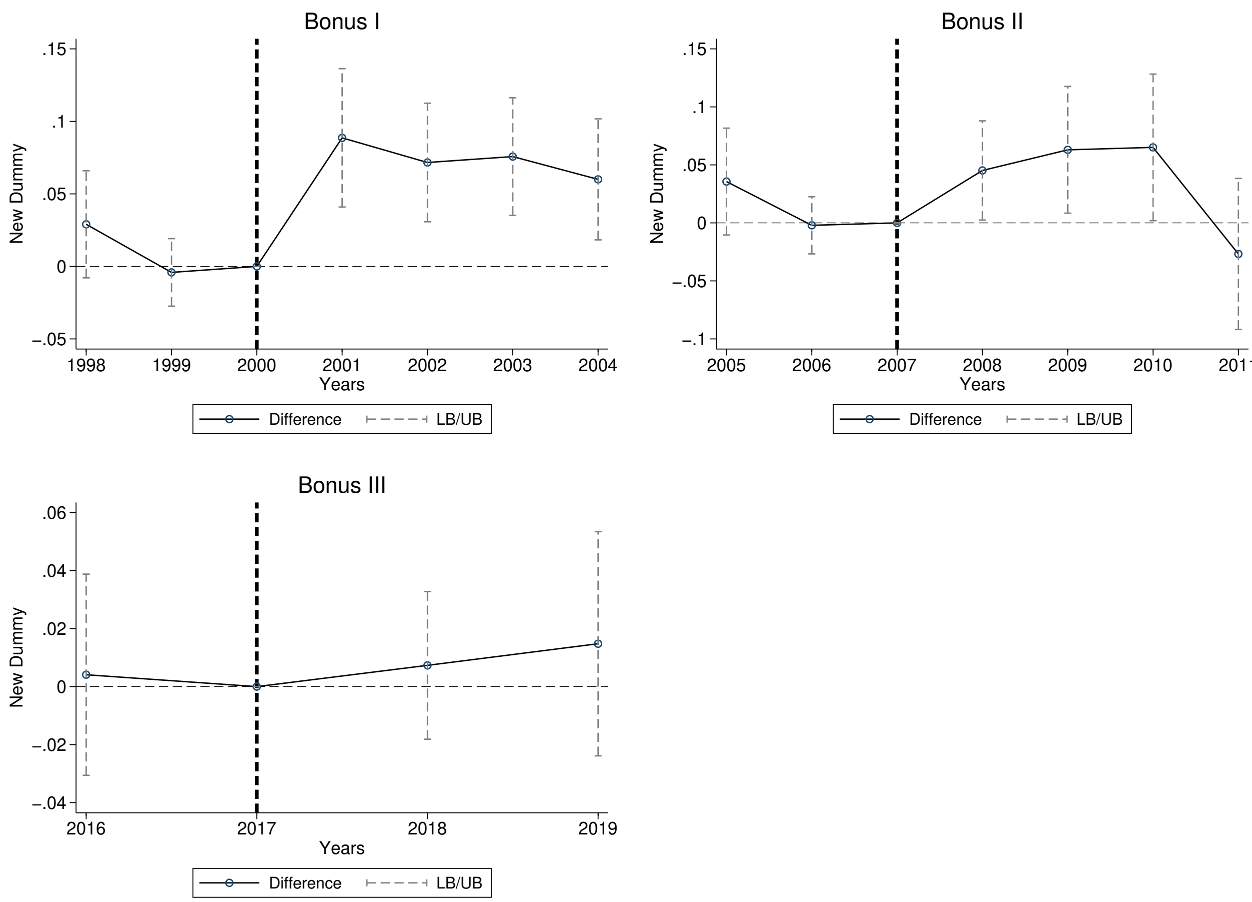

Figure 3: This figure plots the new/old Equipment's for treatment and control groups. *New* dummy takes the value 1 for new equipment purchases and 0 otherwise. For this plot we subdivide the sample into three time periods depending on the changes in bonus depreciation schedule,viz., 1998-2004, 2005-2011, and 2016-2019. We plot the *New* dummy with a 95% confidence interval. The solid line plots the difference-in-differences coefficients with its 95% confidence intervals. The bold dashed line indicates the period immediately before the bonus depreciation schedule change.

