Tax Incentives, Small Businesses, and Physical Capital Reallocation*

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Abstract

Our study presents novel evidence on the physical capital reallocation effect of temporary federal tax incentives. Using data on equipment purchases by small businesses, we found that temporary tax subsidies on new equipment, specifically in accelerated depreciation, increase investment in old capital goods by 9.2%, which represents nearly 44.3% of the direct effect. Additionally, these tax subsidies lead to an augmented supply of old equipment in the secondary market, causing a reduction in its price. Consequently, this cost reduction alleviates capital constraints for select small businesses, enabling them to increase investment in old capital goods, embrace new technology, and achieve accelerated growth. Our empirical results underscore how tax incentives driving investment in new capital goods foster the reallocation of older capital goods within the economy during recessions.

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

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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. Prior studies show that temporary federal tax incentives that accelerate the depreciation of investments in new equipment increase investment activities among small businesses.[1] However, these studies do not distinguish between investment in new and 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 (Eisfeldt and Rampini, 2007; Ma, Murfin, and Pratt, 2022). In this study, we present the first evidence on how tax incentives subsidizing the acquisition of new capital goods affect the reallocation of old capital goods within the economy.

The impact of tax incentives that subsidize the purchase of new capital goods on firms' intensity to invest in new versus old capital is not obvious. Some small businesses may *directly* benefit from *temporary* tax subsidies on new capital goods introduced in response to recessions (e.g., bonus depreciation under Section 168(k) of IRS) and make immediate investments in new capital goods (House and Shapiro, 2008; Zwick and Mahon, 2017). However, tax incentives on new capital can also *indirectly* benefit some other small businesses by possibly affecting the price of the old capital. Lanteri and Rampini (2023) theoretically show that the equilibrium price of old capital is higher than the constrained-efficient price, which results in under-investment by financially constrained firms. With tax subsidies on new capital goods, if some direct beneficiaries choose to replace their old capital with new capital, the supply of old capital may increase and subsequently lower its equilibrium price. Therefore, small businesses with binding constraints may buy old capital goods and indirectly benefit from tax incentives.[2] However, if most direct beneficiaries choose to only expand their capital stock, we may observe muted indirect benefits of tax incentives via the price of the old capital. Thus, a tax policy that temporarily subsidizes new capital goods may help reallocate assets from less productive

[1] For example, Zwick and Mahon (2017) show that small businesses in long-duration industries in the United States are more likely to increase investment in response to federal tax incentives, such as the bonus depreciation under Section 168(k) of the Internal Revenue Service (IRS), that *temporarily* accelerate the depreciation of investment in equipment.

[2] In their model, Lanteri and Rampini (2023) demonstrate how collateral constraints can distort the level of aggregate investment and the allocation of capital across firms. They find that in the absence of tax incentives on new capital, the equilibrium price of the old capital in a competitive market is higher than its social value. As a result, some firms may not invest in either new or old capital goods. However, a tax subsidy on new capital can lead to a more efficient allocation of resources by increasing the supply of old capital and reducing its price, thus benefiting constrained firms that are net buyers of old capital goods.

to more productive firms. Understanding these *direct* and *indirect* benefits from tax incentives is essential for designing effective tax policies that promote economic growth.

We empirically test the direct and indirect benefits of *temporary* tax incentives that subsidize the purchase of new capital goods, using data on equipment purchases and two episodes of investment stimulus from 1998 to 2011. We show a tax subsidy on new equipment increases the new equipment investment by 21% (direct effect), consistent with prior literature. However, we also document an increase in old equipment investment by 9.3% among firms *indirectly* benefiting from bonus depreciation. This effect is almost 44.3% of the direct effect. In terms of mechanism, our results are consistent with a reduction in old equipment's price and not by an increase in the price of new equipment.

Our data consist of 1.7 million purchases of *new* and *old* equipment by 424,768 small U.S. businesses, with median annual sales and employment of $320,000 and three workers, respectively. These data cover purchases of 22,411 models (with a median value of $56,400) 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). This data include a wide variety of equipment such as tractors, loaders, excavators, copiers, mowers, trucks, trailers, sprayers, and cultivators.

The tax policy we utilize is "bonus" depreciation under Section 168(k) of the Internal Revenue Code, which accelerates the timing of deductions of investment purchases from taxable income. The policy was first introduced in 2002 as a *temporary* tax incentive over and above the *permanent* tax provision of Section 179 to help small businesses that may not benefit from Section 179. Small businesses can fully expense the purchase of both new and used qualified assets, but only within certain limits under Section 179. In contrast, tax deductions under Section 168(k) are available only on purchases of new equipment (not previously used by other firms). Bonus depreciation allows firms to accelerate depreciation irrespective of investment size and increase the size of their net operating losses if necessary, which they can claim in the future. Bonus depreciation only alters the timing of the deduction rather than the total amount of deductions. Since future deductions are worth less than the current deductions, bonus depreciation will benefit small businesses, especially those with higher discount rates.

Our empirical strategy is similar to that of Zwick and Mahon (2017) and exploits the technological differences among firms in narrowly defined industries.[3] Firms in industries

[3]We use the four-digit NAICS industry-level tax benefit measure provided by Zwick and Mahon (2017). They use a comprehensive dataset from the IRS to create the tax benefit measure. Consistent with Zwick and Mahon (2017), we use industry-level variation for our primary analysis because measurement error in policy exposure correlated with firm-level characteristics would confound our heterogeneity tests. We find similar results when we use EDA data to create firm-level variation instead of

with most of their investment in *long-duration* categories act as the "treatment group" because bonus depreciation changes their depreciation schedules more significantly compared with those of firms in *short-duration* industries. Although this federal tax policy did not target specific industries, industry variation emerges because firms with longer-lived assets experience a more significant reduction in the present value cost of investment since bonus depreciation accelerates deductions further in the future.

First, we utilize the industry-level variation and estimate the new equipment elasticity at the firm/buyer level. With a tax subsidy on new equipment, we document an average increase in new equipment investment by 20.9 log points to 24.5 log points.[4] This is consistent with Zwick and Mahon (2017), who observe an increase in equipment investment on average by 17.7 log points between 2001 and 2004 and 28.8 log points between 2008 and 2011 in response to bonus depreciation. However, they can not distinguish between new and old equipment investments.[5]

Next, we document our main findings, the indirect benefit of tax incentives via capital reallocation. We document that a tax subsidy on new equipment increases the investment in old equipment by 9.02 log points (9.44%), which is almost 44.3% of the direct effect. Thereafter, we test if our results are consistent with the theory proposed by Lanteri and Rampini (2023). They theoretically show that the equilibrium price of old capital is higher than its social value. This finding implies that some firms with binding constraints may not invest because of the higher price of old capital goods. An increase in the tax subsidy for new capital goods implies that firms with fewer constraints buy new capital and replace their old equipment. This increases the supply of old capital and thereby lowering its equilibrium price. Therefore, some small businesses with binding constraints buy cheaper old capital goods with tax subsidies on new capital goods.

Consistent with the theory, we find a decline in the price of old equipment by 3.2% for long-duration (treatment group) industries, compared with the control industries. However, it is possible that tax incentives on new equipment investment may not benefit the investing firms but the capital suppliers. Suppose the supply of capital is less elastic

industry-level variation. See Section 4.1.3 for details.

[4]Firms with internal finance (i.e., those with less binding financial constraints) prefer to buy new capital goods (Eisfeldt and Rampini, 2007). The EDA data are available only when a firm uses external finance (i.e., uses debt to purchase equipment). We do not observe all new equipment transactions financed using retained earnings; therefore, we observe a lower bound on the impact of tax incentives on new equipment purchases.

[5]The IRS form does not require firms to list used purchases separately. However, our equipment purchase data help us distinguish between the two. Taking advantage of our data at the machine transaction level, we also find that conditional on investing, small businesses in treated industries are 4.4–5.4% more likely to buy new capital equipment. This magnitude is almost three times the effect of firm age on the likelihood of buying new equipment documented by Ma, Murfin, and Pratt (2022).

and suppliers increase the price of new capital goods. In that case, it may force small businesses to buy used capital goods in the secondary market (Goolsbee, 1998a). We find a slight marginal increase in new equipment prices but not economically significant. Our result suggests that a tax subsidy on new capital goods does not increase the price of new equipment and does not crowd out financially constrained firms from the new capital goods market.[6] We further investigate the reallocation mechanism and show increased equipment resale transactions when buyer and seller belong to the same 4-digit NAICS industry. This test validates our empirical setting. Further, we also find that tax incentives help with capital replacement. We see a significantly larger increase in new investments for firms that sold their old equipment around the bonus depreciation events.

Additionally, we use two measures of machine vintage to perform a more granular analysis of old equipment purchases. 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 first introduction of the machine's model type. Interestingly, we find a decline in the average machine age (by 7.5 to 13.2 months, with average machine age of 4.6 years) and technological age (by 3 to 11.5 months, with average model age of 6.2 years) for older machines purchased by the treated firms. The results suggest that these firms buy used but upgraded technology equipment from the secondary market.

Furthermore, we test the implications of buying used but upgraded technology equipment from the secondary market on small businesses. We find that future sales increase by 7% and employment increases by 3.4% for buyers of old capital that observe a decline in the average machine age and model age due to tax incentives. We also document subsequent effects on business entry due to this indirect reallocation. The entry of small businesses in the treatment industries increases by 2%, especially for industries with the ex-ante higher relative price of old equipment. Our findings suggest that some small businesses may indirectly benefit from lower prices of old capital goods in addition to direct tax benefits. A decline in the price of old equipment by 3.2% helps increase the investment in used upgraded technology equipment by almost 9% and helps increase sales growth by 7%. Overall, we document several unintended positive effects of new equipment investment tax incentives on small businesses.

[6] Our finding of no increase in prices of new capital goods does not imply that the supply of such goods is elastic, which is consistent with House and Shapiro (2008). We know that both rounds of tax incentives are introduced due to declining economic growth when manufacturers of such goods face increased inventory due to lower demand. Therefore, increased demand for such new capital goods does not necessarily increase their prices. However, these findings may not be generalizable during expansions.

During bonus years, firms can choose Section 179 and Section 168(k) of the IRS for accelerated depreciation on qualified assets. Section 179 must be applied first for either new or used equipment purchased. Firms may take any amount over the statutory limit to Section 179 under Section 168(k) of bonus depreciation, but only for new equipment purchased. Section 179 allows business owners to deduct a fixed dollar investment amount, and bonus depreciation lets them deduct a percentage of the cost. However, some firms in our sample may be responding directly to changes in Section 179 limits and buying old equipment. We exploit heterogeneity in the state's conformity to Section 168(k) and Section 179 to show that our capital reallocation results are mainly driven by changes in bonus depreciation. Also, during periods with no bonus depreciation, we do not see any differential effect on the price of old equipment and old equipment investment for treated firms.

Next, we test the heterogeneous response of small businesses to tax incentives based on access to small business finance (Petersen and Rajan, 1994). Prior literature shows that the prevalence of small banks in an area increases the availability of external financing to small firms (Berger, Bouwman, and Kim, 2017). We find that businesses located in counties with greater availability of small bank lending increase investment in old equipment. We find that these results are driven by a greater increase in investment in new capital goods and a decline in the price of old capital goods. We use another proxy for access to finance for small businesses and find similar results for firms located in areas where treatment industries have a greater ex-ante share of Small Business Administration (SBA) loans. Further consistent with the literature (Murfin and Pratt, 2019), we observe lower price depreciation for equipment sold by the manufacturer with greater market power resulting in a lower increase in old equipment investment with bonus depreciation.

A major challenge for our empirical design is that the time-varying industry shocks may overlap with the timing of bonus depreciation. We conduct various tests to alleviate this concern. First, we plot the aggregate county-industry trends for short- and long-duration industries for bonus and non-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. The absence of differential pre-trends for short- and long-duration industries provides some validity to the natural experiment. 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. Second, we control for macroeconomic trends in the data by including sector-specific linear and quadratic trends in our regressions. Controlling these macroeconomic trends increases the magnitude of our estimates. To further address the concern that time-varying industry shocks overlap with the timing of bonus depreciation, we utilize the variation across states by using the state's conformity to Section 168(k). This allows us to control for time-varying industry-level omitted variables.

Our paper relates to the large literature on tax incentives, capital reallocation, and vintage capital. The previous literature exploits cross-sectional variations to study the effect of tax policy on *investment* (Summers, 1981, 1987; Cummins, Hassett, and Hubbard, 1996; Goolsbee, 1998b; Chirinko, Fazzari, and Meyer, 1999; Desai and Goolsbee, 2004; House and Shapiro, 2008; Zwick and Mahon, 2017; Ohrn, 2018) and *labor* (Gaggl and Wright, 2017; Garrett, Ohrn, and Suárez Serrato, 2020; Tuzel and Zhang, 2021; Curtis, Garrett, Ohrn, Roberts, and Serrato, 2021). To the best of our knowledge, the current paper is the first paper to provide empirical evidence on the capital reallocation effect of tax incentives. In a closely related work, Zwick and Mahon (2017) show that financially constrained firms are more likely to increase investments as a response to tax incentives. However, we do not know whether those firms invest in new or vintage capital and in what proportion. Our data allow us to observe these investment characteristics at a more granular level. We document that tax incentives not only induce firms to invest in new capital but also reduce the price of old capital goods, allowing financially constrained firms to invest in old capital. This indirect investment tax elasticity is significant and about 40% of the direct tax elasticity.

We also contribute to the capital reallocation literature. Early work by Eisfeldt and Rampini (2006) shows that capital reallocation among firms is pro-cyclical. Eisfeldt and Rampini (2007) document that financially constrained firms tend to acquire older investment goods. Benmelech and Bergman (2011) find that weak creditor rights are associated with aircraft of both older vintage and older technology. More recently, Ma, Murfin, and Pratt (2022) 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 (2023) and provides empirical evidence for the capital reallocation effect of tax incentives. Our results contribute to the vintage capital literature, which shows that capital of older vintage adversely affects 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.

In Section 2, we discuss conceptual framework and empirical strategy. Section 3 discuss data. In Section 4, we present empirical results and conclude in Section 5.

2 Conceptual Framework and Empirical Strategy

In this section, we first discuss the history of the tax incentive policy used in our study (Section 2.1). We then present the conceptual framework (Section 2.2) and discuss why we analyze changes in bonus depreciation, i.e., Section 168 (k) (Section 2.3). Finally, we discuss our empirical strategy (Section 2.4).

2.1 History of Tax Incentives via Depreciation Allowance

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 (IRC) is a *permanent* tax provision that allows firms of all sizes and in all industries to fully expense, within certain limits, the cost of *new* and *used* qualified assets 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 periods of time using the MACRS schedule. The maximum expense allowance have gradually increased in the past three decades.[7]

Although Section 179 of the IRC is intended to help small businesses, some small firms may not fully utilize the accelerated depreciation if they reach the relevant threshold. In an effort to help such small businesses, Congress introduced bonus depreciation through the Job Creation and Worker Assistance Act under Section 168(k) of the IRC in 2002 as a *temporary* tax incentive. Under this act, small business owners can claim first-year bonus depreciation for qualifying property and equipment used for business purposes. Bonus depreciation lets companies deduct 30% of the cost of eligible assets before the standard depreciation method is applied. The bonus increased to 50% later in 2003. The policy was temporary and expired at the end of 2004. During the financial crisis of 2008, Congress reinstated the 50% bonus depreciation as an economic stimulus. The Tax Relief Act increased the bonus to 100% for tax years ending between September

[7] For example, the maximum expense allowance was only $10,000 from 1987 to 1992. Later, the maximum expense allowance increased to $24,000 , starting in 2002. From May 28, 2003, to May 24, 2007, the maximum expense allowance increased to $100,000. Then on May 24, 2007, the maximum expense allowance increased to $125,000. To further support small businesses during the great recession of 2007-2009, the maximum expense allowance first increased to $250,000 on February 13, 2008, for 2008-2010. Later on September 27, 2010, the maximum expense allowance further increased to $500,000.

2010 and December 2011.[8] Figure I plots the maximum first-year deduction for qualified equipment during the bonus and non-bonus depreciation years.[9] In contrast to Section 179, bonus depreciation was *temporary* and has only been available on *new* equipment. Furthermore, bonus depreciation allows firms to accelerate depreciation irrespective of investment size, thus affecting all types of firms, especially those firms not eligible for Section 179.

Introducing policies that temporarily subsidize new capital goods can directly benefit some small firms. Still, it may indirectly benefit or hurt other small businesses by impacting the market price of new and old capital goods. Next, we discuss the conceptual framework for such effects.

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, which is reduced by tax incentives. Consequently, the optimal capital stock and net investment level increase and bring the capital stock up to its new desired level. Early work suggests that tax incentives on investment do not benefit the investing firms, but rather the capital suppliers by increasing the price of capital goods (Goolsbee, 1998a). They show that changes in the investment tax credit, which were more *permanent* and often did not occur during recessions, coincide with price increases that mute quantity responses, especially in less competitive industries.

Bonus depreciation, particular tax incentives we use in our study are *temporary* in nature and are primarily used during recessions. Further, bonus depreciation incentives are available only on purchases of *new* capital goods. House and Shapiro (2008) utilize the first round of bonus depreciation and show that estimated elasticity is high—between

[8]The Protecting Americans from Tax Hikes 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 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 Tax Cuts and Jobs Act (TCJA) of 2017 brought 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, TCJA also made an important change to the qualified property rules by allowing businesses to claim bonus depreciation on used assets. This change in 2018 is a 50% increase in the bonus rate for new capital and a 100% increase in the bonus rate for used capital not eligible for Section 179. Therefore, we limit our analysis to only the first two waves of bonus depreciation.

[9]See House and Shapiro (2008) for the legislative history of the first round of bonus depreciation and Kitchen and Knittel (2016) for the legislative history of the second round. Further details about the depreciation policy are provided in the Internet Appendix, Table IA.I.

6 and 14. They find no evidence that market prices reacted to the subsidy, suggesting that adjustment costs are internal. Later, Zwick and Mahon (2017) show heterogeneous responses to the two rounds of bonus depreciation. They find that small firms are more responsive to bonus depreciation by increasing their overall investment.

