Spillover Effects of Accelerated Depreciation on Small Business Investment*

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Abstract

We provide new evidence on the spillover effect of temporary federal tax incentives. Using granular data on equipment purchases, we find that tax subsidies on new equipment investment via accelerated depreciation increase small business investment in used capital by 9.2%. This spillover effect arises as some direct beneficiaries replace their old capital with new capital, causing a reduction in prices of old equipment. This further enables small businesses entry, adoption of new technology, and accelerated growth. Our empirical results underscore how tax incentives driving investment in new capital goods foster the reallocation of used capital goods within the economy during recessions.

Keywords: Taxes, Bonus Depreciation, Small Business, Old Capital, Capital Reallocation

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1 Introduction

Corporate taxes are important policy tools that may affect firms' investment and have important implications for firms' real decision-making (Hanlon and Heitzman, 2010; Graham, 2013). Therefore, governments introduce various tax policies to encourage firms to invest which may help create jobs (Suárez Serrato and Zidar, 2016; Ohrn, 2018; Lester, 2019; Chen, De Simone, Hanlon, and Lester, 2023). However, there is less evidence of how small firms respond to various tax policies. It is important to know because small businesses accounted for nearly 50% of non-farm GDP and were responsible for over 70% of job gains and losses in 2018 (Bureau of Labor Statistics). The lack of data on small businesses' investment behavior further makes it challenging for researchers to study the impact of tax policy on small business investment.

In this paper, we study the *temporary bonus depreciation* investment-based tax incentive used by the government as a counter-cyclical measure. Recent research shows that such incentives encourage investment and job growth for some small businesses (Zwick and Mahon, 2017; Tuzel and Zhang, 2021). Nevertheless, such incentives are typically available exclusively for *new* capital purchases, even though many such firms invest in *old* capital (Eisfeldt and Rampini, 2007; Ma, Murfin, and Pratt, 2022; Darmouni and Sutherland, 2023). In addition, some small businesses may not invest at all because *old* capital can also be costly for them (Lanteri and Rampini, 2023). As a result, while some firms can directly take advantage of these subsidies, many others are not able to utilize the benefits due to capital constraints. Can these federal investment-based tax incentives still indirectly benefit small businesses that cannot afford either new or old capital? If so, how? Using detailed data on equipment-level transactions, this paper seeks to uncover a more comprehensive understanding of such investment-based tax stimuli by examining their direct and indirect effects and how these are distributed across firms. Understanding these effects is crucial for designing effective tax policies aimed at supporting small businesses.[1]

The impact of accelerated depreciation incentives that subsidize the purchase of new capital goods on firms' intensity to invest in new versus used (or old) capital is not obvious. Some firms may *directly* benefit from these *temporary* incentives introduced in response to recessions (e.g., bonus depreciation under Section 168(k) of IRC) and make immediate investments in new capital goods (Zwick and Mahon, 2017). However, investment incentives on new capital can also *indirectly* benefit some other firms via the prices

[1] For example, the Tax Cut and Jobs Act of 2017 made an important change to the qualified equipment rules by allowing businesses to claim accelerated depreciation on both "new" and "used" capital goods.

of old capital. A subsidy on new capital goods allows some direct beneficiaries to replace their old capital with new capital (*capital replacement*). This will increase the supply of older capital in the market and subsequently lower their equilibrium price (Lanteri and Rampini, 2023). Consequently, some small businesses with binding constraints can buy these old capital goods and indirectly benefit from investment incentives. As an alternative, it is also possible that many direct beneficiaries choose only to purchase new capital to expand their capital stock without selling their old machines (*capital expansion*). In such a scenario, we would observe muted indirect spillover from these investment incentives via the price of old capital. Thus, it is unclear whether government incentives that temporarily subsidize the purchase of new capital goods will foster the reallocation of old capital in the economy and benefit some small businesses that can not afford either new or old capital.

We empirically test the *direct* and *indirect* effects of *temporary* investment incentives that subsidize the purchase of new capital goods. We use data on equipment purchases and two episodes of investment stimulus from 1998 to 2011.[2] Firstly, we show an investment-based tax subsidy on new equipment increases the new equipment investment by 21% (direct effect), consistent with prior literature. Next, we document a novel result, i.e., an increase in old equipment investment by 9.2% 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 by 3.8% and not by an increase in the price of new equipment. Our findings suggest that some small businesses may indirectly benefit from lower prices of old capital goods. A decline in the price of old equipment helps increase the investment in used but upgraded technology equipment by almost 9% and helps increase sales growth by 7%. Overall, we document a novel mechanism for several unintended positive effects of investment-based incentives on small businesses.