Table 1: Standard and Accelerated Depreciation Schedule

This table displays the yearly deductions accruing to a firm for a $500,000 investment in machinery having a five year depreciation schedule. The top panel shows the normal deductions available under half-year MACRS convention. Investments are depreciated by 20% in the year of purchase, followed by 32%, 19.2%, 11.5%, 11.5% and 5.8% for the remaining years. Panel B shows the total depreciation schedule under 50% Bonus method, where 50% of the total cost is depreciated in the year of purchase, while the remaining 50% follows the traditional MACRS method. Panel C show the total depreciation schedule under 100% Bonus method. In this case, the whole cost of investment is depreciated in the year of purchase.

Year	0	1	2	3	4	5	Total
Normal Depreciation Schedule							
Deductions($1000s)	100	160	96	57.5	57.5	29	500
50% Bonus Depreciation Schedule							
Deductions($1000s)	300	80	48	28.75	28.75	14.5	500
100% Bonus Depreciation Schedule							
Deductions($1000s)	500	0	0	0	0	0	500

Table 2: Affected Industries

This table presents five most common three- digit industries (NAICS code) in the bottom and top three deciles of z^0. In our regression analysis we use four-digit variation.

NAICS3	Industry
	More Affected
111	Crop Production
112	Animal Production and Aquaculture
332	Fabricated Metal Product Manufacturing
115	Support Activities for Agriculture and Forestry
327	Nonmetallic Mineral Product Manufacturing
	Less Affected
532	Rental and Leasing Services
561	Administrative and Support Services
541	Professional, Scientific, and Technical Services
213	Support Activities for Mining
621	Ambulatory Health Care Services

Table 3: Descriptive Statistics

This table presents descriptive statistics for the variables used in the regression analyses for the full sample, which consists of 3,322,000 machine-year observations representing 687,996 US businesses for the period 1998-2019.

	Summary Statistics					
	N	**Mean**	**SD**	**P10**	**Med**	**P90**
z_{jt}^{Θ}	3,322,000	0.940	0.039	0.924	0.943	0.948
EQTVALUE (in $)	3,322,000	87,718.0	90,486.4	27,000	60,752	115,322
Log(EQTVALUE)	3,322,000	10.920	1.004	10.204	11.015	11.655
Sales (in $ million)	3,322,000	43.028	322.765	0.175	0.604	4.334
Log(Sales)	3,322,000	13.866	2.272	12.073	13.313	15.282
Employees	3,322,000	34.5	107.8	2.0	5.0	24.0
Log(Employees)	3,322,000	2.014	1.610	0.693	1.609	3.178
New	3,322,000	0.545	0.498	0.000	1.000	1.000
Machine Age (Years)	3,322,000	4.125	6.792	0.000	1.000	5.000
Log(Machine Age)	3,322,000	1.016	1.051	0.000	0.693	1.792
Model Age (Years)	3,322,000	6.901	5.593	3.000	5.000	10.000
Log(Model Age)	3,322,000	1.806	0.758	1.386	1.792	2.398

Table 4: Effect of tax incentives on New Equipment Purchase

This table reports results estimating the effect of tax incentives via bonus depreciation on an establishment's purchase of new and old equipment. The indicator variable *New* takes the value 1 for purchase of new equipment, 0 otherwise. Panel A reports the results where we use ZM's measure z_j^0. We define treatment and control group using industry variation based on four digit NACIS. We define the treatment indicator variable (*Treat*) based on the bottom three deciles of z_j^0. The control group involves the four-digit industries in top three deciles of z_j^0. We define 1998-2000, 2005-2007, and 2016-2017 as the pre-shock window when the bonus depreciation levels were low (*Post=0*). We further define (Sep 2001-2004), (July 2008-2011) and (2018-2019) as the post shock window when there is an increase in bonus depreciation levels. The variable of interest for this design is *Treat*$\times$ *Post*. In column (1), we estimate the regression equation without establishment controls using only industry and year fixed effects. In columns (2) and (3) we control for time variant omitted industry level factors using linear and quadratic industry trends with two digit NAICS industry dummies. In column (4) we report the results using establishment-level control variables ($X_{i,t-1}$) in our regressions: *Size* (measured as Log of *Sales*), and *Log(Employees)* (measured as log of *Employees*). Panel B reports results where we use continuous measure of present value of depreciation deductions (z_{jt}^{Θ}). Column (1) to column (4) are similar to columns (1) to (4) in Panel A. In column (5) we include Size $\times$ Year fixed effects and Employee $\times$ Year fixed effects. In column (6), we control for establishment age. In column (7) we include equipment type fixed effects. In column (8), we control for Industry $\times$ State fixed effects and Year $\times$ State fixed effects. Finally, in column (9), we include buyer fixed effects. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. All variables are winsorized at their 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A:	*New (Purchase of New Equipment)*			
	(1)	(2)	(3)	(4)
Treat × *Post*	0.055***	0.058***	0.058***	0.053***
	(5.065)	(5.323)	(5.323)	(5.086)
Log(Sales)				0.032***
				(7.647)
Log(Employees)				0.015***
				(2.832)
Constant	0.530***	0.529***	0.529***	0.056
	(240.109)	(242.850)	(242.799)	(0.999)
Observations	1,960,460	1,960,460	1,960,460	1,960,460
Adjusted R-squared	0.054	0.054	0.054	0.078
Industry Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Linear Industry Trends		✓	✓	✓
Quadratic Industry Trends			✓	✓