However, the previous literature can not distinguish if these increases are due to in *new* equipment or *used* equipment.[10] Some small businesses with tax subsidies on new equipment (eligible capital under bonus depreciation) may take advantage of the tax code and benefit *directly* by making more investments in eligible capital, i.e., new capital goods. While it is possible that certain small businesses will increase investment in old capital goods (not eligible under bonus depreciation) with tax subsidies on new capital goods and *indirectly* benefit from tax incentives.

The two rounds of tax incentives that accelerate the depreciation of equipment investments were introduced as a counter-cyclical policy to promote investment activities and increase jobs among small businesses. In such a scenario bonus depreciation that affects both large and small firms can benefit small businesses indirectly. In their model, Lanteri and Rampini (2023) show that the stationary-equilibrium price of old capital goods is inefficiently high. They argue that financial frictions can distort the allocation of capital across firms.[11] In the absence of tax subsidies on new capital, they show that some firms may not invest at all because of the higher price of old capital goods.

A tax policy that subsidizes purchases of only new capital and *not* the old capital enables firms with fewer binding constraints to directly respond to tax subsidies by buying new capital goods. These firms can either choose to expand their capital stock or may replace old capital with new capital. If most of the firms in the economy choose to expand their capital stock and do not sell their old capital, we may not observe an increase in the supply of old capital in the secondary market. Thus, there will not be an *indirect* benefit of tax incentives on new capital. However, in case there are enough firms in the economy that replace old capital with new capital, such tax subsidies may increase the supply of old capital and hence lower its equilibrium price. Thus, some small businesses may increase investment in ineligible capital, i.e., used capital goods, due to a decline in the price of old capital goods.

Next, we discuss why we utilize the industry and time-series variations in Section 168(k).

[10] The IRS form does not require firms to list used purchases separately. However, our equipment purchase data help us distinguish between the two.

[11] Their model features two types of pecuniary externalities: collateral externalities (because the resale price of capital affects collateral constraints) and distributive externalities (because older capital goods typically flow from less financially constrained firms to more financially constrained firms).

2.3 Why Section 168(k)?

When businesses buy *new* equipment, they can choose both Section 179 and Section 168(k) of accelerated depreciation on qualified assets. However, if a firm buys a *used* equipment it can only take the advantage of Section 179. In the case of *new* equipment purchase, Section 179 allows business owners to deduct a set dollar amount of investment, and bonus depreciation lets them deduct a percentage of the cost. In the bonus years, 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. In the case of Section 179, a company must be profitable in order to take the Section 179 deduction, which 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 use bonus depreciation to take net operating losses (NOLs). The Section 168(k) policy was primarily aimed to lower the cost of capital for new investments for some small firms not eligible under Section 179.

In our case, we utilize time-series 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 (except for tax years after September 27, 2017, excluded from our analysis), while Section 179 applies to both new and old qualified assets. As per the theory proposed by Lanteri and Rampini (2023), the capital reallocation effect depends on subsidizing the purchase of *only* new capital goods such that some firms in the economy purchase the subsidize new capital and sell old capital. Second, the direct benefits of Section 179 are available only to eligible small businesses. In contrast, Section 168(k) allows firms to accelerate depreciation irrespective of investment size, thus affecting all types of firms. In terms of policy takeup, Kitchen and Knittel (2016) shows a positive relationship between bonus use and the firm's size. This variation is important to test the indirect benefits of tax incentives arising from a decline in the prices of old equipment. Finally, during the bonus years, the dollar value of claims for Section 168(k) is significantly more than that for Section 179, 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 \$548.4 billion in 2011 with bonus depreciation of 100%, while Section 179 claims were only \$53.2 billion.[12]

[12] During the period 2002-2011, the net total Section 179 deductions account for \$500.7 billion, while total bonus amount claimed were \$1.781 trillion. See Kitchen and Knittel (2016) and `https://www.irs.gov/statistics/soi-tax-stats-corporation-tax-statistics` for details.

2.4 Identification Strategy

We follow Zwick and Mahon (2017) to calculate z^0, the present value of depreciation deductions. 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 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 changes 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

$$z^\theta = \tau \left(\theta + (1-\theta)\, z^0\right).$$

Long-lived assets are depreciated more slowly over a longer time period and have smaller z^0s compared with short-lived assets. Therefore, tax deductions generated by long-lived assets are less in present value terms. 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 the measure z^0_j from Zwick and Mahon (2017) for industry variation.[13] The variation in z^0_j across industries provides the basis for a difference-in-differences research design with continuous treatment, that is,

$$z^\theta_{j,t} = \theta_t + (1-\theta_t)\, z^0_j,$$

where $z^\theta_{j,t}$ varies between zero and one across industries before tax changes, and equal to one when bonus deprecation is 100%. Thus, industries with lower z^0_j before the bonus will benefit the most after bonus depreciation. Internet Appendix, Table IA.II lists the most and the least affected industries based on z^0_j. The most affected industries at the three-digit industry code level in our data are crop production (111) and fabricated metal manufacturing (327). The least affected industries include professional, scientific,

[13] Zwick and Mahon (2017) calculate z^0 for each asset class defined by MACRS assuming a 7% discount rate. Next, they use tax return data to calculate the share of each bonus-eligible asset class purchased by each four-digit NAICS industry. Finally, Zwick and Mahon (2017) weigh the asset class z^0s by the industry shares to create z^0_j, which measures the present value of depreciation deductions for the average asset in which industry j invests.

and technical services (541) and administrative and support services (561).

To measure the firm-level investment elasticities, we aggregate the equipment purchases at the buyer-year level and estimate the following difference-in-differences specification,

$$y_{i,t} = \alpha + \beta z^{\theta}_{j,t} + \gamma X_{i,t} + \omega_t + \delta_j + \epsilon_{i,t}, \tag{1}$$

where index i refers to the buyer firm, j denotes the four-digit NAICS industry, and t indicates the year. The coefficient of interest is β. We include two sets of fixed effects: year fixed effects (ω_t) and industry fixed effects (δ_j). We also include sector-level trends and buyer fixed in different specifications. We also add buyer-level controls such as logged sales and logged employees, which are collectively represented as $X_{i,t}$. For the dependent variable $y_{i,t}$, we use the logarithm of total investment in new equipment and the logarithm of total investment in old equipment.

3 Data and Descriptive Statistics

3.1 Data Sources and Sample Selection

The main source of data that we use for the empirical analysis is EDA, which collects and processes UCC-1 statements. A UCC-1 statement is filed by a 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, no states except California and Texas allow for bulk downloads. Thus, a large sample of UCC-1 statements are only available through EDA, which has a contract with all states to allow for bulk downloads. While all UCC-1 statements are collected, only those with collateral on equipment[14] in the agriculture, construction, copier, lift truck, logging, machine tool, printing, trucking, and woodworking industries are processed.[15]

[14]In our case, we observe the capital purchase decisions of small businesses that use business loans. We do not observe purchase transactions for businesses that rely on internal sources. To address the concern that the EDA data may not completely follow the aggregate trends in the type of equipment purchased, we plot the aggregated trends of used to total equipment in Figure IA.II for EDA data along with National Income and Product Accounts (NIPA) data. The trend analysis suggests that the percentage of old equipment exhibits similar trends across both datasets over the entire time series of bonus depreciation between 1998-2011.

[15]Certain industries like agriculture, construction etc. are oversampled in the EDA data. We address this issue in two ways. First, we reweight the EDA data to match the distribution of machine purchases across two-digit NAICS industries in the Annual Capital Expenditure Survey (ACES) and distribution of GDP in the Bureau of Economic Analysis (BEA) data in Section 4.1.3.

The greatest strength of the EDA data is that we are able to observe the type of capital investments i.e. if it is a *new* machine or *used/old* machine, how old is the machine purchased, each machine's model so that we can estimate the machine age and technological age. EDA data also provides an estimated value of the equipment. EDA uses various sources to determine the estimates of the equipment values. In addition to the actual selling prices on the UCC-1 filings, EDA uses a combination of published values, auction guides, telephone survey work, asking values from trade magazines, Internet-published MSRP, and statistical modeling. The EDA sells this data to various banks, sales representatives, and other industry participants, in addition to the academic community (See Internet Appendix IA.1 for more details). 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 (See Internet Appendix Table IA.XIV where we include leases in our baseline results.) In addition to the nature of the transaction, EDA also provides machine-level characteristics such as the manufacturer, manufacturing year, model, serial number, and equipment value, and whether the equipment is new or used. For each equipment transaction, we construct the log value of the 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 obtained by EDA 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 the Great Recession. Murfin and Pratt (2019) use EDA data and show how equipment manufacturers use captive finance to maintain higher resale price for their products. Ma, Murfin, and Pratt (2022) use EDA data to document the importance of the local availability of old capital goods for business formations and capital reallocation. Gopal and Schnabl (2022) utilize a comprehensive set of UCC filings data, documenting that the gap left by the contraction in small business lending by banks has been filled by finance companies and fintech lenders. Further description of the data can be found in Edgerton (2012) and Gopal (2019).

3.2 Summary Statistics

Table I displays summary statistics of the equipment and firm characteristics for our sample period from 1998 to 2011. The raw dataset has 1.7 million equipment purchases by 424,768 small U.S. businesses. For our main analyses, we aggregate the individual machine transaction data of purchases to the firm-year level. The average (median) amount of investments in new equipment is $\$126,437$ ($\$61,629$), while that of old equipment is $\$90,644$ ($\$55,996$). The average (median) value of new equipment purchased is $\$71,895$ ($\$50,347$), while the median value of old equipment is $\$56,366$ ($\$40,281$). The average (median) age of machines acquired by firms in a given year is 4.603 (1.4) and the average (median) model age of a machine is 6.242 (5) years. The average (median) value of $z^{\theta}_{j,t}$, which is our main variable of interest that represents the present discounted value of a dollar of depreciation deductions, is 0.927 (0.929).

Note that our sample includes many small businesses. The firms that acquire the equipment have an average (median) of approximately \$3.184 (\$0.32) million in sales and 12.97 (3) employees. On the other hand, the median firm in Zwick and Mahon (2017) has a sale of \$26 million and sales of the median firm in the Compustat sample is \$98.6 million, during the same sample period. The presence of many small businesses in our data makes it more suitable to test the capital reallocation theory since the reallocation of old equipment is more likely to happen from large sellers to smaller buyers. In our data, we observe the average size of new and old equipment buyers in our sample are \$4.383 million and \$2.463 million, respectively. This sample for new equipment purchases is different from old equipment purchases because some buyers only buy new equipment while others buy mostly old equipment. Internet Appendix Table IA.III provide the definition of all the variables used in our analysis and Internet Appendix Table IA.IV provides the sample statistics at the machine transaction level.

4 Results

We begin our analysis by testing the direct impact of tax subsidies on new equipment purchases. Then, we show our main results documenting the indirect effect of tax incentives on old equipment investment (Section 4.1). Next, we document the mechanism based on the price of old and new machines (Section 4.2). Next, we rule out alternative mechanisms using state-level variation in Section 179 (Section 4.3). After that, we provide results on the real effects of physical capital reallocation on a firm's sales growth and how the ex-ante price of old capital affects new business formation at the aggregate industry-geography level (Section 4.4). Finally, in terms of heterogeneity, we show how old equipment prices and investment elasticity varies based on the state's conformity to bonus depreciation, access to small business credit, and the market power of the equipment manufacturers (Section 4.5).

4.1 Do Tax Incentives on New Equipment Encourage Firms to Invest in Old Equipment?

We begin our analysis by documenting the direct effect i.e., effect of incentives that subsidized purchase on new equipment on investment in such machines. Then we document the spillover effect of these tax incentives, i.e., investment in old machines. First, we provide graphical evidence on the effect of bonus depreciation on new and old equipment purchases at the aggregate industry-county level (Section 4.1.1). Next, we provide results for our baseline regression model (Section 4.1.2). Then, we test the impact of bonus depreciation on machine vintage and model age of old equipment purchased (Section 4.4.1). Finally, we discuss the robustness of our results (Section 4.1.3).

4.1.1 Graphical Evidence

We start with a simplified setup to provide graphical intuition on the main result by aggregating the data at the four-digit NAICS industry, county, and year level. To construct the treatment and control groups, we use the z_j^0 measure from Zwick and Mahon (2017), which is based on the four-digit NACIS codes. We define the treatment group based on the bottom three deciles of z_j^0. The control group consists of the four-digit industries in the top three deciles of z_j^0.

We estimate the dynamic regression specification for the two episodes of bonus depreciation changes between 1998 and 2011 and use the year 2001 as the benchmark year, which is the period immediately before the bonus depreciation schedule change. Figure II plots the estimates of difference-in-differences regression along with 95% confidence intervals. Our dependent variables of interest are *Log($ New Equipment Investment)* and *Log($ Old Equipment Investment)*, defined as the logarithm of the total investment of new and old equipment purchased at the four-digit industry-county-year level, respectively. We include unit fixed effects at the county level to control for unobservables at the county level, state × year fixed effects, and state × industry fixed effects to control for time-varying state-level shocks (like conformity to Section 168(k) or Section 179 for state-level taxes) and unobservable differences at the state-industry level, respectively.

Firstly, we observe that the pre-bonus differences between the treatment and control groups are statistically insignificant for both new and old/used equipment investment. This finding suggests that the industries in the treatment and control groups followed parallel trends before the bonus depreciation schedule change, increasing our confidence that our results can be interpreted as causal. Next, we see a greater increase in new equipment investment for treated industries compared with the control group during the first phase of bonus depreciation. However, surprisingly, we also noticed a similar increase in investment for old equipment that is not eligible for bonus depreciation deduction. For example, during Bonus I years, we find on average there is a 4–6% year-on-year increase in new and old equipment investment for treatment industries than the control industries. Interestingly, we find a negligible increase in new and old equipment investment during non-bonus years i.e., 2005 and 2006. Finally, for Bonus II years we observe an average year-on-year increase in investment by 36% and 20% for new and old equipment, respectively.

4.1.2 Economic Magnitudes

The graphical analysis based on industry-county aggregates suggests a significant spillover effect of bonus depreciation, i.e., with tax subsidy on new equipment. In addition to the purchase of directly subsidized new equipment, we also observe an increase in the purchase of old equipment for firms in the treatment industries. However, our previous estimates do not differentiate the magnitude of bonus depreciation schedules over the years. Also, they ignore the industry-level variation in present value factors by combining all treatment industries into a single group. Finally, unobserved firm-specific and time-specific heterogeneity that may lead to higher equipment investment for treatment industry firms is ignored. In this subsection, we discuss the economic magnitudes of direct and indirect effects of bonus deprecation on investments at the firm level.

a) Direct Effect: New Equipment Investment: Firstly, we estimate the direct benefits of tax incentives. The previous literature could not classify the equipment investment by type (i.e., whether the firm is investing in new or old equipment). With our data, we can measure the change in investment composition. We start by aggregating the individual new purchase transactions for a given buyer-year to calculate the natural logarithm of new equipment dollar investment (*Log($ New Equipment Investment)*$_{i,t}$). We implement a difference-in-differences model at the buyer-year level according to specification (1) using a continuous measure of the present value of depreciation deductions ($z^{\theta}_{j,t}$). The coefficient of interest is β. The results are documented in Table II Panel A. We begin with *Log($ New Equipment Investment)* as the dependent variable. Therefore, column

(1) provides the investment elasticity of tax incentives. The coefficient suggests that a one standard deviation increase in $z^{\theta}_{j,t}$ would increase equipment purchases by the firm by 39.9 log points (0.045 $\times$ 8.881). To address the issue that time-varying industry shocks may overlap with the timing of bonus depreciation, we include sector-specific (two-digit NAICS) linear and quadratic trends in columns (2)– column(4). We also include Buyer fixed and *Buyer Size* $\times$ *Year* fixed effects to control for the non-linear time trends in buyer size that could drive the relation between $z^{\theta}_{j,t}$ and new equipment purchase. The number of observations drops after including buyer fixed effects because many small businesses purchase equipment once during our sample period. The effect on new investment elasticity due to bonus depreciation varies between 20.9 log points to 24.5 log points. We also find a 5.4%—8.8% increase in the probability of investing in new capital for the treatment group (See Internet Appendix, Section IA.2 and Table IA.V for estimates of the transaction level results). Overall, the results suggest a significant direct effect of bonus depreciation on new investment elasticity, consistent with the graphical evidence we document at the aggregate county-industry level.[16]

Next, we test if some of the direct beneficiaries who choose to sell their old machines invest more in new machines. Our data also allow us to track the buyers who sold their used equipment during bonus depreciation years. If this is true, some firms may replace their old used equipment with new machines. We find that the direct effect on investment elasticity is almost 1.7 times stronger for these buyers (See Internet Appendix Table IA.VII).

b) Indirect Effect: Old Equipment Investment: Next, we document our main findings, i.e., indirect effects of tax incentives by examining whether some firms in the treated industries purchase used equipment. As we discussed before, only new equipment purchases are eligible for deduction under Section 168(k). However, some firms are likely to indirectly benefit from bonus depreciation and purchase old equipment. This happens because, with tax subsidies on new equipment, some firms replace old capital with new capital. Such subsidies increase the supply of old capital and hence lower the equilibrium price of old equipment. This suggests a positive investment elasticity on used equipment purchases in response to tax incentives on new capital. However, if most direct beneficiaries choose to only expand their capital stock, we may observe muted indirect benefits of tax incentives via the price of the old capital.

[16]This intensive margin semi-elasticity of investment is comparable and in fact larger compared to Zwick and Mahon (2017). Please see Internet Appendix, Table IA.VI for total investment elasticity effects. They find an average increase in equipment investment of 17.7 log points between 2001 and 2004 and 28.8 log points between 2008 and 2011 in response to bonus depreciation.