PANEL B:	*New (Purchase of New Equipment)*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z_{jt}^{Θ}	0.871***	0.872***	0.873***	0.862***	0.829***	1.067***	0.937***	0.859***	0.898***
	(7.593)	(9.384)	(9.393)	(9.229)	(9.074)	(6.674)	(11.102)	(11.153)	(11.538)
Log(Sales)				0.031***		0.033***	0.035***	0.036***	0.007
				(9.862)		(10.799)	(11.500)	(12.772)	(1.153)
Log(Employees)				0.018***		0.015***	0.019***	0.016***	0.004
				(3.630)		(3.134)	(4.831)	(4.666)	(0.741)
Log(Firm Age)						0.010***			
						(4.943)			
Constant	-0.273**	-0.275***	-0.275***	-0.734***	-0.234***	-0.964***	-0.862***	-0.791***	-0.411***
	(2.536)	(3.146)	(3.154)	(7.264)	(2.725)	(6.315)	(8.751)	(8.690)	(3.477)
Observations	3,322,000	3,322,000	3,322,000	3,322,000	3,322,000	2,112,496	3,322,000	3,321,488	3,046,166
Adjusted R-squared	0.049	0.049	0.049	0.074	0.076	0.083	0.145	0.175	0.384
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓		
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓		✓
Linear Industry Trends		✓	✓	✓	✓	✓	✓	✓	✓
Quadratic Industry Trends			✓	✓	✓	✓	✓	✓	✓
Size × Year Fixed Effects					✓				
Employee × Year Fixed Effects					✓				
Equipment Fixed Effects							✓	✓	
Industry × State Fixed Effects								✓	
Year × State Fixed Effects								✓	
Buyer Fixed Effects									✓

Table 5: Effect of Tax Incentives on Equipment Age and Vintage

This table reports results from Equation 1 estimating the effect of tax incentives via bonus depreciation on an establishment's transacted machine age and technological age. We use the dependent variable *Log(Machine Age)* defined as the log of one plus the age of the machine in the UCC transaction data in Panel A. In Panel B, we report the results using *Log(Model Age)*, defined as the log of one plus the age of the model in the UCC transaction data, as the dependent variable. In both panels, we use the same specifications for the according columns. In column (1), we estimate the regression equation without establishment controls using only industry and year fixed effects. In columns (2) and (3) we control for time variant omitted industry level factors using linear and quadratic industry trends with two digit NAICS industry dummies. In column (4) we report the results using establishment-level control variables ($X_{i,t-1}$) in our regressions: *Size* (measured as log of *Sales*), and *Log(Employees)* (measured as log of *Employees*). In column (5) we include Size × Year fixed effects and Employee × Year fixed effects. In column (6), we control for establishment age. In column (7) we include equipment type fixed effects. In column (8), we control for Industry × State fixed effects and Year × State fixed effects. Finally, in column (9), we include buyer fixed effects. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. All variables are winsorized at their 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A:	*Log(Machine Age)*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z^{Θ}_{jt}	-3.637***	-3.698***	-3.700***	-3.672***	-3.649***	-4.267***	-3.684***	-3.562***	-3.531***
	(11.575)	(13.400)	(13.412)	(13.276)	(13.530)	(11.745)	(14.345)	(13.847)	(14.605)
Log(Sales)				-0.080***	-0.047***	-0.081***	-0.088***	-0.091***	-0.012
				(12.334)	(6.137)	(13.373)	(13.340)	(14.997)	(0.929)
Log(Employees)				-0.046***	-0.013	-0.040***	-0.051***	-0.044***	-0.005
				(4.587)	(1.128)	(3.917)	(5.837)	(5.589)	(0.558)
Log(Firm Age)						-0.012***			
						(3.242)			
Constant	4.433***	4.490***	4.492***	5.675***	5.127***	6.239***	5.801***	5.714***	4.513***
	(15.016)	(17.317)	(17.332)	(21.127)	(17.552)	(18.497)	(21.819)	(22.377)	(21.714)
Observations	3,322,000	3,322,000	3,322,000	3,322,000	3,322,000	2,112,496	3,322,000	3,321,488	3,046,166
Adjusted R-squared	0.047	0.047	0.047	0.085	0.088	0.093	0.165	0.201	0.481
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓		
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓		✓
Linear Industry Trends		✓	✓	✓	✓	✓	✓	✓	✓
Quadratic Industry Trends			✓	✓	✓	✓	✓	✓	✓
Size × Year Fixed Effects					✓				
Employee × Year Fixed Effects					✓				
Equipment Fixed Effects							✓	✓	
Industry × State Fixed Effects								✓	
Year × State Fixed Effects								✓	
Buyer Fixed Effects									✓

PANEL B:	*Log(Model Age)*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
z^{Θ}_{jt}	-1.631***	-1.931***	-1.932***	-1.916***	-1.983***	-2.265***	-2.030***	-1.852***	-1.789***
	(5.070)	(7.076)	(7.079)	(7.044)	(8.512)	(7.004)	(8.474)	(9.039)	(7.229)
Log(Sales)				-0.038***	-0.028***	-0.034***	-0.044***	-0.040***	-0.004
				(9.547)	(4.293)	(9.023)	(12.140)	(12.937)	(0.359)
Log(Employees)				-0.011	0.041	-0.011	-0.016**	-0.022***	0.011
				(1.342)	(1.453)	(1.325)	(2.181)	(5.010)	(0.818)
Log(Firm Age)						-0.010***			
						(4.656)			
Constant	3.339***	3.620***	3.621***	4.159***	3.975***	4.439***	4.360***	4.148***	3.512***
	(11.045)	(14.120)	(14.125)	(15.382)	(15.959)	(14.310)	(18.752)	(21.951)	(16.944)
Observations	3,322,000	3,322,000	3,322,000	3,322,000	3,322,000	2,112,496	3,322,000	3,321,488	3,046,166
Adjusted R-squared	0.044	0.045	0.045	0.058	0.062	0.061	0.180	0.203	0.335
Industry Fixed Effects	✓	✓	✓	✓	✓	✓	✓		
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓		✓
Linear Industry Trends		✓	✓	✓	✓	✓	✓	✓	✓
Quadratic Industry Trends			✓	✓	✓	✓	✓	✓	✓
Size × Year Fixed Effects					✓				
Employee × Year Fixed Effects					✓				
Equipment Fixed Effects							✓	✓	
Industry × State Fixed Effects								✓	
Year × State Fixed Effects								✓	
Buyer Fixed Effects									✓