The results are documented in Table II Panel B. We aggregate the used equipment transactions for a given buyer-year to calculate the natural logarithm of the total investment in used equipment (*Log($ Old Equipment Investment)*). The results in column (1) suggest a positive and significant effect on the investment elasticity of used equipment ($0.045 \times 3.431 = 15.43$ log points). The magnitude is 38.6% (= 3.431/8.881) of the new equipment investment elasticity (direct effect). In the next few columns, we add additional fixed effects to control for unobservable factors. In column (4) the investment elasticity of used equipment ($0.045 \times 2.066 = 9.3$ log points) is 44.2% (= 2.066/4.666) of the new equipment investment elasticity (direct effect).

We follow the previous tax literature to estimate a tax-term elasticity model. In these specifications, one needs investment to lag capital stock as an outcome variable. However, we do not observe capital stock or total assets for small businesses in our data. Therefore, we estimate the capital stock for firms in our data using the sales-to-tangible assets ratio for the lowest quintiles of firms in Compustat data within 2-digit-NAICS industry codes for each year. We find the tax-term elasticity of -9.269 for new equipment and -3.260 for old equipment (See Internet Appendix Table IA.VIII).[17]

Notice that bonus depreciation is available only on new equipment during our sample period. Hence, one possible explanation is a spillover effect arising due to a reduction in the price of old equipment. We discuss this mechanism in Section 4.2. Another alternate possibility is that some firms in our sample are responding directly to changes in Section 179 limits and are buying old equipment. When businesses buy equipment, they can choose both Section 179 and Section 168(k) of accelerated depreciation on qualified assets. Section 179 must be applied first for either new or used equipment purchased. To minimize this concern, we show that our results are stronger when state's are more likely to adopt federal bonus depreciation policies (Section 4.3)[18]. Further in Section 4.3, we exploit the state's conformity to Section 179 to provide additional insights.

[17]There are possibly two reasons why we observe large tax-term elasticity. First, in our data, we observe small businesses that may be more sensitive to tax changes. For example, Zwick and Mahon (2017) find this elasticity to range between -3 to -4 for the lowest decile (Figure 4) in their sample. In Zwick and Mahon (2017) study, he average sales for the bottom decile firms are about $834,000. While our median firm has sales of $320,000. Second, estimating capital stock for firms in our data using Compustat may introduce measurement bias in our estimates.

[18]It is also possible that there are other unobserved policy changes that results in a differences in firm distribution across states and industries over time. Hence we add state $\times$ year and state $\times$ industry fixed effects in Table IA.IX This allows us to compare long vs. short duration industries within the same state-industry and state-year pairs.

4.1.3 Robustness Checks

In this section we discuss robustness of our baseline results.

i) *Sample selection:* Note that EDA data are only available for firms that utilize business loans to purchase equipment. Therefore, we do not observe transactions for firms that use internal capital to buy equipment. Prior literature suggests that financially constrained small businesses are bank-dependent (Sharpe, 1990; Rajan, 1992) and are less likely to buy new equipment (Rampini, 2019). So, our estimate of purchasing new machines after tax incentives is a lower bound.

We address the issue of sample selection in the EDA data. Hence, we re-weight the EDA data to match the distribution of machine purchases across two-digit NAICS industries with the distribution of equipment purchases as a proportion of total capital expenditure in the ACES data during our sample period and distribution of GDP in the 2019 BEA data. Although we find similar results, the economic magnitude is smaller compared with the unweighted sample (see Internet Appendix, Table IA.X and Internet Appendix, Table IA.XI for regression results.). For example, with ACES data re-weighting, we find the investment elasticity of used equipment ($0.045 \times 2.385=$) 10.73 log points, compared to our baseline magnitudes of 9.03 log points.

ii) *Sector-Trends:* It is possible that bonus has a different impact across firms in different sectors, so including the sector trends (measured at NAICS two-digit level) may bias our results. Also netting out a linear or quadratic trend through both the pre- and post-period, may create spurious variation. In Table II we showed our results by omitting the sector-level trends. The results are quantitatively similar. To further address the concern about sector trends, we use the pre-period industry growth rate as an alternative. The results are quantitatively and qualitatively similar. For example, with pre-period industry growth rate as control, we find the investment elasticity of used equipment ($0.045 \times 1.935=$) 8.71 log points (See Internet Appendix, Table IA.XII).

iii) *Alternative Depreciation Deduction Measure:* Following previous literature, in the baseline specification, we use variation at the industry level (Zwick and Mahon, 2017). As robustness, we create a firm-level measure by using the purchase-level data. We redefine the depreciation deduction measure and calculate the tax benefit at each equipment level BKS^{θ}_{emt}.[19] We provide consistent evidence in favor of direct effect at the transaction level

[19] We use the general depreciation system, where we hand-match each piece of equipment with each asset class defined by MACRS. We calculate BKS^0 for each asset class defined by MACRS, assuming a 7% discount rate. Letting D_s denote the depreciation rate at period s for an asset with remaining lifespan T^*, the present value of depreciation deductions associated with \$1 of investment in equipment

in Internet Appendix Table IA.XIII Panel A. Further, we aggregate BKS^{θ}_{emt} average at the NAICS4-year level and repeat our analysis in Table II. Panel B of Internet Appendix Table IA.XIII documents qualitatively similar results on the investment elasticity of old and new equipment, respectively. For example, we find the investment elasticity of used equipment (0.045×2.788=) 12.54 log points.

iv) *Including Leases:* In our baseline results, we drop lease transactions for two reasons. First, in our data, we cannot distinguish capital leases from operating leases. Per the IRS tax code, only capital leases are eligible for bonus depreciation. Second, most leases are on new transactions, which removes variation in the machine age. However, we run our baseline regressions including leases and find consistent results. For example, we find the investment elasticity of used equipment including leases (0.045×2.228=) 10.02 log points(See Table IA.XIV for details.)

4.2 Mechanism: Price of Old and New Equipment

So far we observe that there is a positive effect on new capital (direct effect) and used capital (indirect effect) investment with the introduction of tax subsidies on new capital. Next, we explore the underlying mechanism for the unexpected increase in old equipment investment. The capital reallocation model suggests that the competitive-equilibrium price of old capital is higher than its socially optimal level because of financial frictions (Lanteri and Rampini, 2023). Bonus depreciation on investment in new capital leads to a more efficient allocation by increasing the supply of old capital. This will reduce the price of old capital goods and allow financially constrained firms to purchase older equipment. However, if a majority of firms in the economy choose to expand their capital stock and prefer not to sell their old capital, we may observe a muted or no effect on the price of old capital.

In our data, we observe the estimated collateral value of the equipment. We use this value as our approximation for the equipment price.[20] For example, consider a

can be written as $BKS^0 = \sum_{s=0}^{T^*} \frac{D_s}{(1+r)^s}$, where r denotes the discount rate applied to future cash flows. BKS^0 measures the present value of depreciation deductions for each transacted equipment. Thus, under bonus depreciation, the present value of tax benefits with the effective tax rate, τ, is $BKS^{\theta} = \tau\left(\theta + (1-\theta)\,BKS^0\right)$. See Internet Appendix Section IA.3 for details.

[20]To estimate the value of each type of equipment, EDA uses a combination of published values, auction guides, actual selling prices gathered from UCC-1 filings and telephone survey work, asking values from trade magazines, Internet-published MSRP, and statistical modeling. Next, they use year of manufacture, the equipment category (four-digit equipment code), and the size within that equipment category to determine an estimate, which is shared among all manufacturers within the category. See Appendix IA.1 for details.

windrower (EDA equipment code: 8850) sold by John Deere in the oilseed and grain farming industry (four-digit NAICS code: 1111). The estimated value of a brand new John Deere windrower with model number W-235 for the year 2019 is $61,079. The corresponding estimate for the older version of the same equipment in the same industry in 2019 is $34,935. Of course, the variation in equipment prices or collateral value can be due to many factors other than tax incentives. For instance, it can be due to differences in equipment type, manufacturer, equipment age, equipment model, equipment size, and other macroeconomic conditions. Hence, they are not directly comparable. So we start by calculating the residual equipment price for each piece of equipment by estimating the effect of the machine age, model age, four-digit equipment code, equipment size, and manufacturer model on prices. The residual estimation results are documented in Table III Panel A. The high R^2 provides some assurance that we controlled for a variety of observable and unobservable determinants of equipment price.

Next, we calculate the average residual prices of old and new equipment by aggregating all the transactions in a four-digit NAICS code for a given equipment type (four digit) in a given county during each year (see Internet Appendix, Table IA.XV and Table IA.XVI for alternative levels of aggregation). We define *Price of New Equipment* and *Price of Old Equipment* as the average residual price of new and old equipment, respectively. This aggregation at the year-equipment type-county-industry level results in fewer observations for old and new equipment prices than our transaction-level data. Our main objective is to document the effect on prices of old and new capital in the treatment group after bonus depreciation.

We begin our analysis graphically similar to Section 4.1.1. We present our results in Figure III. Here, we include four-digit industry fixed effects, equipment fixed effects, and county fixed effects. We use *Price of New Equipment* and *Price of Old Equipment* as the dependent variables, respectively. We notice that for bonus I, old equipment price declines by approximately 1% with the tax subsidy on new equipment. We also observe some increase in the prices of new capital. This could be a possible reason for muted effect on old equipment investment during bonus I. However, during bonus II, we observe a steep decline in the price of old capital without a corresponding increase in the price of new capital except for the year 2011. From 2009 to 2011, we notice a decline in the price of old equipment by about 3% more for treatment industries, compared to short-duration industries when first-year deduction increases from 20% in 2007 to 100% in 2010–2011. We observe some delayed effects on old prices and old investments because it takes time for capital to relocate from the buyers of new capital.

Next, we estimate our results using the following difference-in-differences specification,

$$Price_{j,m,c,t} = \alpha + \beta z^{\theta}_{j,t} + \gamma X_{j,m,t} + \delta_j + \omega_t + \kappa_m + \eta_c + \epsilon_{j,m,c,t} \tag{2}$$

where *Price* refers to *Price of New Equipment* or *Price of Old Equipment*, respectively. The index m refers to machine type, j denotes the four-digit NAICS industry, c denotes the county, and t indicates the year. $z^{\theta}_{j,t}$ is measured at the four-digit NAICS industry level and increases during bonus years. 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 and year fixed effects (ω_t) to control for time trends. In addition, we include equipment fixed effects (κ_m) to control for technological differences in machines and county fixed effects (η_c) to control for unobserved heterogeneity at the county level. We also have linear and quadratic sector trends at the two-digit NAICS level to control for macroeconomic shocks. Following Zwick and Mahon (2017), we cluster standard errors at the four-digit NAICS level.

As discussed before, bonus depreciation is only available on new equipment in our data period. In Section 4.1.2, we report a positive and significant impact on old equipment purchases. We examine the effect on old equipment prices according to specification (2), using the continuous measure of the present value of depreciation deductions (z^{θ}_{jt}) in Table III Panel B. The results in columns (1)–(4) show an economically significant decrease in the residual price of used equipment for the treatment group. For one standard deviation increase in $z^{\theta}_{j,t}$, the average price of old equipment decreases by approximately 3.2% (column (1): 0.039×0.838). The results are consistent with the theory suggesting that a tax subsidy on new capital may benefit the buyers of the old capital. In Panel C, we find a slight marginal increase in new equipment prices, which is not economically significant. To test the robustness of our specifications for price results, we re-estimate residuals for which we control for time-varying unobservables for equipment of a given size (See Internet Appendix, Table IA.XV) and also aggregate the baseline specification at equipment code-equipment size-county-industry-year (see Internet Appendix, Table IA.XVI). We find consistent results.

The null result on new prices does not imply that the supply of such goods is perfectly elastic, which is consistent with House and Shapiro (2008). Since both rounds of tax incentives were introduced as a consequence of declining economic growth, manufacturers of such goods faced increased inventory due to lower demand. Therefore, increased demand for such new capital goods does not necessarily increase their prices. Our result suggests that a tax subsidy on new capital goods does not increase the price of new equipment and does not crowd out financially constrained firms from the new capital goods market. Consistent with the capital reallocation theory, the results collectively document a significant reduction in used equipment price.

4.3 Bonus Depreciation vs. Section 179

In this study we utilize temporary changes in Section 168 (k) and find that some small businesses choose to purchase old equipment. This is due to a decline in the prices of the old capital, consistent with capital reallocation theory. However, it is possible that some firms in our sample are responding directly to tax breaks under Section 179 and buying old equipment. One way to rule out this possibility is by exploiting heterogeneity in the state's conformity to Section 168(k) and Section 179.[21]

In the United States, firms file corporate taxes both at the federal and state level. When federal depreciation incentives are implemented some states do conform to those changes for state taxes, while others do not. For the states that do not conform to depreciation policies, it not only reduces the tax benefit for state taxes but complicates bookkeeping processes for small businesses, thus discouraging firms to claim federal Section 168(k) deductions or Section 179 deductions (Kitchen and Knittel, 2016).[22] In this section, we test how our results vary based on state's-conformity to bonus depreciation and Section 179. In addition, it also allows us to use industry-by-year fixed effects to control for industry shocks or trends and use the cross-sectional variation across states. Further, combining the variation in state conformity to depreciation policies with industry-level variation allows us to reinforce the idea that reallocation is more likely to be attributable to bonus depreciation.

We start by testing the state-level variation in conformity with Section 168(k). We predict that some buyers located in states that conform to Section 168(k) are more likely to take advantage of the tax break by purchasing new equipment while selling their existing old equipment. This will result in an incremental decline in the price of old equipment and a corresponding increase in old equipment elasticity. We start by creating

[21]In equilibrium some firms directly benefit from bonus depreciation and if some of these firms sell their old capital, this may increase the supply of old capital and hence lower its equilibrium price. It is possible that a decline in the price of old capital due to bonus depreciation may help some small businesses to utilize Section 179 and buy older capital. Therefore, even if not all firms in our sample are eligible for Section 168(K) directly, they are indirectly benefited via a decline in the price of the old capital. Our main results are consistent with this spillover benefit of bonus depreciation on old equipment via lower price.

[22]For example, when bonus depreciation was first initiated 17 states fully conformed to federal bonus incentives while 25 states did not offer any bonus incentives. Some states like Minnesota, Nebraska, and Pennsylvania partially adopted bonus depreciation. In 2008, when bonus depreciation was reintroduced, 12 states fully adopted it while five partially adopted the 50% rate (Ohrn, 2019).

an indicator *Bonus State Conformity*$_{s,t}$ identifying buyers located in states that fully conform to federal bonus depreciation. We implement a difference-in-differences model as before, except that we add the interaction between *Bonus State Conformity*$_{s,t}$ and $z^{\theta}_{j,t}$. Firstly, we find that the interaction effect of *Bonus State Conformity*$_{s,t}$ and $z^{\theta}_{j,t}$ on new equipment purchase is positive and significant (See Internet Appendix Table IA.XVII). Table IV documents the results on the price of old equipment and investment in old equipment. In Panel A, we find the effect of state bonus conformity on used equipment price is incrementally negative. A one standard deviation change in $z^{\theta}_{j,t}$ would decrease the price of used equipment by up to 4.1% $(= -0.039/-0.938)$ over the baseline effect. Further, in Panel B, we find the incremental effect on used investment is positive and statistically significant. The incremental effect on investment elasticity of used equipment in column (5) is 25.5% $(= 0.53/2.08)$ more in conformity states. This effect remains equally strong after adding industry-by-year fixed effects to control for industry-level shocks that may coincide with the bonus depreciation schedule. These results suggest that a state's conformity to temporary federal tax incentives amplifies the direct effect and hence helps in reallocating old capital via lower prices.

Next, we utilize the variation in state conformity to Section 179. Similar to Section 168(k), some states choose to conform to changes in the limits of Section 179 at the federal level for state-level corporate taxes. The purchase of new or old equipment is treated similarly under Section 179. Therefore, we do not expect a differential change in the price of old equipment in states that conform to Section 179. We start by creating an indicator *Sec179 State Conformity*$_{s,t}$ identifying the states that match 100% to federal Section 179 allowance during a given year. For example, in 2001, 25 states fully conformed to Section 179. The results are documented in Table V, Panel A. We see that the main effect on $z^{\theta}_{j,t}$ is negative and statistically significant. The coefficient on *Sec179 State Conformity*$_{s,t}$ is insignificant in most of the specifications. Overall, we find there is no incremental negative effect of Section 179 on used equipment prices. Further, if Section 179 drives the documented increase in used investment elasticity, we expect the effect to increase in states that conform fully to Section 179. Similar to prices, we find that the main effect on $z^{\theta}_{j,t}$ is positive and significant, However, the incremental effect on *Sec179 State Conformity*$_{s,t}$ is very small and statistically insignificant.

These results from IV and Table V suggest that our main results are more likely to be driven by changes in bonus depreciation policies. In order to provide additional evidence that our reallocation results are less likely to be driven by the Section 179 effect we did additional robustness tests. We find no effect of tax incentives on old equipment prices and old equipment investment during years with no bonus depreciation when Section 179 limits increase (See Internet Appendix, Table IA.XVIII). These results further suggest the importance of bonus depreciation for the effect of capital reallocation triggered by subsidizing new equipment purchases.

4.4 Real Effects of Physical Capital Reallocation

So far, our evidence suggests that in response to tax incentives on new equipment, some firms increase investment in old equipment. Further, our results on the decline in the price of old equipment are consistent with the reallocation model (Lanteri and Rampini, 2023). In this section, firstly we test for firms that are buying old machines, whether there is any change in the used equipment's average machine and model age. Next, we test its real implication by testing if buying used equipment from the secondary market impacts small business's growth. After that, we test in aggregate if the decline in the price of old equipment helps increase the small business entry rate.

4.4.1 Impact on Machine Vintage

One possible consequence of tax incentives can be that direct beneficiaries would sell existing machines that are relatively less dated. Therefore, we test if there is a decline in the average vintage of the old capital purchased by firms in our sample. The granularity of our data allows us to document the effect of tax incentives on a set of continuous measures of machine vintage. The first measure of vintage is 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. We examine the effect on the average machine and model age of used equipment at the buyer-year level.

We report the regression results in Table VI. Panel A reports that there is a decrease in the *Log(Machine Age of Old Equipment)* of equipment purchased by the firms in the treatment group. In Column (1), a one standard deviation change in $z^{\theta}_{j,t}$ would decrease the machine age by 16 log points (-3.554×0.045). In terms of percentage, this translates to a reduction in machine age by 14.8% ($= e^{-0.1599}$). Given the average machine age of 4.4 years, this result translates to roughly 7.84 months. We find consistent results for columns (2)–(4). These results collectively suggest that bonus depreciation lowers the average age of machines by 7.5–13.2 months for the treatment industries. In Panel B of Table VI, we document the effect of tax incentives on the second measure of vintage, *Log(Model Age)*, which captures the technological age of the machine. By observing the technological age we are able to document the effect of tax incentives on the purchase of newer technology of machines for the treatment group compared with the control group. Column (1) shows the presence of an economically negative and significant effect on the *Log(Model Age of Old Equipment)* for firms in the treatment industries. In terms of economic effect, a one standard deviation change in $z^{\theta}_{j,t}$ would decrease the model age by 5.6 log points (-1.261×0.045). In terms of percentage, this result translates to a reduction in technology age by 5.5%. Further, given the average model age of 4.4 years, this translates into roughly 3 months. For columns (2)–(4), we find a 3–11.5-month decrease in model age across all specifications for the treatment group.

This decline implies that although some firms are buying used equipment, there is an average decline in the machine age and technological age, respectively. This result is interesting as it suggests the effect on used equipment purchases could be driven by reallocation from buyers who sold their used but relatively newer vintage machines.

4.4.2 Impact on Small Business Growth

Prior literature suggests that capital of older vintage adversely affects firm productivity and growth (Benhabib and Rustichini, 1991; Hsieh, 2001). So, we further document the effect of a tax incentive-driven average decline in machine and model age on future sales and employment growth. The sample is restricted to firms that buy only old machines so that we can compare across buyers of different vintages of used machines. *Newer Vintage* and *Newer Model* are two indicator variables to identify the firms that purchase newer vintage equipment and newer technology equipment, respectively. The dependent variables are sales and employee growth, the annual percentage change in sales, and employee growth in the next year.

Table VII reports the regression results. In columns (1) and (2), we test the incremental effect of $z^{\theta}_{j,t}$ on *Sales_growth* and *Employee Growth* with respect to the newer vintage machine. For the firms which do not buy newer vintage machines, we observe an increase in sales growth by 19.2% ($=e^{3.904\times 0.045} = 1.192$). Interestingly, we find an even bigger positive incremental effect of $z^{\theta}_{j,t}$ on *Sales Growth* when buyers purchase relatively newer vintage used machines. This effect is almost 42% ($= 1.630/3.904$) of the base effect, with similar incremental results for newer model machines. Further, we find a consistent incremental effect on employment growth when buyers purchase relatively newer vintage used machines. Overall, these results suggest the positive impact of the newer vintage and newer model of used equipment on a firm's sales and employment growth. Thus, the results highlight the real effect of physical capital reallocation on firm growth.

4.4.3 Impact on Small Business Entry

In the following analysis, we examine whether the reallocation of old capital via bonus depreciation would encourage entry of small businesses. One implication of the inefficiently high price of used capital is that some firms may not enter the market (Lanteri and Rampini, 2023). With tax incentives, the relative price of old capital goes down owing to increased supply from new equipment buyers. Thus, we expect 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 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 for the period 1998–2011. This process allows us to identify the treatment group of industries, controlling for the geographical variations in business formation. The County Business Patterns defines firm size using the following categories: one to four employees, five to nine employees, 10 to 19 employees, and 20 or more employees. The median group of employees in the EDA database is five. Hence, we focus our analysis on establishments with five to nine employees (*est5_9*) and 10–19 employees (*est10_19*). Our dependent variables are the log of the number of establishments with five to nine employees and 10–19 employees.

Table VIII reports the regression results. In column (1) and column (3), we document a positive and significant effect on the count of small businesses. In other words, a one standard deviation increase in $z^{\theta}_{j,t}$ would increase the entry of small businesses with five to nine and 10–19 employees by approximately 1.8% ($e^{0.401\times0.045} = 1.018$) and 1.7% ($e^{0.374\times0.045} = 1.0169$) respectively. In column (2), we test the incremental effect of $z^{\theta}_{j,t}$ on *est5_9* and *est10_19* with respect to the ex-ante old equipment prices. To calculate the ex ante old price, we start with the residual price for used equipment, controlling for the variation in four-digit NAICS codes, machine age, and model age as before. Next, we calculate the ex ante price at industry-state during the pre-bonus depreciation period. $High\_old\_price\_pre$ takes a value of one for the above-median ex ante price during the pre-bonus depreciation period, and zero otherwise. The results of this cross-section are reported in columns (2) and (4) of Table VIII. We document a positive and significant effect of $z^{\theta}_{j,t}$ on *est5_9* (1.5% increase $e^{0.392\times0.039} = 1.015$) and *est10_19* (1% increase $e^{0.268\times0.039} = 1.010$) when ex ante old equipment prices are above median. This finding is consistent with our expectations that tax incentives result in more new businesses, especially in industries and locations with a higher ex ante relative price of old equipment.

4.5 Heterogeneity

So far, we provided evidence that bonus depreciation indirectly affected the purchase of old equipment due to a decline in old equipment prices. We are interested in further exploring what kind of firms benefit from this indirect spillover effect. In other words, how heterogeneity across firms amplifies the direct effect thereby also resulting in an increased indirect effect. In this section, we document the incremental effect of access to small business credit (Section 4.5.1). Further, we test how the market power of the equipment manufacturers (Section 4.5.2).

4.5.1 Access to Finance

Access to small business credit is important for firms to be able to take advantage of tax incentives. We test the heterogeneous response of small businesses to tax incentives based on access to small business finance (Petersen and Rajan, 1994). We predict that access to finance allows firms to respond to tax incentives by increasing their new equipment investment (Zwick and Mahon, 2017). This will further allow other relatively more constrained firms to buy cheaper old capital as the price of older capital decreases(Lanteri and Rampini, 2023). We use two measures of access to small business credit based on prior literature: small bank lending and SBA lending.

The first proxy for access to credit is based on geographic variation in the availability of small business lending. Prior literature shows that the prevalence of small banks in an area increases the availability of external financing to small firms (Berger, Bouwman, and Kim, 2017). Consistent with Gopal and Schnabl (2022), we calculate small bank share as the deposit share of small banks (defined as banks that are not classified as top 4 banks or acquired by top 4 banks) in each county based on information from quarterly bank call reports. *High Small Bank Share* is an indicator equal to 1 for the above-median availability of small business lending during the pre-bonus depreciation years.

Firstly, we find that firms with access to small banks have an incrementally positive effect on new investment elasticity (See Internet Appendix Table IA.XXI). Further, columns (1) and (2) of Table IX documents that there is an incremental decline in the price of old equipment (Panel A) which is 11% (=-0.091/-0.834) of the base effect. Consistently, there is a greater increase in the investment elasticity of old equipment to the order of 29.5%(0.61/2.065) (Panel B) for firms with access to small banks.

SBA lending is an alternative proxy of access to credit that is independent of firm fundamentals. We use SBA 7(a) loan data and create an ex-ante loan availability measure at the two-digit NAICS-county level. *High SBA Loan* is an indicator variable that takes the value 1 for firms that are in county-industry with the above-median share of SBA loans during the pre-bonus depreciation years. The main variable of interest is *High SBA Loan* $\times$ $z^{\theta}_{j,t}$. We find similar results. This outcome means that firms with better access to SBA lending within treated industries benefit more from bonus depreciation, thereby allowing for a bigger spillover effect on old prices and investment.

Overall, our results in this section suggest that small businesses with access to credit play an important role in capital reallocation.

4.5.2 Market Power of Equipment Manufacturer

In the United States, a substantial proportion of the equipment purchases are financed by the manufacturer themselves. Therefore, manufacturers can exhibit market power to control equipment prices. Murfin and Pratt (2019) show that captive finance subsidiaries of manufacturers are able to lower price depreciation by committing to high resale values of the used equipment. Hence, the presence of a relatively higher proportion of equipment manufacturers with market power is more likely to reduce the spillover effect of the decline in old equipment prices. This will lower the indirect effect on old investment elasticity.

We calculate market concentration measure (HHI) using all new equipment transactions in our data at the equipment code level. Next, we average the HHI measure across the four-digit NAICS industry and define *High HHI* as an indicator variable identifying industries in the top quartile of market concentration during the pre-period. Table X documents that there is a smaller decline in old equipment prices (Panel A) for equipment manufacturers exhibit greater market power. The reduced effect is around 10% (0.094/0.99) of the baseline effect on prices. We find a significant negative effect interaction term for the old equipment investment (Panel B). Overall, the results suggest that the market power of the equipment manufacturer dampens some of the baseline spillover effects of bonus depreciation due to the manufacturer's ability to control the price decline of old equipment.

We also use other cross-sectional features in our data to provide additional evidence on capital reallocation. Internet Appendix Section IA.4.2 we document that reallocation is more likely to occur within the same industry, between larger sellers and smaller buyers, and between closely located buyers and sellers.

5 Conclusion

This paper uses equipment purchase transactions covering 22,411 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 encourage firms to invest in the old capital and helps reallocate old capital? For the two waves of bonus depreciation during 1998–2011, we find that temporary federal tax incentives in the form of accelerated depreciation encourage firms to buy new capital and replace their old capital with new capital. This increases the supply of old capital and hence lowers its equilibrium price. Our results suggest that lower prices of old capital encourage small businesses to buy old capital and indirectly benefit from tax incentives. Our findings highlight the direct and indirect benefits of depreciation policies.

While our paper talks about subsidizing purchases of new capital, one can design a policy to reduce the costs of producing new machines. For example, Chips and Science Act 2022 includes $39 billion in funds to stimulate semiconductor manufacturing and $24 billion worth of manufacturing tax credits. The objective of these policies is to reduce the effective price for semiconductors and ultimately lower the price for all the machines using semiconductors as input. However, whether such lower input costs translate into lower prices of new capital depends on the market mechanism including the market power of equipment manufacturers. If equipment manufacturers choose to keep most of the cost-reduction benefit and do not pass it on to the buyer of these machines, we may not observe a similar increase in new capital investment.

In this paper, our objective is to highlight how policies designed to encourage the purchase of new capital by reducing its effective price via accelerated depreciation lead to increases in investment in both new and old capital, especially for small businesses.

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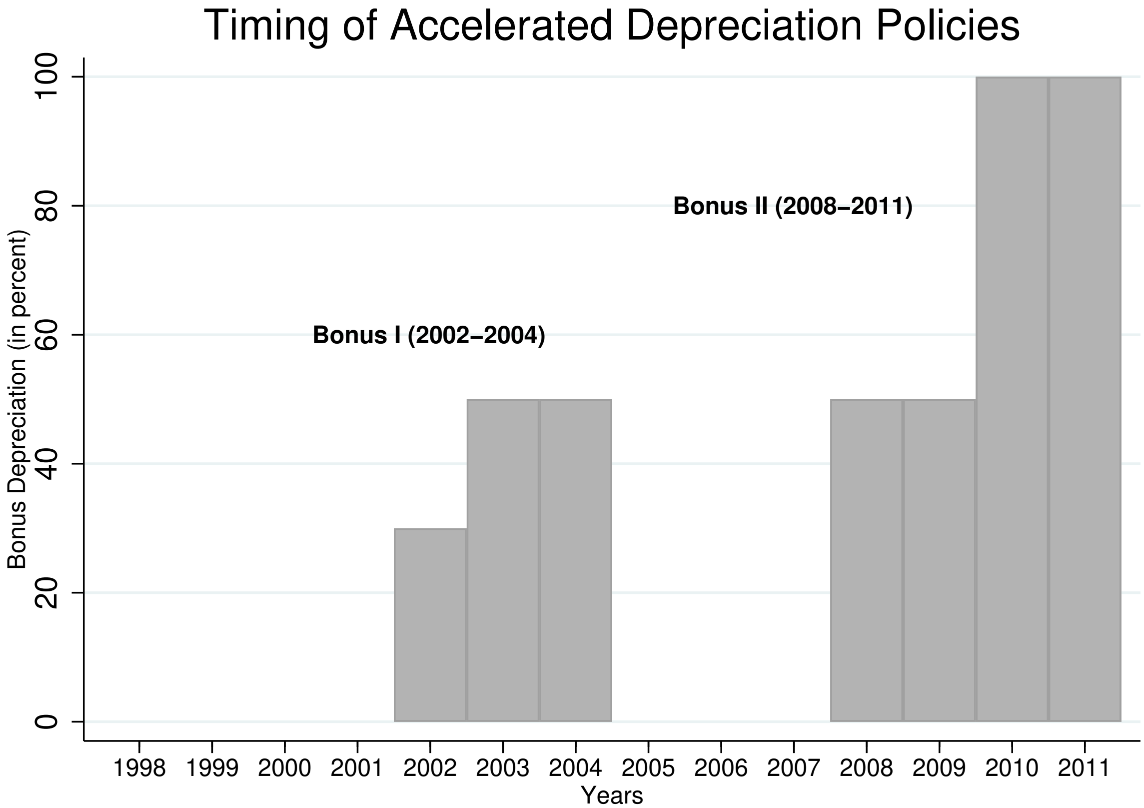

Figure I: This figure plots the depreciation deductions that are accelerated into the first year of the investment for the two episodes of bonus depreciation from 2001 to 2004 and 2008 to 2011. Starting in 2002, firms could immediately deduct 30% of the cost of qualifying investments. This was later extended to 50% for 2003 and 2004. Bonus depreciation was reinstated in 2008 at 50% and increased to 100% during the years 2010 and 2011. Firms can deduct 20% in the year of purchase in non-bonus years under Modified Accelerated Cost Recovery System (MACRS).

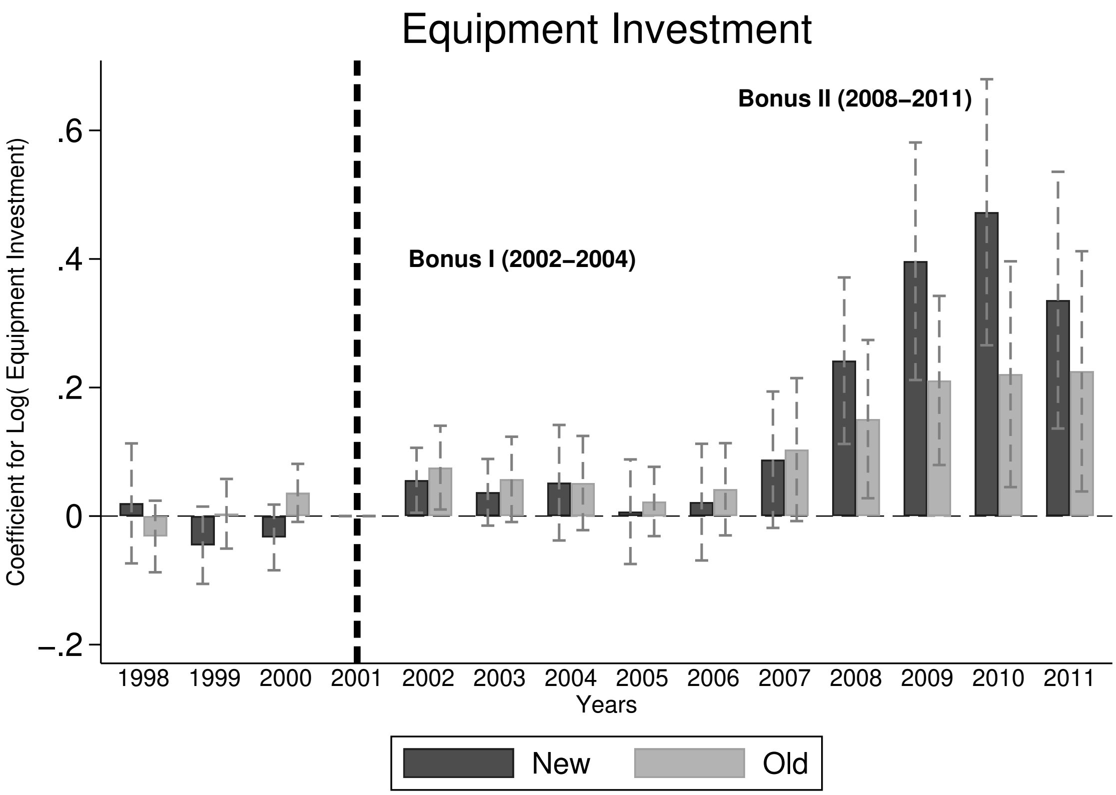

Figure II: New and Old Equipment Investment Elasticity: This figure plots regression estimates of difference-in-differences coefficients with their 95% confidence intervals for data aggregated at the four-digit NAICS industry-county-year level. We define the treatment indicator variable, $Treatment_j$, based on the bottom three deciles of z_j^0. The control group consists of the four-digit industries in the top three deciles of z_j^0. We implement a difference-in-differences model according to the following equation:

$$Y_{j,c,t} = \alpha + \sum_{\substack{y=1998, \\ y \neq 2001}}^{y=2011} \beta_y \times Treatment_j \times \mathcal{I}\left[y = t\right] + \gamma_c + \omega_{s,t} + \delta_{j,s} + \epsilon_{j,c,t},$$

where $Y_{j,c,t}$, our dependent variables of interest are *Log($ New Equipment Investment)* and *Log($ Old Equipment Investment)*, defined as the logarithm of the total investment of new and old equipment purchased at the four-digit industry-county-year level, respectively. We include unit fixed effects at the county level (γ_c) to control for unobservables at the county level, state $\times$ year fixed effects ($\omega_{s,t}$), and state $\times$ industry fixed effects ($\delta_{s,j}$) to control for time-varying state-level shocks and unobservable differences at state-industry level, respectively. For this plot, we use the full sample time period consisting of the two episodes of bonus depreciation from 1998 to 2011 and the bold dashed line indicates the benchmark year, 2001, which is the period immediately at the bonus depreciation schedule change.