Table 6: Cross-section Effect of Financial Constraint Measures

This table reports the heterogeneous response to tax incentives based on firms' financial constraints. Columns (1)-(3) report the cross-section effects of establishment size estimating the effect of tax incentives via bonus depreciation on an establishment's vintage. Columns (4)-(6) report the cross-section effect of financial constraint based on SBA lending availability on an establishment's vintage. Columns (7)-(9) report the cross-section effect of financial constraint based on small bank (defined as banks with total assets below $50 billion dollars) lending availability on an establishment's vintage. *Low_Sales* as an indicator variable that takes value 1 for firms with above-median sales during the pre-bonus depreciation years (Figure 1), *Low_Loan_Share* is an indicator variable that takes value 1 for firms with below-median availability of SBA lending during the pre-bonus depreciation years (Figure 1) and *Low_Small_Bank_Share* is an indicator variable that takes value 1 for counties with below-median deposit share of small banks during the pre-bonus depreciation years, 0 otherwise. We include both linear and quadratic industry fixed effects and year fixed effects with clustering at the industry level across all specifications. We also control for Industry × State × Sales Fixed effects and Year× State × Sales fixed effects in columns (1)-(3), for Industry × State × Loan_Share fixed effects and Year× State × Loan_Share fixed effects in columns (4)-(6) and for Industry × State × Low_Small_Bank_Share fixed effects and Year× State × Low_Small_Bank_Share fixed effects in columns (6)-(9). The results are documented for the dependent variables, *New*, *Log(Machine Age)*, and *Log(Model Age)*. These variables are winsorized at their 1st and 99th percentiles. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Establishment Size			SBA Lending Availability			Small Bank Lending Availability		
Dependent Variable:	*New*	*Log(Machine Age)*	*Log(Model Age)*	*New*	*Log(Machine Age)*	*Log(Model Age)*	*New*	*Log(Machine Age)*	*Log(Model Age)*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low_Sales × z_{jt}^{Θ}	-0.268**	0.658**	0.483**						
	(2.536)	(2.294)	(2.140)						
Low_Loan_Share × z_{jt}^{Θ}				-0.301**	0.960**	0.691**			
				(2.391)	(2.366)	(2.182)			
Low_Small_Bank_Share × z_{jt}^{Θ}							-0.335***	0.663***	0.135
							(3.124)	(3.024)	(0.950)
z_{jt}^{Θ}	0.949***	-3.937***	-2.025***	0.552***	-2.861***	-1.269***	0.692***	-3.412***	-1.790***
	(9.266)	(12.248)	(7.106)	(5.041)	(9.632)	(6.216)	(6.753)	(12.068)	(7.403)
Log(Sales)	0.033***	-0.081***	-0.030***	0.029***	-0.078***	-0.030***	0.028***	-0.074***	-0.029***
	(8.502)	(10.616)	(8.895)	(8.841)	(11.292)	(9.846)	(8.598)	(10.599)	(9.436)
Log(Employees)	0.014***	-0.034***	-0.014**	0.015***	-0.041***	-0.018***	0.014***	-0.040***	-0.018***
	(3.289)	(3.865)	(2.527)	(3.516)	(4.450)	(3.245)	(3.413)	(4.372)	(3.225)
Constant	-0.749***	5.695***	3.996***	-0.655***	5.645***	4.012***	-0.635***	5.549***	3.968***
	(8.065)	(22.586)	(18.995)	(6.546)	(21.495)	(18.644)	(6.282)	(20.665)	(18.678)
Observations	2,726,127	2,726,127	2,726,127	3,253,061	3,253,061	3,253,061	3,152,662	3,152,662	3,152,662
Adjusted R-squared	0.122	0.145	0.096	0.109	0.126	0.092	0.116	0.135	0.099
Linear Industry Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓
Quadratic Industry Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry × State × Sales Fixed Effects	✓	✓	✓						
Industry × State × Loan_Share Fixed Effects				✓	✓	✓			
Industry × State × Small_Bank_Share Fixed Effects							✓	✓	✓
Year × State × Sales Fixed Effects	✓	✓	✓						
Industry × State × Loan_Share Fixed Effects				✓	✓	✓			
Year × State × Small_Bank_Share Fixed Effects							✓	✓	✓

Table 7: Capital Reallocation and Price of Old Capital

This table reports results from estimating the effect of tax incentives via bonus depreciation on the price of old equipment's, new equipment's , and the price ratio of old to new equipment's. The dependent variable *Old_Price* and *New_Price* measures the average price of old equipment and new equipment respectively within four digit NAICS code for a given equipment type and equipment manufacturer-model for each year. The dependent variable *Old_to_New_Price* is measured as the ratio of the average price of old equipment to average price of new equipment for each year. In each of the column we report the results using average establishment-level control variables : *Avg. Size* (measured as mean of *Sales*), and*(Avg. #Employees)* (measured as mean of *Employees*) aggregated at equipment type-equipment manufacturer-model-industry level. We also include Avg. Size × Year fixed effects, Avg. Employee × Year fixed effects, and equipment fixed effects. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. All variables are winsorized at their 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log(Old_Price)*	*Log(New_Price)*	*Old_to_New_Price*
	(1)	(2)	(3)
z_{jt}^{Θ}	-0.488**	-0.149	-0.123**
	(-2.13)	(-1.00)	(-2.08)
Constant	10.757***	10.932***	0.680***
	(46.27)	(73.88)	(11.97)
Observations	769,350	596,953	125,323
R-squared	0.546	0.675	0.418
Controls	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Quadratic Industry Trends	✓	✓	✓
Linear Industry Trends	✓	✓	✓
Avg. Size×Year Fixed Effects	✓	✓	✓
Avg. #Employee×Year Fixed Effects	✓	✓	✓
Equipment Fixed Effects	✓	✓	✓
SE Clustering	Industry	Industry	Industry