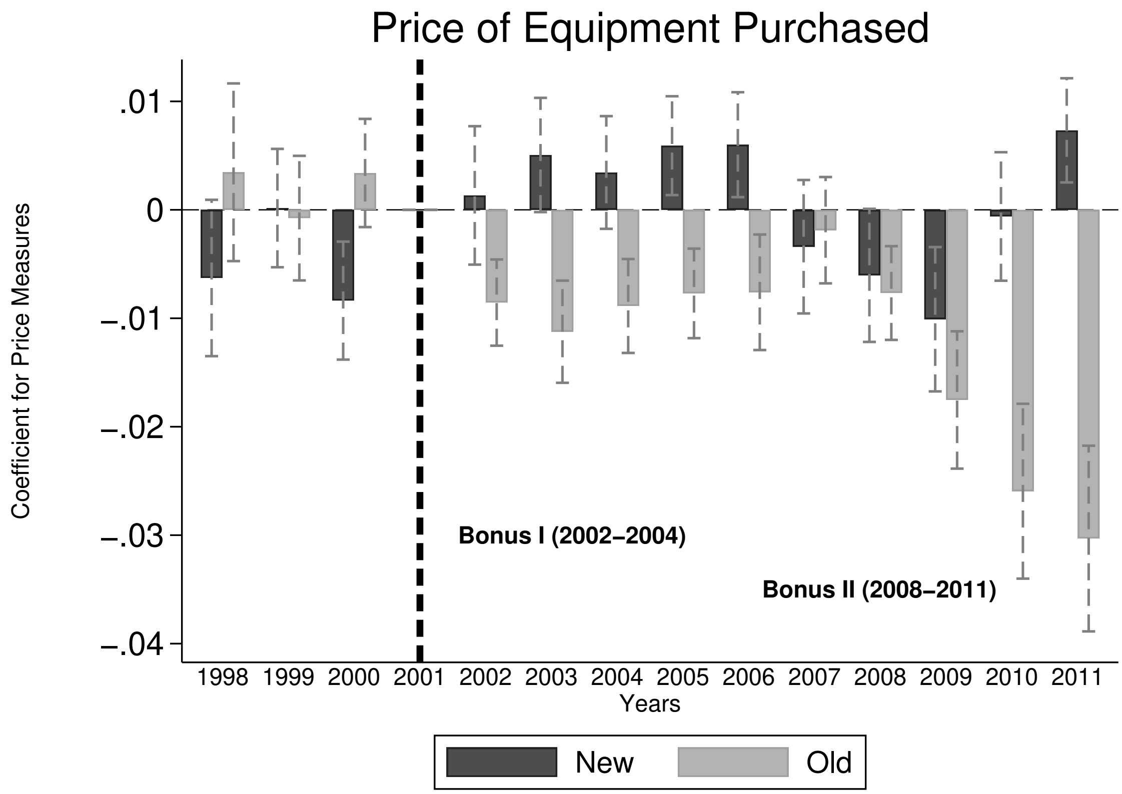

Figure III: **Price of Equipment Purchased:** This figure plots regression estimates of difference-in-differences coefficients with their 95% confidence intervals. The dependent variable is *New* (*Old*) *Price Residual*. We calculate the variable *New* (*Old*) *Price Residual* as the average residual price of new (old) equipment at the county-industry-equipment type-year level (refer to Section 4.2 for details on price residuals). We define the treatment group based on the bottom three deciles of z_j^0 while the control group involves the four-digit NAICS industries in the top three deciles of z_j^0. For this plot, we use the full sample time period consisting of the two episodes of bonus depreciation from 1998 to 2011 and use the year 2001 as the benchmark for each bonus event. The bold dashed line indicates the benchmark year, 2001, which is the period immediately at the bonus depreciation schedule change.

Table I: Descriptive Statistics

This table presents descriptive statistics for the variables used in the regression analyses for the sample period 1998–2011. $z^{\theta}_{j,t}$ is the present value of depreciation deductions for the average asset in which industry j invests at time t following Zwick and Mahon (2017). *New (Old) Equipment Value* is the dollar value of new (old) equipment. *New (Old) Equipment Investment* is the dollar value of all the new (old) equipment purchased by the establishment in a given year. *Equipment Investment* is the total dollar value of the equipment (including both new and old equipment) purchased by the establishment in a given year. *Machine Age* is the age (in years) of machines purchased by the establishment as defined in the UCC transaction data. *Model Age* is the age (in years) of the particular model calculated as the difference between the transaction year and the first year the model was introduced. *Sales* is the dollar value of sales in millions by the establishment. *Employees* is the number of employees in an establishment.

	Mean	SD	Median
$z^{\theta}_{j,t}$	0.927	0.045	0.929
New Equipment Value (in \$ 1,000)	71.895	79.832	50.347
Old Equipment Value (in \$ 1,000)	56.366	52.942	40.281
New Equipment Investment (in \$ 1,000)	126.437	186.444	61.629
Old Equipment Investment (in \$ 1,000)	90.644	106.370	55.996
Equipment Investment (in \$ 1,000)	121.578	198.113	60.415
Machine Age (Years)	4.603	6.930	1.4
Model Age (Years)	6.242	4.489	5
Sales (in \$ million)	3.184	10.70	0.320
Employees	12.97	26.67	3

Table II: Effect of Tax Incentives on Investment Elasticity

This table reports the investment tax elasticity results based on equation (1). We aggregate the individual new and used equipment transactions for a given buyer-year to calculate the natural logarithm of the total investment in new (*Log($ New Equipment Investment)*) and used equipment (*Log($ Old Equipment Investment)*) and report results in Panel A and Panel B, respectively. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Direct Effect: New Equipment Investment**

Dependent Variable:	*Log($ New Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	8.881***	5.260***	5.443***	4.666***
	(5.570)	(4.174)	(4.046)	(3.765)
Observations	543,670	543,670	376,494	376,494
Clusters (Industry)	240	240	237	237
R^2	0.24	0.24	0.69	0.69
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

PANEL B: **Indirect Effect: Old Equipment Investment**

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	3.431***	1.995***	2.330***	2.066***
	(3.111)	(3.202)	(3.624)	(3.508)
Observations	545,869	545,869	396,142	396,142
Clusters (Industry)	238	238	237	237
R^2	0.17	0.17	0.62	0.62
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table III: Why Firms are Buying Old Equipment? Price of Old and New Equipment

This table reports results from estimating the effect of tax incentives via bonus depreciation on the price of old and new machines. Panel A reports the first stage estimation of residual equipment price at the equipment level. We begin with the raw transaction-level data for the sample period. In Column (1), we include a log of the machine's age, and the following fixed effects: four-digit equipment code, make-model (to control for model age and manufacturer), and equipment size. Column 2 includes year-fixed effects while column (3) substitutes with make-model $\times$ year-fixed effects. We estimate the residuals from Column (3) and average it for new and old equipment. Panel B (Panel C), reports the results from equation (2) with *Old Price Residual* (*New Price Residual*) as the dependent variable. The dependent variables *Old Price Residual* and *New Price Residual* measure the average residual price of old equipment and new equipment, respectively, within a four-digit NAICS code for a given equipment type in a given county for each year (Equipment Code-County-Industry-Year level). The sample period is from 1998 to 2011. Column 1 includes industry and year-fixed effects. Column (2) adds equipment fixed effects, column (3) adds county fixed effects, and finally column (4) adds sector trends. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Calculating Price Residuals**

Dependent Variable:	*Log(Equipment Value)*		
Level: Transaction-Level	(1)	(2)	(3)
Log(Machine Age)	-0.274***	-0.342***	-0.348***
	(-71.605)	(-67.950)	(-60.083)
Observations	1,706,055	1,706,055	1,674,085
Clusters (Make Model)	18,205	18,205	15,666
R^2	0.96	0.96	0.97
Equipment Code Fixed Effects	Y	Y	Y
Make-Model Fixed Effects	Y	Y	
Equipment Size Fixed Effects	Y	Y	Y
Year Fixed Effects		Y	
Make-Model $\times$ Year Fixed Effects			Y

PANEL B: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	-0.838***	-0.940***	-0.931***	-0.640***
	(-5.590)	(-5.401)	(-5.435)	(-4.067)
Observations	553,601	553,580	553,573	553,573
Clusters (Industry)	238	238	238	238
R^2	0.02	0.05	0.06	0.06
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects			Y	Y
Sector Trends				Y

PANEL C: **Impact on Price of New Equipment**

Dependent Variable:	*New Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	0.130**	0.014	0.010	0.006
	(2.467)	(0.315)	(0.217)	(0.139)
Observations	546,459	546,437	546,432	546,432
Clusters (Industry)	240	240	240	240
R^2	0.02	0.07	0.08	0.08
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects			Y	Y
Sector Trends				Y

Table IV: State Conformity to Bonus Depreciation

This table reports the heterogeneity based on state adoption of bonus depreciation. *Bonus State Conformity*$_{s,t}$ is an indicator variable identifying buyers located in states that conform 100% to federal bonus depreciation in a given year. The sample period is from 1998 to 2011. Panel A reports the cross-sectional effect of state bonus conformity on the price of old equipment. All regressions include group fixed effects that consist of the bonus state conformity dummy. Column (1) reports the effect on old equipment price with industry fixed effects and year fixed effects. Column (2) includes equipment and county-fixed effects. Column (3) adds industry × year fixed effects. Finally, Column (4) adds sector trends in addition to fixed effects in Column (2). Panel B documents the cross-section effect on the elasticity of old equipment purchase. Column (1) includes group fixed effects, buyer controls, industry × year fixed effects, and state fixed effects. Column (2) adds Buyer Size by Year fixed effects. Column (3) adds Buyer fixed effects while column (4) adds Industry by Year fixed effects in addition to Column (3) fixed effects. Finally, Column (5) includes Buyer fixed effects, Buyer size by Year fixed effects, and Sector trends. In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size by Year fixed effects). Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}\times$ Bonus State Conformity$_{s,t}$	-0.039**	-0.058***	-0.048**	-0.052**
	(-2.185)	(-2.882)	(-2.261)	(-2.548)
$z^{\theta}_{j,t}$	-0.938***	-0.926***		-0.638***
	(-5.396)	(-5.430)		(-4.066)
Observations	553,580	553,573	553,421	553,573
Clusters (Industry)	238	238	237	238
R^2	0.05	0.06	0.07	0.06
Group Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y		Y
Industry Fixed Effects	Y	Y		Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects		Y	Y	Y
Industry × Year Fixed Effects			Y	
Sector Trends				Y

PANEL B: **Impact on Old Equipment Investment**

Dependent Variable:	*Log($ Old Equipment Investment)*				
Level: Buyer-Year	(1)	(2)	(3)	(4)	(5)
$z^{\theta}_{j,t}\times$ Bonus State Conformity$_{s,t}$	0.413***	0.401***	0.579***	0.457***	0.530***
	(3.626)	(3.537)	(4.724)	(3.082)	(3.958)
$z^{\theta}_{j,t}$			2.122***		2.084***
			(2.766)		(3.610)
Observations	545,719	545,719	396,142	395,687	396,142
Clusters (Industry)	236	236	237	223	237
R^2	0.19	0.19	0.62	0.62	0.62
Group Fixed Effects	Y	Y	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y	Y
Buyer Controls	Y		Y	Y	
Year Fixed Effects			Y		
Industry × Year Fixed Effects	Y	Y		Y	
Buyer Fixed Effects			Y	Y	Y
Buyer Size × Year Fixed Effects		Y			Y
Sector Trends					Y

Table V: State Conformity to Section 179

This table reports the heterogeneity based on state adoption of Section 179. *Sec179 State Conformity*$_{s,t}$ is an indicator variable identifying buyers located in states that conform 100% to federal Section 179 in a given year. The sample period is from 1998 to 2011. Panel A reports the cross-sectional effect of state bonus conformity on the price of old equipment. All regressions include group fixed effects that consist of the bonus state conformity dummy. Column (1) reports the effect on old equipment price with industry fixed effects and year fixed effects. Column (2) includes equipment and county-fixed effects. Column (3) adds industry $\times$ year fixed effects. Finally, Column (4) adds sector trends in addition to fixed effects in Column (2). Panel B documents the cross-section effect on the elasticity of old equipment purchase. Column (1) includes group fixed effects, buyer controls, industry $\times$ year fixed effects, and state fixed effects. Column (2) adds Buyer Size by Year fixed effects. Column (3) adds Buyer fixed effects while column (4) adds Industry by Year fixed effects in addition to Column (3) fixed effects. Finally, Column (5) includes Buyer fixed effects, Buyer size by Year fixed effects, and Sector trends. In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size by Year fixed effects). Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}\times$ *Sec179* State Conformity$_{s,t}$	-0.014	-0.010	-0.015	-0.016*
	(-1.399)	(-1.082)	(-1.610)	(-1.747)
$z^{\theta}_{j,t}$	-0.936***	-0.927***		-0.631***
	(-5.332)	(-5.383)		(-3.984)
Observations	553,580	553,573	553,421	553,573
Clusters (Industry)	238	238	237	238
R^2	0.05	0.06	0.07	0.06
Group Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y		Y
Industry Fixed Effects	Y	Y		Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects		Y	Y	Y
Industry $\times$ Year Fixed Effects			Y	
Sector Trends				Y

PANEL B: **Impact on Old Equipment Investment**

Dependent Variable:	*Log($ Old Equipment Investment)*				
Level: Buyer-Year	(1)	(2)	(3)	(4)	(5)
$z^{\theta}_{j,t}\times$ *Sec179* State Conformity$_{s,t}$	0.076	0.053	0.088	-0.003	0.047
	(1.126)	(0.755)	(0.953)	(-0.035)	(0.483)
$z^{\theta}_{j,t}$			2.109***		2.042***
			(2.695)		(3.446)
Observations	545,719	545,719	396,142	395,687	396,142
Clusters (Industry)	236	236	237	223	237
R^2	0.19	0.19	0.62	0.62	0.62
Group Fixed Effects	Y	Y	Y	Y	Y
State Fixed Effects	Y	Y	Y	Y	Y
Buyer Controls	Y		Y	Y	
Year Fixed Effects			Y		
Industry $\times$ Year Fixed Effects	Y	Y		Y	
Buyer Fixed Effects			Y	Y	Y
Buyer Size $\times$ Year Fixed Effects		Y			Y
Sector Trends					Y

Table VI: Type of Old Equipment Purchased

This table reports the indirect benefits of tax incentives by estimating equation (1). The outcome variable is measured as the natural logarithm of the mean machine age (*Log(Machine Age of Old Equipment)*) and model age (*Log(Model Age of Old Equipment)*) for purchased used equipment at the buyer-year level. The regression results using *Log(Machine Age of Old Equipment)* and (*Log(Model Age of Old Equipment)*) as the dependent variable are reported in Panel A and Panel B, respectively. The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) and year fixed effects, while column (2) adds sector trends. Columns (3) and (4), includes buyer fixed effects and additionally add non-linear buyer size by year fixed effects in column (4). In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size × Year fixed effects). Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Machine Age of Old Equipment Purchased**

Dependent Variable:	*Log(Machine Age of Old Equipment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	-3.554***	-4.153***	-6.401***	-4.416***
	(-4.433)	(-4.667)	(-4.677)	(-3.670)
Observations	538,493	538,493	389,719	389,719
Clusters (Industry)	238	238	237	237
R^2	0.10	0.10	0.61	0.61
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

PANEL B: **Model Age of Old Equipment Purchased**

Dependent Variable:	*Log(Model Age of Old Equipment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	-1.261**	-3.535***	-5.368***	-3.574***
	(-2.525)	(-4.037)	(-4.362)	(-3.676)
Observations	544,366	544,366	394,927	394,927
Clusters (Industry)	238	238	237	237
R^2	0.10	0.11	0.55	0.55
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table VII: Impact of New Vintage of Used Equipment on Small Business Growth

This table reports the welfare consequences of the indirect effect of tax incentives on machine and model age. We aggregate the individual used equipment transactions for a given buyer-year to calculate the average machine age and model age of used equipment between 1998 and 2011. We construct two indicator variables *Newer Vintage* and *Newer Model* to identify the firms that purchase newer vintage equipment and newer technology equipment, respectively. The dependent variables are *Sales Growth* and *Employee Growth* defined as the annual percentage change in sales and employee growth, respectively. In columns (1) and (2) we test the incremental effect of $z^{\theta}_{j,t}$ on *Sales Growth* and *Employee Growth* with respect to *Newer Vintage*. In columns (3) and (4) we test the incremental effect of $z^{\theta}_{j,t}$ on *Sales Growth* and *Employee Growth* with respect to *Newer Model*. All specifications include buyer fixed effects, sector trends, and Year × *Newer Vintage* (*Newer Model*) fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Impact on Sale and Employment Growth

Dependent Variable:	*Sales Growth* $_{it+1}$	*Employment Growth* $_{it+1}$	*Sales Growth* $_{it+1}$	*Employment Growth* $_{it+1}$
Level: Buyer-Year	(1)	(2)	(3)	(4)
Newer Vintage$_{it}$ × $z^{\theta}_{j,t}$	1.630***	0.712***		
	(3.723)	(3.053)		
Newer Model$_{it}$ × $z^{\theta}_{j,t}$			1.656***	0.710***
			(3.562)	(3.376)
$z^{\theta}_{j,t}$	3.904***	0.604	3.999***	0.657
	(6.254)	(1.169)	(6.138)	(1.229)
Observations	357,923	359,643	357,923	359,643
Clusters (Industry)	235	235	235	235
R^2	0.30	0.31	0.30	0.31
Buyer Controls	Y	Y	Y	Y
Buyer Fixed Effects	Y	Y	Y	Y
Year × Vintage Indicator Fixed Effects	Y	Y	Y	Y
Sector Trends	Y	Y	Y	Y