Table 8: Reallocation between Buyer and Seller

This table reports the capital reallocation results based on size differences between seller and buyers of old capital goods. For each year, the data is aggregated at the industry-buyer state-seller state level. *Log*(*Old_Count*) is measured as the log of the number of old equipment transactions (*Old_Count*) within each four-digit industry-buyer state-seller state pair. The final sample has 93,292 buyer seller pairs of old equipment purchases. *Size_Diff* is an indicator variable that takes value of 1 when the difference in size between sellers and buyer is above median, 0 otherwise. In column (1), we estimate the regression equation without establishment controls using Industry × Size and Year fixed effects. In columns (2) and (3) we report the results using buyer and seller fixed effects, respectively. Column (4) reports results with linear and quadratic industry trends. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. All variables are winsorized at their 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log(Old_Count)*			
	(1)	(2)	(3)	(4)
z^{Θ}_{jt}	3.991***	4.072***	4.103***	1.363***
	(6.447)	(6.243)	(5.994)	(2.679)
Size_Diff × z^{Θ}_{jt}	0.568***	0.543***	0.538***	0.541***
	(3.145)	(2.965)	(3.006)	(3.019)
Constant	-3.440***	-3.505***	-3.533***	-0.920*
	(5.688)	(5.506)	(5.299)	(1.846)
Observations	93,292	93,292	93,292	93,292
Adjusted R-squared	0.087	0.105	0.114	0.115
Industry × Size Fixed Effects	✓	✓	✓	✓
Year Fixed Effects	✓	✓	✓	✓
Buyer State Fixed Effects		✓	✓	✓
Seller State Fixed Effects			✓	✓
Linear Industry Trends				✓
Quadratic Industry Trends				✓

Table 9: Effect of reallocation on Small business Entry

This table reports results from estimating the effect of tax incentives via bonus depreciation on entry of small business. We measure small business as the log of the number of businesses with 5-9 employees in a given county industry year. This aggregation results in 428,307 county industry year pairs. In column (1), we estimate the effect on small business for the treatment group. In columns (2) and (3) we report the cross-section effect of old to new equipment price on the count of new businesses with 5-9 employees. *oldtonewprice_withinstate* is calculated as the ratio of old to new equipment price within the state-industry-machine type-equipment manufacturer-model group. In column (2) we use linear, and quadratic industry trends, County fixed effects and State × Year fixed effects. In Column (3) we add county by year fixed effects. Standard errors are clustered at the four digit NAICS industry level. t-statistics are reported in parentheses. All variables are winsorized at their 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log of Small Business Count (5-9 Employees)*		
	(1)	(2)	(3)
z_{jt}^{Θ}	0.461***	0.092	0.038
	(2.885)	(0.728)	(0.290)
oldtonewprice_withinstate		-0.314***	-0.274**
		(2.758)	(2.231)
oldtonewprice_withinstate$\times z_{jt}^{\Theta}$		0.362***	0.319**
		(2.921)	(2.383)
Constant	0.837***	1.174***	1.238***
	(5.553)	(9.747)	(10.055)
Observations	428,307	428,293	421,794
Adjusted R-squared	0.297	0.705	0.695
Linear Industry Trends	✓	✓	✓
Quadratic Industry Trends	✓	✓	✓
State ×Year Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓
County Fixed Effects		✓	
County × Year Fixed Effects			✓

Appendix for Online Publication Only

Table IA1: Bonus Depreciation

Year	Act	First-Year Deduction	Placed-in-service date	Equipment Type
2002	Job Creation and Worker Assistance Act 2002	30%	September 10, 2001- September 11, 2004	New
2003	Jobs and Growth Tax Relief Reconciliation Act	50%	May 3, 2003-December 31, 2004	New
2008	Economic Stimulus Act	50%	January 1, 2008 – September 8, 2010	New
2010	Tax Relief Act	100%	September 9, 2010- December 31, 2011	New
2011	Tax Relief Act (Extension)	50%	January 1, 2012 – December 31, 2012	New
2012	Tax Relief Act (Extension)	50%	January 1, 2013 – December 31, 2013	New
2013	Tax Increase Prevention Act	50%	January 1, 2014 – December 31, 2014	New
2015	Protecting Americans from Tax Hikes (PATH) Act 2015	50%	January 1, 2015 – December 31, 2017	New
2017	Tax Cuts and Jobs Act	100%	Sept. 27, 2017-December 31 2022	New and Old