Table VIII: Impact of Price of Old Equipment on Small Business Entry

This table reports results for regressions estimating the effect of tax incentives via bonus depreciation on the entry of small businesses. We use the County Business Patterns 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 and 2011. We focus our analysis on establishments with five to nine employees (*est5_9*) and 10 to 19 employees (*est10_19*). Our dependent variables are the log of the number of establishments with five to nine employees and 10 to 19 employees. In columns (2) and (4) we test the incremental effect of $z^{\theta}_{j,t}$ on *est5_9* and *est10_19* with respect to the ex ante old equipment prices. To calculate the ex ante old price, we start with the residual price for used equipment, controlling for the variation in four-digit NAICS, the machine age, and model age as before. Next, we calculate the ex ante price at the industry buyer's state during the pre-bonus depreciation period. Finally, *High_old_price_pre* takes a value of 1 for the above-median ex ante price during the pre-bonus depreciation period, and 0 otherwise. We include industry fixed effects, sector trends, and county × year fixed effects in all specifications. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Impact on Small Business Entry

Dependent Variable:	Log of # of Establishments with			
	(5-9 employees)		*(10-19 employees)*	
Level: Industry-County-Year	(1)	(2)	(3)	(4)
High_old_price_pre × $z^{\theta}_{j,t}$		0.392***		0.268**
		(2.866)		(2.512)
High_old_price_pre		-0.349***		-0.231**
		(-2.663)		(-2.246)
$z^{\theta}_{j,t}$	0.401***	0.253**	0.374***	0.284**
	(3.808)	(2.017)	(3.436)	(2.324)
Observations	440,585	426,644	440,585	426,644
Clusters (Industry)	228	226	228	226
R^2	0.75	0.75	0.72	0.72
Sector Trends	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
County × Year Fixed Effects	Y	Y	Y	Y

Table IX: Role of Access to Small Business Credit

This table reports the heterogeneity based on a buyer's access to small business finance. Access to finance is measured using *High Small Bank Share (High SBA Loan)* which is an indicator variable identifying buyers located in states that have above the median level of banks lending (SBA loans). The sample period is 1998–2011. We calculate small bank shares as the deposit share of small banks in each county. *High Small Bank Share* is an indicator equal to 1 for the above-median availability of small business lending during the pre-bonus depreciation years. We use SBA 7(a) loan data and create an ex-ante loan availability measure at the two-digit NAICS-county level. *High SBA Loan* is an indicator variable that takes the value 1 for firms that are in county-industry with the above-median share of SBA loans during the pre-bonus depreciation years. Panel A reports the cross-sectional effect of access to credit on the price of old equipment. All regressions include group fixed effects that consist of the *High Small Bank Share (High SBA Loan)* dummy. Columns (1) and (3) also include industry, year, and equipment fixed effects. Columns (2) and (4) add sector trends in addition to the fixed effects in columns (1) and (3). Panel B documents the cross-section effect on the elasticity of old equipment purchase. Columns (1) and (4) include industry and buyer size × year fixed effects. Columns (2) and (5) add sector trends. Finally, Columns (3) and (6) include buyer-fixed effects in lieu of industry-fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size × Year fixed effects). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$ × *High Small Bank Share*	-0.091***	-0.084***		
	(-6.226)	(-6.077)		
$z^{\theta}_{j,t}$ × *High SBA Loan*			-0.086***	-0.074***
			(-3.897)	(-3.845)
$z^{\theta}_{j,t}$	-0.834***	-0.553***	-0.711***	-0.389*
	(-4.926)	(-3.601)	(-3.490)	(-1.961)
Observations	553,420	553,420	340,262	340,262
Clusters (Industry)	238	238	237	237
R^2	0.06	0.06	0.12	0.12
Group Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects	Y	Y	Y	Y
Sector Trends		Y		Y

PANEL B: **Impact on Old Equipment Investment**

Dependent Variable:	*Log($ Old Equipment Investment)*					
Level: Buyer-Year	(1)	(2)	(3)	(4)	(5)	(6)
$z^{\theta}_{j,t}$ × *High Small Bank Share*	0.610***	0.567***	0.547***			
	(6.837)	(6.235)	(6.538)			
$z^{\theta}_{j,t}$ × *High SBA Loan*				0.574***	0.308***	0.434***
				(3.924)	(2.648)	(2.798)
$z^{\theta}_{j,t}$	2.065**	1.296**	1.585***	-0.055	0.395	0.084
	(2.092)	(2.140)	(2.715)	(-0.039)	(0.419)	(0.075)
Observations	545,726	545,726	396,047	319,011	319,011	222,670
Clusters (Industry)	238	238	237	236	236	232
R^2	0.20	0.21	0.62	0.29	0.29	0.64
Group Fixed Effects	Y	Y	Y	Y	Y	Y
Buyer Size × Year Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y		Y	Y	
Sector Trends		Y	Y		Y	Y
Buyer Fixed Effects			Y			Y

Table X: Market Power of Equipment Manufacturer

This table reports the heterogeneity based on a seller's market power. Market power is measured using *High HHI*$_j$ which is an indicator variable identifying industries that are in the highest quartile of market concentration. Market concentration is calculated as the HHI of the manufacturer for a given equipment during the pre-period. The sample period is 1998–2011. Panel A reports the cross-sectional effect of *High HHI*$_j$ on the price of old equipment. All regressions include group fixed effects that consist of the *High HHI*$_j$ dummy. Columns (1) include equipment, industry, and year fixed effects, columns (2) add county fixed effects, and column (3) adds sector trends. Panel B documents the cross-section effect on the elasticity of old equipment purchase. Columns (1) and includes industry and buyer size × year fixed effects. Columns (2) adds sector trends and Columns (3) includes buyer fixed effects in lieu of industry fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size × Year fixed effects). Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*		
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)
$z^{\theta}_{j,t}$ × *High HHI*$_j$	0.094***	0.079***	0.073***
	(2.884)	(2.763)	(3.389)
$z^{\theta}_{j,t}$	-0.994***	-0.883***	-0.708***
	(-6.574)	(-6.770)	(-5.055)
Observations	553,576	553,597	553,597
Clusters (Industry)	237	237	237
R^2	0.05	0.02	0.02
Group Fixed Effects	Y	Y	Y
Industry Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Equipment Fixed Effects	Y	Y	Y
County Fixed Effects		Y	Y
Sector Trends			Y

PANEL B: **Impact on Old Equipment Investment**

Dependent Variable:	*Log($ Old Equipment Investment)*		
Level: Buyer-Year	(1)	(2)	(3)
$z^{\theta}_{j,t}$ × *High HHI*$_j$	-0.510**	-0.402**	-0.196*
	(-2.307)	(-2.484)	(-1.771)
$z^{\theta}_{j,t}$	2.667***	1.961***	2.203***
	(2.984)	(3.510)	(3.814)
Observations	545,865	545,865	396,139
Clusters (Industry)	237	237	236
R^2	0.17	0.17	0.62
Group Fixed Effects	Y	Y	Y
Buyer Size × Year Fixed Effects	Y	Y	Y
Industry Fixed Effects	Y	Y	
Sector Trends		Y	Y
Buyer Fixed Effects			Y

Internet Appendix

IA.1 Equipment Value

EDA provides equipment values for the machines on the UCC-1 statements. The majority of the values are estimates rather than the actual selling price of the machines since prices are usually not indicated in the filings. The equipment values are estimated based on the year of manufacture and size (based on horsepower) within each equipment category. For instance, within the category of backhoe loaders, Caterpillar 416-E Loader Backhoe, John Deere 410-J, and Case 580-Super-M are competing machines. If these machines were manufactured in the same year, any unpopulated equipment value would be filled with a representative value for that particular equipment category and size.

EDA uses various sources to determine the estimates of the equipment values. In addition to the actual selling prices on the UCC-1 filings, EDA uses a combination of published values, auction guides, telephone survey work, asking values from trade magazines, Internet-published MSRP, and statistical modeling. The EDA sells this data to various banks, sales representatives, and other industry participants, in addition to the academic community.

Our sample has a total of 455 different equipment categories. Some examples of the categories are utility tractors, excavators, air compressors, helicopters, and metal 3D printers. Equipment size is divided into 26 bins based on horsepower. EDA assigns an alphabetical letter to each size bin, with A representing the smallest category and Z representing the largest. There are equipment of various size bins for each equipment category.

We plot the relationship between the depreciation of equipment value with respect to machine and model age in Figure IA.I. First, we regress equipment value or log of equipment value on various fixed effects such as equipment size, equipment code, and year. Next, we plot the bins scatter of residuals from the regression as a function of machine and model age. The top two figures show that equipment value depreciates considerably as the machine gets older, with the greatest decline in price happening in the first two to three years. The average price continues to decline, albeit at a slower rate, between 3–10 years. The bottom two figures show that equipment value depreciates more steadily with model age.

Another aspect of the EDA data is that they cover certain industries with collateral on equipment such as agriculture, construction, copier, lift trucks, logging, machine tool, printing, trucking, woodworking, etc. Due to this restriction and given the fact that most of these transactions are debt-financed we compare the aggregate dynamics with BEA data. The National Income and Product Accounts data from BEA has aggregated New and Old equipment purchases across the economy. Figure IA.II plots the proportion of old to total equipment over time for both the EDA and NIPA data. The plot suggests similar trends over time across both data, which suggests that equipment transactions covered in EDA data do not substantially bias our results.

Overall, these plots provide credibility to the quality of data used.

IA.2 Probability of Buying New Equipment

The transaction level data can be used to determine the probability of buying new equipment. We define the treatment indicator variable, *Treatment*, based on the bottom three deciles of z_j^0. The control group consists of the four-digit industries in the top three deciles of z_j^0. For transaction-level capital investment data, the regression framework implements the following difference-in-differences specification,

$$New\ Dummy_{i,m,t} = \alpha + \beta Treatment_j \times Post_t + \gamma X_{i,t} + \delta_j + \omega_t + \kappa_m + \epsilon_{i,m,t}, \quad (3)$$

where the dependent variable of interest is *New Dummy*, which takes the value one for new equipment purchases and zero otherwise. We implement a difference-in-differences model according to equation (3) to test whether the treated firms invest in new capital equipment when there is an increase in bonus depreciation rates. The transaction-level results in Table IA.V include buyer-level controls for buyer size and the number of employees (i.e., the natural logarithm value of sales and the natural logarithm value of the number of employees). It also includes industry and year fixed effects with clustering standard errors at the four-digit NAICS industry level. The results suggest that a one standard deviation increase in $z_{j,t}^\theta$ increases the likelihood of buying new equipment by 5.4% ($0.045 \times 8.881 = 0.054$) for the treatment group. The other specifications have a similar effect on *New Dummy* as the baseline specification. Overall, there is a 5.4%–8.8% increase in the probability of investing in new capital for the treatment group. The results imply that the tax incentives on new equipment work as intended and increase the probability of new equipment purchase for the treated group.

IA.3 Equipment-level Depreciation Measure

In addition to the $z_{j,t}^\theta$ measure from Zwick and Mahon (2017), we leverage our granular data and create a novel measure, $BKS_{e,m,t}^\theta$, at the equipment level. This measure replicates the calculations for an individual machine. We first calculate the present value of one dollar for each machine incorporating its class life and age. The machines are depreciated according to the half-year convention and a 200% declining balance method over a general depreciation system recovery period. All machines are manually matched to their class lives and recovery periods under the general depreciation system method from Table B-1 and Table B-2 in IRS publication 946[23]. We use 7% for the risk-adjusted rate, r, to calculate present values following Zwick and Mahon (2017). Once the present value of a dollar for each machine is calculated, we calculate $BKS^{\theta}_{e,m,t}$ at the equipment-year-month level. The key difference from the measure in Zwick and Mahon (2017) is that our approach takes into account the effect of bonus depreciation for each machine.

IA.4 Physical Capital Replacement and Reallocation

One advantage of the data is that we can observe several characteristics of buyers and sellers, including their sizes, locations, and industries. Another advantage is that the data have the unique serial number of every machine that was transacted in the database. We use this unique serial number to identify the sellers of old equipment that previously acquired these machines. We use this information to further dissect the reallocation mechanism.

IA.4.1 Capital Replacement by Seller of Old Equipment

Physical capital reallocation would imply that some firms are able to sell their used pieces of equipment to prospective buyers and replace them with new equipment. Hence, we expect these firms that sell old equipment to be more likely to take advantage of the tax incentives by spending more on new equipment. Our data allow us to track the buyers who sold their used equipment to a prospective seller. We define *Seller of Old Equipment* as an indicator that takes a value of one for buyers that sold their used equipment within two years of the bonus depreciation periods (1999–2002 and 2006–2009), and zero otherwise. The variable of interest is *Seller of Old Equipment* $\times$ z^{θ}_{jt}. The results are reported in Table IA.VII. We document a positive and significant incremental effect on the elasticity of new investment for buyers that sold their old equipment. In terms of economic effect, a one standard deviation increase in z^{θ}_{jt} incrementally increases the elasticity of new equipment investment by approximately 4.2% ($e^{1.054\times 0.039} = 1.042$).

[23]https://www.irs.gov/pub/irs-pdf/p946.pdf

IA.4.2 Capital Reallocation based on Industry, Size and Distance

We provide additional evidence on the type of firms that are more likely to reap the indirect benefits of capital reallocation. We start by showing that reallocation is more likely to occur among firms in the same industry. First, we identify the buyer-seller pair for each transaction. In doing so, we drop transactions with missing seller information. We also limit our focus to used capital transactions since they are the key to reallocation. To show that reallocation effects are stronger within the same industry, we aggregate the number of old equipment transactions (Log(# of Old Equipment Transactions)) within each *buyer industry-seller industry* pair every year, where industry is defined at the four-digit NAICS level. The baseline specification includes buyer and seller industry fixed effects to control for industry-specific unobservables and year fixed effects to control for time trends. Table IA.XIX provides the regression results. In column (1), we find an increase in the number of old capital goods purchased in the treatment industries, consistent with reallocation. In terms of economic magnitude, a one standard deviation increase in z_{jt}^{θ} would increase the count of old equipment sold by approximately 5.9% ($e^{1.466\times0.039} = 1.059$).

We also provide evidence that reallocation is more likely to occur between bigger sellers and smaller buyers. As before, we aggregate the number of old equipment transactions (Log(# of Old Equipment Transactions)) within each *buyer state-seller state* pair every year. Next, we compare the average size differences between sellers and buyers within our level of aggregation (*size_diff*). Capital reallocation would suggest that large-sized sellers in treatment industries sell older equipment to small buyers. Our primary variable of interest is the logarithm of the number of old equipment transactions (*Log(# of Old Equipment Transactions*)) within each buyer industry-buyer state-seller state. As before, we use industry fixed effects, year fixed effects, and industry-specific trends to control for time-varying industry shocks. We also include state *(Buyer, Seller)* $\times$ *Year* fixed effects to control for time-varying trends in buyer and seller states. Table IA.XX provides the regression results. In column (1), we find an increase in the number of old capital goods purchased in the treatment industries consistent with reallocation. Column (2) documents the cross-section effect of size differences between buyer and seller industries. (*size_diff*) takes a value of one for the top tercile of the size difference between buyer and seller, and 0 otherwise. Since we do not observe seller size for many transactions, we have a considerably smaller sample. The result suggests that large sellers are more likely to sell their used equipment to small-sized constrained buyers after the tax shock (3% increase $e^{0.750\times0.039} = 1.029$). Finally, we show that the distance between buyers and sellers drives reallocation. Ma, Murfin, and Pratt (2022) highlight the importance of co-location of potential buyers and sellers of old capital goods for reallocation. As a result, we expect more reallocation to occur between buyers and sellers located within close proximity of each other. Ma, Murfin, and Pratt (2022) highlight the importance of co-location of potential buyers and sellers of old capital goods for reallocation. The use of co-location will ensure that transactions between buyers and sellers occur within close proximity of each other. In column (3), we identify the cross-section effect of distance between buyers and sellers based on zip code. The variable *Low_Distance* takes a value of 1 for the lowest tercile of the distance between buyer and seller, and 0 otherwise. The result suggests that reallocation is more likely to occur when buyers and sellers are located within closed vicinity of each other (2.2% increase $e^{0.566\times 0.039} = 1.022$). Overall, the results suggest that the indirect reallocation effect is more likely to occur when sellers and buyers are located in the same industry, sellers are bigger than buyers, and when sellers and buyers are in close proximity to each other.