Table IA2: Aggregate results at Firm Level

This table reports results from equation (1) aggregated at the firm level. In column (1), we estimate the effect tax incentives via bonus depreciation on an establishment's investment in equipment. In column (2) we estimate the effect of an establishment's purchase of new/old equipment. In column (3) and column (4) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the geographical variation by including Industry × State fixed effects and Year × State fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	(1) Log(EQTVALUE)	(2) *Log(EQTVALUE_New)*	(3) *Log(EQTVALUE_Old)*	(4) *percent_new_dollar*
z^{Θ}_{jt}	2.452***	2.398***	0.550	1.566***
	(3.409)	(2.613)	(1.038)	(4.047)
Log(Sales)	0.007	0.008	-0.001	0.008**
	(0.813)	(0.921)	(0.166)	(2.126)
Log(Employees)	-0.006	0.000	-0.001	-0.002
	(0.880)	(0.004)	(0.105)	(0.571)
Constant	8.874***	8.982***	10.662***	-1.071***
	(12.892)	(10.334)	(22.457)	(2.863)
Observations	1,553,882	784,836	766,199	1,553,882
Adjusted R-squared	0.544	0.577	0.472	0.344
Quadratic Industry Trends	✓	✓	✓	✓
Linear Industry Trends	✓	✓	✓	✓
Firm Fixed Effects	✓	✓	✓	✓
Industry×State Fixed Effects	✓	✓	✓	✓
Year×State Fixed Effects	✓	✓	✓	✓

Table IA3: Main tables using BEA weights

This table reports results from equation (1) addressing the issue of sample selection in EDA data. In this table we re-weight the data to match the distribution of machine purchases across two-digit NAICS industries with the distribution of GDP in the 2019 BEA data. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size $\times$ year fixed effects and Employee $\times$ year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Dependent Variable:	*New*	*Log(Machine Age)*	*Log(Model Age)*
z_{jt}^{Θ}	0.495***	-2.967***	-1.866***
	(3.126)	(6.381)	(3.885)
log_sales	0.028***	-0.057***	-0.035***
	(5.348)	(5.872)	(2.748)
log_emp	-0.010	0.008	0.065**
	(0.631)	(0.322)	(2.191)
Constant	-0.191	4.418***	3.768***
	(1.217)	(10.316)	(6.527)
Observations	3,322,000	3,322,000	3,322,000
Adjusted R-squared	0.097	0.104	0.152
Quadratic Industry Trends	✓	✓	✓
Linear Industry Trends	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Size×Year Fixed Effects	✓	✓	✓
Employee×Year Fixed Effects	✓	✓	✓

Table IA4: Main tables with IHS Transform

This table reports results from equation (1) after transforming machine age and model age variable using inverse hyperbolic instead of log transformation . In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size × year fixed effects and Employee × year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)
Dependent Variable:	*IHS(1 + Machine Age)*	*IHS(1+ Model Age)*
z^{Θ}_{jt}	-3.206***	-1.875***
	(13.155)	(8.409)
Log(Sales)	-0.044***	-0.027***
	(6.217)	(4.298)
Log(Employees)	-0.011	0.040
	(1.063)	(1.432)
Constant	5.436***	4.575***
	(20.514)	(19.250)
Observations	3,322,000	3,322,000
Adjusted R-squared	0.087	0.062
Quadratic Industry Trends	✓	✓
Linear Industry Trends	✓	✓
Industry Fixed Effects	✓	✓
Size×Year Fixed Effects	✓	✓
Employee×Year Fixed Effects	✓	✓

Table IA5: Conformity States

This table reports the cross-section effects of states in conformity with federal bonus depreciation on an establishment's vintage. The variable conformity takes the value of 1 for states conforming to federal bonus deprecation limits. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size × year fixed effects and Employee × year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Dependent Variable:	*New*	*Log(Machine Age)*	*Log(Model Age)*
z_{jt}^{Θ}	0.460***	-2.949***	-1.321***
	(2.898)	(6.871)	(3.779)
conformity$\times z_{jt}^{\Theta}$	0.518***	-0.951**	-0.743**
	(2.821)	(2.299)	(2.455)
Log(Sales)	0.032***	-0.081***	-0.033***
	(10.070)	(12.880)	(10.361)
Log(Employees)	0.015***	-0.041***	-0.016***
	(3.311)	(4.149)	(2.744)
Constant	-0.669***	5.560***	3.992***
	(6.795)	(20.984)	(17.778)
Observations	3,213,322	3,213,322	3,213,322
Adjusted R-squared	0.084	0.097	0.064
Quadratic Industry Trends	✓	✓	✓
Linear Industry Trends	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Size×Year Fixed Effects	✓	✓	✓
Employee×Year Fixed Effects	✓	✓	✓