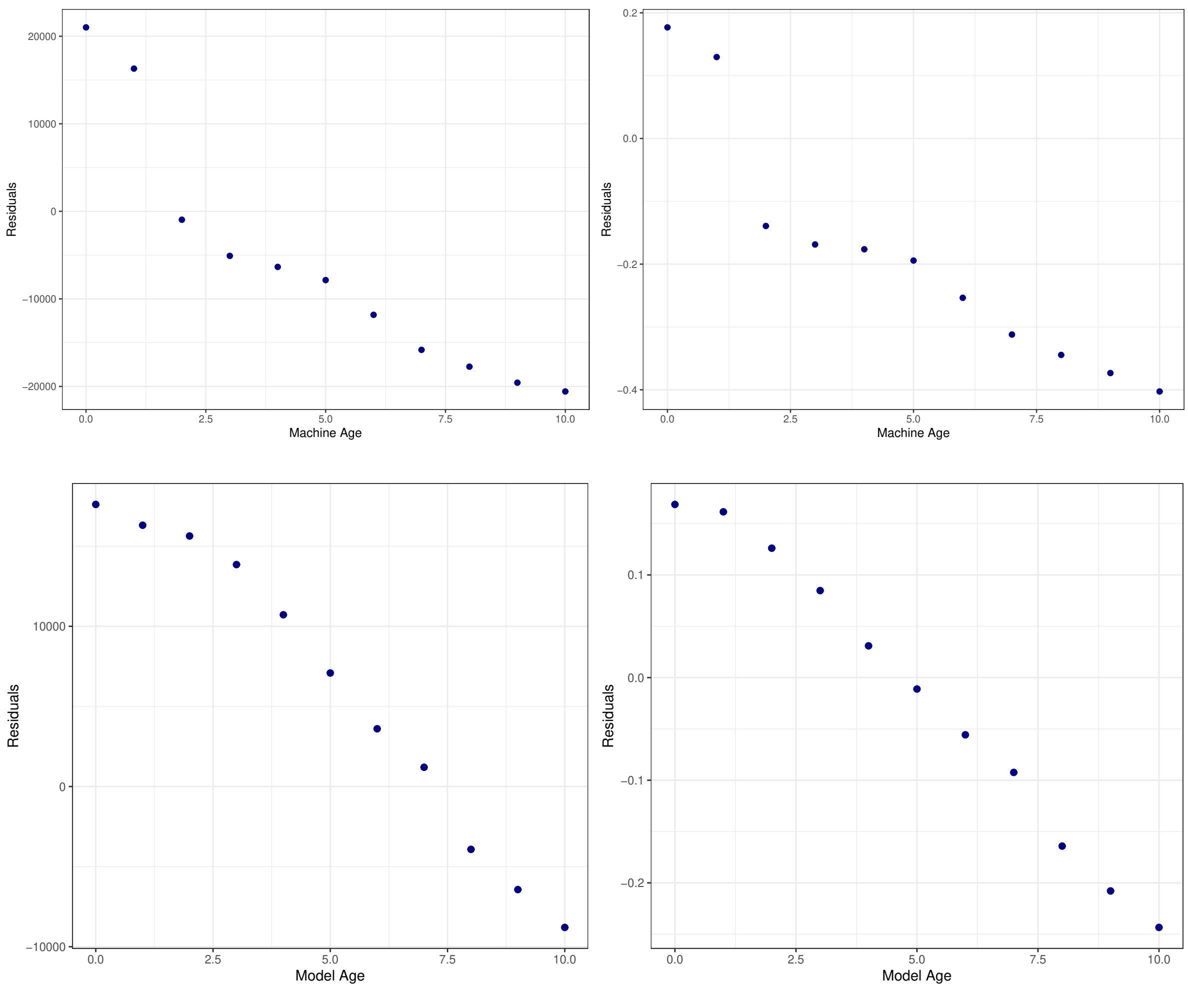

Figure IA.I: Equipment Depreciation: These figures plot results from binscatter regressions to depict the relationship between depreciation of equipment value and machine and model age. We first regress equipment value or log of equipment value on various equipment characteristic fixed effects such as equipment size, equipment code, and year fixed effects. Then we plot the binscatter of residuals from the regression as a function of machine and model age. The top two figures show that equipment value depreciates with machine age with a sharp decline for three-year-old machines. Equipment value depreciates rather smoothly with model age as displayed in the figures on the bottom row.

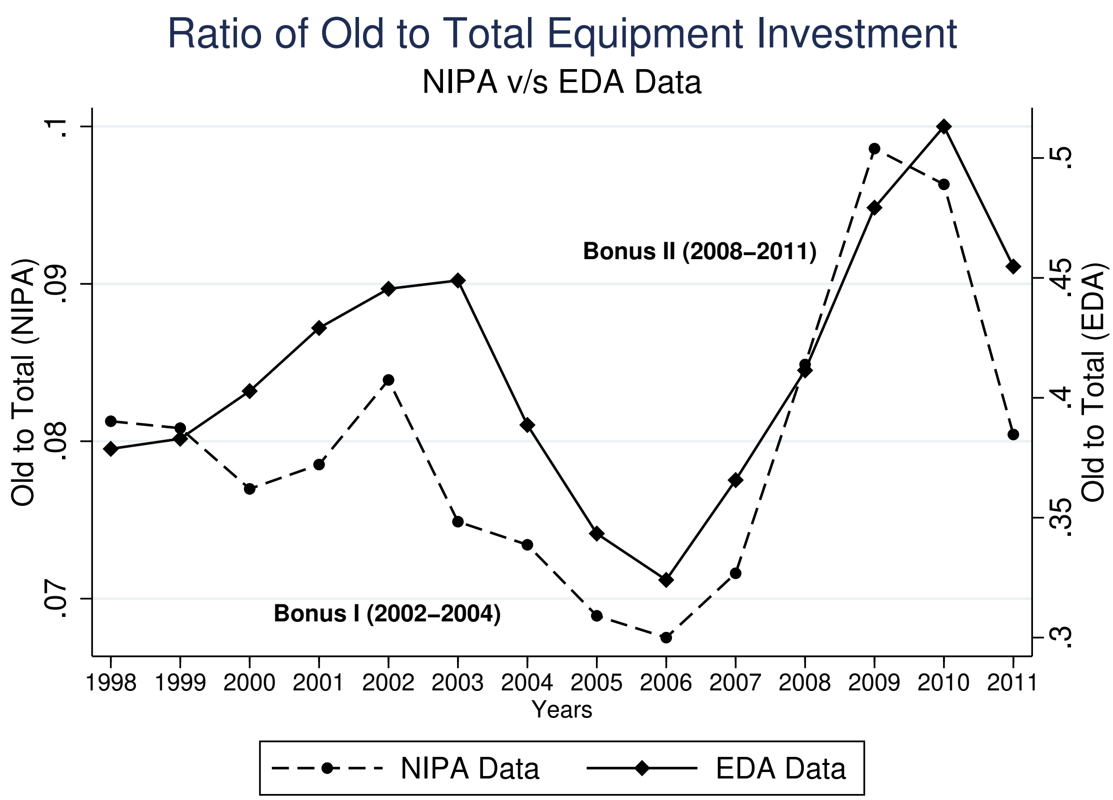

Figure IA.II: NIPA vs. EDA Data: This figure plots the time-series of aggregated ratio of old to total equipment obtained from National Income and Product Accounts, and compare it to the ratio of old to total equipment from the EDA data.

Table IA.I: History of Bonus Depreciation

This table presents the history of bonus depreciation.

Year	Act	First-Year Deduction	Placed-in-service date	Equipment Type
2002	Job Creation and Worker Assistance Act of 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 of 2015	50%	January 1, 2015 – December 31, 2017	New
2017	Tax Cuts and Jobs Act	100%	September 27, 2017 - December 31 2022	New and Old

Table IA.II: Affected Industries

This table presents the five most common three-digit NAICS industry codes in the bottom and top three deciles of z^0, the present value of depreciation deductions. We use variation in the four-digit NAICS codes in our regression analyses.

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 IA.III: Description of Key Variables

This table reports variable definitions. Data sources include 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
$z^{\theta}_{j,t}$	Present value of depreciation deductions for the average asset in which industry j invests at time t.	Zwick and Mahon (2017)
Log($ New (Old) Equipment Investment)	Natural logarithm of the aggregated individual new (Old) equipment investment for a given buyer-year	Constructed
Log($ Total Equipment Investment)	Natural logarithm of the aggregated total equipment investment for a given buyer-year	Constructed
New (Old) Price Residual	Average residual price of new (old) equipment within a four-digit NAICS code for a given equipment type in a given county for each year	Constructed (See Table III)
Log(Machine (Model) Age of Old Equipment)	Natural logarithm of the mean machine (model) age (obtained from EDA) of old equipment at the buyer-year level	Constructed
Sales	$ value of sales by the establishment.	EDA, Mergent
Employees	Number of employees in an establishment.	EDA, Mergent
Bonus State Conformity	Indicator variable identifying buyers located in states that conform 100% to federal bonus depreciation in a given year	Constructed
Sec179 State Conformity	Indicator variable that takes the value 1 for purchases in state that conforms 100% to federal Section 179 policy	Constructed
New	Dummy that is assigned a value of one for new equipment purchased, 0 otherwise	EDA
High Small Bank (SBA loan) Share	Indicator variable identifying buyers located in states that have above median level of banks lending (SBA loans)	Constructed
High HHI	Indicator variable identifying industries that are in the highest quartile of market concentration	Constructed
Newer Vintage(Model)	Indicator variable to identify the firms that purchase newer vintage (technology) equipment and newer technology equipment	Constructed
Sales(Employee) Growth	Annual percentage change in sales (employee) growth	Constructed
High_old_price_pre	Indicator variable for the above-median ex ante price during the pre-bonus depreciation period	Constructed

Description of Key Variables: Continued

Variable	Description	Source
Log of # of Establishments with 5-9 employees	Natural logarithm of the number of establishments with five to nine (ten to nineteen) employees	Constructed
Treatment	Indicator variable for those four-digit NAICS industries in the bottom three deciles of $z_{j,t}$	Zwick and Mahon (2017)
Post	Dummy that is assigned a value of one between (Sep 2001–Dec 2004), (July 2008–Dec 2011), and zero otherwise.	Constructed
Same_Industry	Indicator variable that identifies the buyer industry-seller industry pairs where buyer and seller are from same industry	Constructed
size_diff	Indicator variable for the top tercile of the size difference between buyer and seller	Constructed
low_distance	Indicator variable for the lowest tercile of the distance between buyer and seller	Constructed
BKS^{θ}	Present value of the tax adjusted depreciation deductions for each transacted equipment at monthly level	Constructed
Seller of Old Equipment	Indicator variable for firms that sold their used equipment within two years around the bonus depreciation window	Constructed

Table IA.IV: Descriptive Statistics - Transaction Level

This table presents descriptive statistics for the variables used in the regression analyses for the sample period 1998–2011 at the transaction level (1,710,262 purchase transactions). $z^{\theta}_{j,t}$ is the present value of depreciation deductions for the average asset in which industry j invests at time t following Zwick and Mahon (2017). *Equipment Value* is the dollar value of equipment claimed as collateral in the transaction. *Machine Age (Years)* is the age (in years) of machines purchased by the establishment as defined in the UCC transaction data. *Model Age (Years)* is the age (in years) of the particular model calculated as the difference between the transaction year and the first year the model was introduced.

	Mean	SD	Median
$z^{\theta}_{j,t}$	0.927	0.043	0.930
Equipment Value (in $ 1,000)	82.238	93.522	56.400
Machine Age (Years)	4.925	7.255	2
Model Age (Years)	6.838	4.941	6
New Dummy	0.449	0.497	0

Table IA.V: Direct Effect of Tax Incentives: Probability of Buying New Equipment

This table reports results estimating the direct effect of tax incentives via bonus depreciation on an establishment's probability of buying new machines. Panel A reports the results where we use the indicator variable *New Dummy*, which takes a value of 1 for purchases of new equipment and 0 otherwise, as the dependent variable. We use the z_j^0 measure in Zwick and Mahon (2017) to construct the treatment and control groups. The indicator variable *Treat* equals 1 for those four-digit NAICS industries in the bottom three deciles of z_j^0. The control group involves four-digit NAICS industries in the top three deciles of z_j^0. We define 1998–2000, and 2005–2007 as the pre-shock window when the bonus depreciation levels were low (*Post=0*). We further define 2001–2004 and 2008–2011 as the post-shock window when there is an increase in bonus depreciation levels. The variable of interest for this design is *Treatment* × *Post*. In columns (1) and (2), we estimate the regression equation (3) for 1998–2004, the first sub-period of bonus depreciation. Column (1) only includes industry and year fixed effects and controls for time-variant omitted sector-level factors using linear and quadratic sector trends with two-digit NAICS industry dummies. Column (2) replaces industry-fixed effects with buyer-fixed effects to control unobservable buyer-level variations. Columns (3) and (4) show results for the second sub-period of bonus depreciation, and columns (5) and (6) report regression results for the aggregate of the first two sub-periods. Panel B reports results where the variable of interest is a continuous measure of the present value of depreciation deductions ($z_{j,t}^{\theta}$). The sample period is 1998–2011. Column (1) only includes industry-fixed effects, year-fixed effects, and sector trends. In column (2), we include *State* × *Year* fixed effects. In column (3), we control for establishment age. In column (4), we include Size Decile × Year fixed effects and Employees Decile × Year fixed effects. Column (5) includes equipment type-specific linear and quadratic trends. In column (6), we include buyer-fixed effects. In column (7), we include leases in our baseline sample. 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: **Indicator Treatment Variable**

Dependent Variable :	*New Dummy*					
Time Period	(1998-2004)		(2005-2011)		(1998-2011)	
Level: Transaction-Level	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × Post	0.054***	0.058***	0.078***	0.109***	0.044***	0.054***
	(2.953)	(3.313)	(3.093)	(5.277)	(4.855)	(6.467)
Observations	515,677	439,440	813,095	673,802	1,328,773	1,195,998
Clusters (Industry)	159	159	161	161	161	161
R^2	0.06	0.50	0.05	0.55	0.05	0.48
Year Fixed Effects	Y	Y	Y	Y	Y	Y
Sector Trends	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y		Y		Y	
Buyer Fixed Effects		Y		Y		Y

PANEL B: **Continuous Treatment Variable**

Dependent Variable:	*New Dummy*						
Time Period	(1998-2011)						
Level: Transaction-Level	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$z^{\theta}_{j,t}$	1.388***	1.282***	2.263***	1.353***	1.434***	1.517***	1.292***
	(10.602)	(9.893)	(12.115)	(10.617)	(14.064)	(11.876)	(9.846)
Observations	1,710,262	1,710,262	1,084,773	1,710,262	1,710,261	1,528,097	2,053,973
Clusters (Industry)	240	240	240	240	240	240	240
R^2	0.08	0.09	0.08	0.08	0.15	0.48	0.10
Year Fixed Effects	Y		Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Sector Trends	Y	Y	Y	Y	Y	Y	Y
State × Year Fixed Effects		Y					
Firm Age			Y				
Sales Decile × Year Fixed Effects				Y			
Employees Decile × Year Fixed Effects				Y			
Equipment Trends					Y		
Buyer Fixed Effects						Y	
Include Leases							Y

Table IA.VI: Direct Effect of Bonus Depreciation on Aggregate Investment

This table reports results from equation (1) using aggregate investment as the outcome variable. The outcome variable is measured as the natural logarithm of total investment (Log(Total Equipment Investment)) at the buyer-year level. The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Total Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	5.875***	3.218***	3.166***	2.710***
	(4.462)	(4.148)	(4.112)	(3.850)
Observations	999,991	999,991	788,817	788,817
Clusters (Industry)	240	240	239	239
R^2	0.16	0.16	0.59	0.59
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.VII: Who is Buying New Equipment? Capital Replacement Effect

In this table, we test how the direct effect of bonus depreciation varies for firms that sold their used equipment around bonus depreciation events. *Seller of Old Equipment* is defined as an indicator that takes a value of 1 for firms that sold their used equipment within two years around the bonus depreciation window, and 0 otherwise. The sample period is from 1998 to 2011. Column (1) includes industry and year fixed effects, Column (2) adds sector trends. Columns (3) and (4) consists of buyer fixed effects effects and also adds Seller × Year fixed effects. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ New Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
Seller of Old Equipment × $z^{\theta}_{j,t}$	1.054***	0.843***	5.605***	5.179***
	(4.643)	(3.963)	(4.426)	(4.214)
$z^{\theta}_{j,t}$	8.396***	5.133***	3.547***	3.001***
	(5.393)	(3.998)	(3.286)	(2.949)
Observations	543,670	543,670	376,494	376,494
Clusters (Industry)	240	240	237	237
R^2	0.29	0.29	0.69	0.69
Year Fixed Effects	Y	Y		
Seller × Year Fixed Effects			Y	Y
Buyer Controls	Y	Y	Y	Y
Sector Trends		Y	Y	Y
Industry Fixed Effects	Y	Y		
Buyer Fixed Effects			Y	Y

Table IA.VIII: Direct and Indirect Effects with Investment to Lagged Capital Ratio

This table reports the effect on equipment investment to lagged capital stock as an alternate measure of investment elasticity following Zwick and Mahon (2017). We aggregate the individual new and used equipment transactions for a given buyer-year and divide it by estimated lagged capital stock to calculate the ratio of New(old) investment to estimated capital stock. Capital stock is estimated based on sales to tangible assets ratio for the lowest quintiles of firms within 2 digit-NAICS industry codes for each year. We report the effect on new and old equipment investment in Panel A and Panel B, respectively.The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A

Dependent Variable:	*New Equipment Investment/lagged Estimated Capital*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$\frac{1-\tau z^{\theta}_{j,t}}{1-\tau}$	-9.151***	-8.968***	-9.488**	-9.269**
	(-3.012)	(-3.111)	(-2.463)	(-2.289)
Observations	569,492	569,492	483,940	483,940
Clusters (Industry)	238	238	237	237
R^2	0.11	0.11	0.53	0.53
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

PANEL B

Dependent Variable:	*Old Equipment Investment/lagged Estimated Capital*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$\frac{1-\tau z^{\theta}_{j,t}}{1-\tau}$	-3.198***	-3.977***	-3.333**	-3.260*
	(-2.898)	(-3.181)	(-1.997)	(-1.773)
Observations	569,492	569,492	483,940	483,940
Clusters (Industry)	238	238	237	237
R^2	0.14	0.15	0.54	0.55
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.IX: Including State-Year Fixed Effects

This table repeats the analysis in Table II, Panel B, after including state by year fixed effects. The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) $\times$ state and state$\times$ year fixed effects, while column (2) adds sector trends. Columns (3) and (4), includes buyer fixed effects and additionally add non-linear buyer size by year fixed effects in column (4). All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	2.472**	1.233**	1.803***	1.741***
	(2.574)	(2.291)	(3.132)	(3.291)
Observations	544,599	544,599	396,059	396,059
Clusters (Industry)	238	238	237	237
R^2	0.22	0.22	0.62	0.62
Industry × State Fixed Effects	Y	Y	Y	Y
State × Year Fixed Effects	Y	Y	Y	Y
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.X: Weighted Regressions: ACES Weights

This table reports results from Table II, Panel B, after re-weighting the data to match the distribution of machine purchases across two-digit NAICS industries in our data with the distribution of equipment purchases as a proportion of total capital expenditure in the Annual Capital Expenditures Survey (ACES) data during our sample period. The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	3.519***	1.952**	2.878**	2.385**
	(4.190)	(2.589)	(2.277)	(2.459)
Observations	545,869	545,869	396,142	396,142
Clusters (Industry)	238	238	237	237
R^2	0.12	0.12	0.54	0.54
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.XI: Weighted Regressions: BEA Weights