Table IA6: Lease Transactions

This table reports results from equation (1) using only lease financed transactions. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size × year fixed effects and Employee × year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Dependent Variable:	*New*	*Log(Machine Age)*	*Log(Model Age)*
z_{jt}^{Θ}	1.048***	-3.773***	-1.561***
	(5.785)	(8.825)	(3.712)
Log(Sales)	0.010**	-0.016**	-0.017
	(2.234)	(2.206)	(1.523)
Log(Employees)	-0.004	0.013	0.032
	(0.555)	(0.968)	(1.551)
Constant	-0.398**	4.360***	3.225***
	(2.246)	(10.075)	(7.344)
Observations	816,004	816,004	816,004
Adjusted R-squared	0.123	0.132	0.179
Quadratic Industry Trends	✓	✓	✓
Linear Industry Trends	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Size×Year Fixed Effects	✓	✓	✓
Employee×Year Fixed Effects	✓	✓	✓

Table IA7: Bonus Only Firms

This table reports results from equation (1) using only buyers that are more likely to use the bonus depreciation. We exclude firms that invest more than the lower limit under section 179 and hence more likely to use bonus deprecation as a tax incentive. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size × year fixed effects and Employee × year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
Dependent Variable:	*New*	*Log(Machine Age)*	*Log(Model Age)*
z_{jt}^{Θ}	1.286***	-4.486***	-2.668***
	(4.90)	(-8.33)	(-5.77)
Log(Sales)	0.028***	-0.065***	-0.037***
	(6.25)	(-7.02)	(-7.75)
Log(Employees)	0.011**	-0.029***	0.003
	(2.58)	(-3.20)	(0.33)
Constant	-1.049***	6.061***	4.753***
	(-4.05)	(11.21)	(10.73)
Observations	1,332,513	1,332,513	1,332,513
R-squared	0.1460	0.1742	0.1552
Quadratic Industry Trends	✓	✓	✓
Linear Industry Trends	✓	✓	✓
Industry Fixed Effects	✓	✓	✓
Year Fixed Effects	✓	✓	✓
Equipment Fixed Effects	✓	✓	✓

Table IA8: Price Effect Post TCJA

This table reports the price effect of bonus depreciation by separating the sample into pre and post TCJA. In column (1) we estimate the effect of an establishment's purchase of new/old equipment. In column (2) and column (3) we estimate the effect on equipment's machine age and technological age, respectively. We use buyer and year fixed effects, along with industry trends in each of the regression models. We also control for the non linear size variation by including Size × year fixed effects and Employee × year fixed effects. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Pre-2016			*Post-2016*		
	(1)	(2)	(3)	(1)	(2)	(3)
Dependent Variable:	*Log(Old Price)*	*Log(New Price)*	*old_to_New_Price)*	*Log(Old Price)*	*Log(New Price)*	*old_to_New_Price)*
z_{jt}^{Θ}	-0.478**	0.258	-0.256***	0.276	0.314	-0.271
	(-2.15)	(1.21)	(-2.73)	(0.40)	(0.42)	(-1.02)
log_FIRMEMP	-0.040**	0.003	0.005***	-0.049**	-0.005	0.001
	(-2.51)	(0.57)	(2.73)	(-2.06)	(-0.52)	(0.29)
log_FIRMSZ	0.036***	0.005	0.002**	0.026***	0.010	0.005***
	(5.62)	(1.16)	(2.02)	(3.77)	(1.64)	(4.16)
Constant	10.634***	10.537***	0.793***	10.333***	10.562***	0.786***
	(45.66)	(49.47)	(8.90)	(15.17)	(14.31)	(3.02)
Observations	602,019	463,935	97,139	126,370	101,729	21,496
R-squared	0.5384	0.6767	0.1759	0.5570	0.6730	0.1168
Quadratic Industry Trends	✓	✓	✓	✓	✓	✓
Linear Industry Trends	✓	✓	✓	✓	✓	✓
Industry Fixed Effects	✓	✓	✓	✓	✓	✓
Size×Year Fixed Effects	✓	✓	✓	✓	✓	✓
Employee×Year Fixed Effects	✓	✓	✓	✓	✓	✓
Equipment Fixed Effects	✓	✓	✓	✓	✓	✓