This table repeats the analysis in Table II, Panel B, re-weighting the data to match the distribution of machine purchases across two-digit NAICS industries in our data with the distribution of GDP in the BEA data. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	2.473*	1.605**	2.236***	1.951***
	(1.824)	(1.980)	(3.122)	(2.914)
Observations	545,869	545,869	396,142	396,142
Clusters (Industry)	238	238	237	237
R^2	0.18	0.18	0.65	0.65
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.XII: Controlling for Industry Growth

This table repeats the analysis in Table II, Panel B, after controlling for industry-level growth as an alternate to sector trends. Column (1) includes industry (four-digit NAICS) and year-fixed effects and lagged industry growth measured as employment growth using QCEW data. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 2). Column (2) we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. In column (3), we replace industry-fixed effects with buyer-fixed effects. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Old Equipment Investment)*		
Level: Buyer-Year	(1)	(2)	(3)
$z^{\theta}_{j,t}$	3.313***	2.337**	1.935**
	(2.966)	(2.321)	(2.546)
Observations	545,847	545,847	396,127
Clusters (Industry)	238	238	237
R^2	0.17	0.17	0.62
Industry Growth Control	Y	Y	Y
Industry Fixed Effects	Y	Y	
Year Fixed Effects	Y		Y
Buyer Fixed Effects			Y
Buyer Size × Year Fixed Effects		Y	

Table IA.XIII: Present Value of Depreciation Deductions at Equipment-Level

This table reports results where we re-define the present value of depreciation deductions, z^0, at the equipment level. We use the general depreciation system (GDS), where we hand match each piece of equipment with each asset class defined by MACRS. We calculate BKS^0 for each asset class defined by MACRS, assuming a 7 percent discount rate. Letting D_s denote the depreciation rate at period s for an asset with remaining lifespan T^*, the present value of depreciation deductions associated with \$1 of investment in equipment can be written as

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

where r denotes the discount rate applied to future cash flows. BKS^0 measures the present value of depreciation deductions for each transacted equipment. Thus, under bonus depreciation, the present value of tax benefits with the effective tax rate, τ, is

$$BKS^\theta = \tau(\theta + (1-\theta)BKS^0)$$

We define BKS^θ at equipment monthly-level i.e., BKS^θ_{emt}. See Section IA.3 for details. Panel A reports the effect of tax incentives via bonus depreciation (measured using BKS^θ) on an establishment's probability of buying new machines. Panel B repeats the analysis from Table II, where we average the BKS^0_{emt} at the four-digit NAICS industry level during non-bonus years in our data for new machines. Panel C repeats the analysis from Table III with the alternative depreciation measure. All regressions are clustered at the industry level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Probability of New Equipment Purchase**

	Dependent Variable : *New Dummy*: Time Period:1998-2011						
Level: Transaction-Level	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BKS^θ_{emt}	1.415***	1.416***	1.409***	1.426***	1.390***	1.304***	1.416***
	(152.470)	(150.858)	(156.716)	(151.023)	(161.814)	(99.711)	(158.287)
Log(Employees)	0.005**	0.005**	-0.000	0.008**	0.005**	0.031***	0.004*
	(2.157)	(2.355)	(-0.317)	(2.052)	(2.452)	(3.727)	(1.930)
Log(Sales)	0.005***	0.005***	0.001	0.003	0.005***	-0.040***	0.008***
	(2.990)	(2.872)	(1.126)	(1.503)	(4.285)	(-6.640)	(6.247)
Log(Firm Age)			0.003***				
			(2.620)				
Observations	1,705,870	1,705,870	1,080,425	1,705,870	1,705,869	1,522,229	2,050,456
Clusters (Industry)	239	239	238	239	239	239	239
R^2	0.65	0.65	0.74	0.65	0.66	0.76	0.65
Industry-YearMonth Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Non-Linear Size Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Sector Trends	Y	Y	Y	Y	Y	Y	Y
Equipment Trends					Y		
Buyer Fixed Effects						Y	
Include Leases							Y

PANEL B: **Investment Tax Elasticity of Old and New Equipment**

Dependent Variable :	*Log($ Old Equipment Investment)*		*Log($ New Equipment Investment)*	
Level: Buyer-Year	(1)	(2)	(3)	(4)
BKS^{θ}_{jt}	3.294***	2.788***	5.258***	4.461***
	(3.432)	(3.112)	(3.267)	(2.667)
Observations	396,139	396,139	376,491	376,491
Clusters (Industry)	236	236	236	236
R^2	0.62	0.62	0.69	0.69
Year Fixed Effects	Y		Y	
Buyer Fixed Effects	Y	Y	Y	Y
Buyer Size × Year Fixed Effects		Y		Y
Sector Trends	Y	Y	Y	Y

PANEL C: **Price of Old and New Equipment**

Dependent Variable :	*Old Price Residual*		*New Price Residual*	
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
BKS^{θ}_{jt}	-0.955***	-0.645***	0.223***	0.105
	(-3.655)	(-3.403)	(3.536)	(1.625)
Observations	553,569	553,569	546,425	546,425
Clusters (Industry)	237	237	239	239
R^2	0.06	0.06	0.08	0.08
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects	Y	Y	Y	Y
County Fixed Effects	Y	Y	Y	Y
Sector Trends		Y		Y

Table IA.XIV: Including Leases

This table repeats the analysis in Table II, Panel B, after including lease transactions. The sample period is from 1998 to 2011. Column (1) includes industry (four-digit NAICS) and year-fixed effects, while column (2) adds sector trends (two-digit NAICS linear and quadratic trends). Columns (3) and (4), includes buyer fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except Column 4). In Column (4), we replace buyer controls with non-linear buyer size by year fixed effects. We create deciles for firm sales and employees and interact those with the year dummies. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	3.499***	2.179***	2.589***	2.228***
	(3.006)	(3.312)	(4.407)	(4.217)
Observations	586,979	586,979	428,811	428,811
Clusters (Industry)	238	238	237	237
R^2	0.17	0.17	0.62	0.62
Year Fixed Effects	Y	Y	Y	
Industry Fixed Effects	Y	Y		
Sector Trends		Y	Y	Y
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y

Table IA.XV: Price of Old and New Equipment: Controlling for Time-Varying Unobservables at the Equipment Size Level

This table reports results from estimating the effect of tax incentives via bonus depreciation on the price of old and new machines. Here, we control for time-varying unobservables at the equipment size level while calculating the residual equipment price. For each piece of equipment, we estimate the effect of the machine age, model age, four-digit equipment code, *equipment size* × *year* and manufacturer-model on prices. All other variables and estimation are similar to Table III. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	-0.837***	-0.940***	-0.931***	-0.641***
	(-5.574)	(-5.389)	(-5.423)	(-4.054)
Observations	553,601	553,580	553,573	553,573
Clusters (Industry)	238	238	238	238
R^2	0.02	0.05	0.06	0.06

PANEL B: **Impact on Price of New Equipment**

Dependent Variable:	*New Price Residual*			
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	0.129**	0.009	0.009	0.005
	(2.456)	(0.190)	(0.190)	(0.117)
Observations	546,459	546,432	546,432	546,432
Clusters (Industry)	240	240	240	240
R^2	0.02	0.08	0.08	0.08
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects			Y	Y
Sector Trends				Y

Table IA.XVI: Price of Old and New Equipment: Aggregation at Equipment Size Level

This table reports results from estimating the effect of tax incentives via bonus depreciation on the price of old and new machines. We estimate the price residuals similar to Table III. Next, we calculate the average residual prices of old and new equipment by aggregating all the transactions in a four-digit NAICS code for a given equipment type (four digit)-equipment size (26 categories) in given county during each year. The dependent variable *Old Price Residual* and *New Price Residual* measures the average residual price of old equipment and new equipment respectively within a four-digit NAICS code for a given equipment type of a given equipment size in a given county for each year. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A: **Impact on Price of Old Equipment**

Dependent Variable:	*Old Price Residual*			
Level: Equipment Code-Equipment Size-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	-0.914***	-1.038***	-0.974***	-0.623***
	(-6.301)	(-6.077)	(-6.428)	(-4.313)
Observations	657,638	657,617	657,610	657,610
Clusters (Industry)	238	238	238	238
R^2	0.01	0.04	0.06	0.06

PANEL B: **Impact on Price of New Equipment**

Dependent Variable:	*New Price Residual*			
Level: Equipment Code-Equipment Size-County-Industry-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$	0.143***	-0.001	-0.001	-0.025
	(2.618)	(-0.013)	(-0.013)	(-0.490)
Observations	628,510	628,482	628,482	628,482
Clusters (Industry)	240	240	240	240
R^2	0.02	0.08	0.08	0.08
Year Fixed Effects	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
Equipment Fixed Effects		Y	Y	Y
County Fixed Effects			Y	Y
Equipment Size Fixed Effects			Y	Y
Sector Trends				Y

Table IA.XVII: State Conformity to Bonus Depreciation: New Equipment Investment

This table reports the reports the cross-section effect on elasticity of new equipment purchase based on state adoption of bonus depreciation. Bonus State Conformity$_{s,t}$ is an indicator variable identifying buyers located in states that conform 100% to federal bonus depreciation in a given year. The sample period is from 1998 to 2011. Column (1) includes industry and buyer size by year fixed effects. Column (2) adds sector trends and column (3) adds industry by year fixed effects effects. Finally column (4) adds buyer fixed effects in addition to column (3) fixed effects. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ New Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t}$ * State Bonus Conformity	0.528**	0.488***	0.435***	0.333**
	(2.584)	(2.971)	(2.691)	(2.063)
$z^{\theta}_{j,t}$	8.812***	6.908***	5.467***	
	(5.622)	(4.422)	(4.075)	
State Bonus Conformity	-0.418**	-0.452***	-0.404***	-0.305*
	(-2.214)	(-2.874)	(-2.607)	(-1.964)
Observations	543,670	376,494	376,494	376,16
Clusters (Industry)	240	237	237	228
R^2	0.24	0.69	0.69	0.70
Year Fixed Effects	Y	Y	Y	Y
Buyer Controls	Y	Y	Y	Y
Industry Fixed Effects	Y			
Buyer Fixed Effects		Y	Y	Y
Sector Trends			Y	Y
Industry × Year Fixed Effects				Y

Table IA.XVIII: Tax Incentives under Section 179 During Years with No Bonus Depreciation

This table reports results where we estimate the effect of tax incentives under Section 179 during years with no bonus depreciation, i.e., years 2000–2001 and 2005–2007, on old equipment price and investment. We use the z_j^0 measure in Zwick and Mahon (2017) to construct the treatment and control groups. The indicator variable *Treatment* equals 1 for those four-digit NAICS industries in the bottom three deciles of z_j^0. The control group involves four-digit NAICS industries in the top three deciles of z_j^0. We define 1998–1999 as the pre-shock window when the Section 179 limits were low (*Post=0*). We further define 2000–2001 and 2005–2007 as the post-shock window when there is an increase in Section 179 levels. Here we restrict our data to only non-bonus years. The variable of interest for this design is *Treatment* × *Post*. All regressions are clustered at the four-digit NAICS level. t-statistics are in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

PANEL A:

Dependent Variable:	*Price of Old Equipment*		
Level: Equipment Code-County-Industry-Year	(1)	(2)	(3)
Treatment × Post	-0.003	-0.003	-0.002
	(-1.110)	(-0.882)	(-0.557)
Observations	198,750	197,141	197,123
Clusters (Industry)	159	159	159
R^2	0.02	0.12	0.15
Industry Fixed Effects	Y	Y	Y
State × Year Fixed Effects	Y		
County × Year Fixed Effects		Y	Y
Equipment Fixed Effects			Y
Sector Trends	Y	Y	Y

PANEL B

Dependent Variable:	*Log($ Old Equipment Investment)*			
Level: Buyer-Year	(1)	(2)	(3)	(4)
Treatment × Post	-0.013	-0.012	-0.011	-0.016
	(-0.703)	(-0.753)	(-0.643)	(-0.926)
Observations	193,015	193,012	115,558	115,558
Clusters (Industry)	159	159	153	153
R^2	0.17	0.19	0.66	0.66
Year Fixed Effects	Y			
Buyer Controls	Y	Y	Y	
Industry Fixed Effects	Y	Y		
State × Year Fixed Effects		Y		
Buyer Fixed Effects			Y	Y
Buyer Size × Year Fixed Effects				Y
Sector Trends	Y	Y	Y	Y

Table IA.XIX: Reallocation within Same Industry

This table reports results on how buyers' and sellers' industries affect physical capital reallocation. We have a unique machine serial number for every machine transacted in the database. We use these unique machine number to identify the sellers of old equipment that previously procured these machines. We start by identifying the buyer-seller pair for each transaction. Our primary variable of interest is the logarithm of the number of old equipment transactions (Log(# of Old Equipment Transactions)) within each *buyer industry-seller industry* pair every year, where industry is defined at four-digit NAICS level. The sample period is from 1998 to 2011. In columns (1)-(4), we estimate the regression equation (1), where we include year fixed effects, buyer industry fixed effects, seller industry fixed effects, sector trends at the NAICS two-digit level. In some specifications, we include buyer industry × year fixed effects and seller industry × year fixed effects *Same_Industry* dummy identifies the buyer industry-seller industry pairs where buyer and seller are from same industry. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable:			
	Log(# of Old Equipment Transactions)			
Level: Buyer Industry-Seller Industry-Year	(1)	(2)	(3)	(4)
Same_Industry × z^{θ}_{jmt}	1.466*	1.662**	1.603**	1.662**
	(1.802)	(2.027)	(1.998)	(2.025)
z^{θ}_{jmt}	1.706		1.864**	
	(1.443)		(2.103)	
Same_Industry	-0.264	-0.387	-0.392	-0.387
	(-0.340)	(-0.492)	(-0.512)	(-0.491)
Constant	-1.087	0.531***	-1.236	0.531***
	(-0.978)	(264.979)	(-1.483)	(264.715)
Observations	24,895	23,939	24,895	23,939
Clusters (Industry)	230	219	230	219
R^2	0.42	0.48	0.42	0.48
Year Fixed Effects	Y		Y	
Buyer Industry Fixed Effects	Y		Y	
Seller Industry Fixed Effects	Y		Y	
Buyer Industry × Year Fixed Effects		Y		Y
Seller Industry × Year Fixed Effects		Y		Y
Sector Trends			Y	Y

Table IA.XX: Reallocation based on Size Differences and Geographic Location

This table reports results on how buyers' and sellers' size differences and geographic distance affect physical capital reallocation. We have a unique machine serial number for every machine transacted in the database. We use these unique machine number to identify the sellers of old equipment that previously procured these machines. We start by identifying the buyer-seller pair for each transaction. Our primary variable of interest is the logarithm of the number of old equipment transactions (*Log(# of Old Equipment Transactions)*) within each buyer industry-buyer state-seller state each year. The sample period is from 1998 to 2011. In column (1), we estimate the regression equation (1), where we include year fixed effects, industry fixed effects, sector trends, and *Buyer State* $\times$ *Seller State* $\times$ *Year* fixed effects. Column (2) documents the cross-section effect of size differences between buyer and seller industries. *size_diff* takes a value of 1 for the top tercile of the size difference between buyer and seller, and 0 otherwise. Since we do not observe seller size for many transactions, we have a considerably smaller sample. Finally, in column (3), we identify the cross-section effect of distance between buyers and sellers based on the zip code. The variable *low_distance* takes a value of 1 for the lowest tercile of the distance between buyer and seller, and 0 otherwise. Standard errors are clustered at the four-digit NAICS industry level. t-statistics are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log(# of Old Equipment Transactions)*		
Level: Industry-Buyer State-Seller State-Year	(1)	(2)	(3)
$z^{\theta}_{j,t}$	1.833***	2.779**	1.535***
	(3.062)	(2.327)	(3.001)
size_diff		-0.807***	
		(-2.929)	
size_diff $\times$ $z^{\theta}_{j,t}$		0.750***	
		(2.631)	
low_distance			0.222
			(0.768)
low_distance $\times$ $z^{\theta}_{j,t}$			0.566**
			(2.025)
Observations	71,466	31,574	70,368
Clusters (Industry)	234	210	234
R^2	0.43	0.60	0.29
Year Fixed Effects	Y	Y	Y
Sector Trends	Y	Y	Y
Industry Fixed Effects	Y	Y	Y
Buyer State $\times$ Seller State $\times$ Year Fixed Effects	Y	Y	
Seller State $\times$ Year Fixed Effects			Y
Buyer State $\times$ Year Fixed Effects			Y

Table IA.XXI: Heterogeneity based on Access to Small Business Credit

This table reports the heterogeneity based on a buyers access to finance on new investment elasticity. Access to finance is measured using *High Small Bank Share (High SBA Loan)* which is an indicator variable identifying buyers located in states that have above median level of banks lending (SBA loans). The sample period is 1998–2011. Columns (1) and (4) include industry and buyer size × year fixed effects. Columns (2) and (5) add sector trends. Finally, Columns (3) and (6) include buyer-fixed effects in lieu of industry-fixed effects. In all columns, we include buyer-level controls such as logged sales and logged employees (except for columns where we include Buyer Size × Year fixed effects). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable:	*Log($ New Equipment Investment)*					
Level: Buyer-Year	(1)	(2)	(3)	(4)	(5)	(6)
$z^{\theta}_{j,t}$ × *High Small Bank Share*	0.482***	0.413***	0.380***			
	(5.525)	(5.127)	(4.204)			
$z^{\theta}_{j,t}$ × High SBA Loan				0.860***	0.583***	0.392***
				(5.227)	(4.541)	(2.731)
$z^{\theta}_{j,t}$	7.801***	4.333***	4.389***	4.684***	2.043	2.959**
	(5.571)	(3.875)	(3.552)	(3.118)	(1.508)	(2.017)
Observations	543,582	543,582	376,442	380,771	380,771	264,734
Clusters (Industry)	240	240	237	240	240	237
R^2	0.27	0.27	0.69	0.34	0.34	0.70
Group Fixed Effects	Y	Y	Y	Y	Y	Y
Buyer Size × Year Fixed Effects	Y	Y	Y	Y	Y	Y
Industry Fixed Effects	Y	Y		Y	Y	
Sector Trends	Y	Y	Y	Y	Y	Y
Buyer Fixed Effects			Y			Y