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).

[2]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.

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 (IRC), which accelerates the timing of deductions of investment purchases from taxable income. The policy was first introduced in 2002 as a *temporary* 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.

Firms that typically buy machines in *long-duration* categories act as the "treatment group" because bonus depreciation changes their depreciation schedules more significantly than those buying *short-duration* machines. Although this federal investment-based subsidy did not target specific industries or machines, 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.

We closely follow the recent literature (Zwick and Mahon, 2017; Curtis, Garrett, Ohrn, Roberts, and Serrato, 2023) to ensure consistency and facilitate comparison. We first examine the technological disparities among firms operating in narrowly defined industries. As an additional robustness measure, we conduct the analysis that exploits the heterogeneity at the equipment level using EDA data to create tax benefit measures. This allows us to use industry-year fixed effects in our tests to control for unobservable industry shocks. Our findings are consistent in both cases. Furthermore, we include industry-year fixed effects in our cross-section tests to control for industry shocks or trends and use the cross-sectional variation across states.

We begin our analysis by estimating the new equipment elasticity at the firm level. With a tax subsidy on new equipment, we document an average increase in new equipment investment by 20.9 to 24.5 log points.[3] Next, we document our main findings,

[3]This is consistent with Zwick and Mahon (2017). They observe an average increase in equipment investment 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. Zwick and Mahon (2017) use IRS data. While the IRS form does not require firms to list

i.e., the indirect benefit of investment stimulus policy via capital reallocation. We find that tax subsidy on new equipment increases the investment in old equipment by 9.02 log points (9.44%). After that, we test the mechanism for our results. Consistent with the theory, we observe a 3.8% decrease in the price of old equipment for long-duration (treatment group) industries compared to short-duration industries (control group).[4]

It is, however, also possible that some firms may buy old capital because investment subsidies increase demand for new capital, thereby making it more expensive. In such a scenario, tax incentives for new equipment investment may not directly benefit the investing firms but rather the capital suppliers. If the supply of capital is less elastic and suppliers raise the prices of new capital goods, it could compel small businesses to purchase used capital goods in the secondary market (Goolsbee, 1998). Although we found a slight marginal increase in new equipment prices, it wasn't economically significant. Our findings indicate that a subsidy on new capital goods doesn't lead to higher prices for new equipment and doesn't exclude financially constrained firms from the new capital goods market.[5] As a support to the reallocation mechanism, we also find increased equipment resale transactions when buyer and seller belong to the same four-digit NAICS industry. Furthermore, we find that investment incentives aid in capital replacement. Firms that sold their old equipment around the bonus depreciation events exhibited a significantly larger increase in new investments.

We then investigate whether reallocating old capital allows for new technology adoption and growth. Prior literature suggests that relatively newer vintage capital aids firm productivity and growth (Benhabib and Rustichini, 1991; Hsieh, 2001; Benmelech and Bergman, 2011). A subsidy on new capital purchases directly benefits some firms in buying new machines. However, it is also possible that as the supply of older machines goes up, constrained firms can get upgraded technology at a cheaper price. Interestingly, for the older machines, we find a decline in the average machine age (between 7.5 to 13.2 months) and technological age (between 3 to 11.5 months). The results suggest that treated firms buy used but upgraded technology equipment from the secondary market.

used purchases separately, our equipment-level data help us distinguish the two.

[4]Lanteri and Rampini (2023) theoretically show that the equilibrium price of old capital is higher than its social value. Therefore, some firms may not invest because of the higher price of old capital goods. A tax subsidy for new capital goods encourages firms with fewer constraints to buy new capital and replace their old equipment. This increases the supply of older capital, thereby lowering its equilibrium price.

[5]This 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.

One of the main objectives of the Job Creation and Worker Assistance Act of 2002 that introduced bonus depreciation includes promoting job creation. Therefore, we test the further implications of buying used but upgraded technology equipment from the secondary market on small business sales and employment. We find that future sales increase by 7% and employment increases by 3.4% for buyers of old capital, given that they now have access to upgraded technology machines. 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.

We also exploit heterogeneity in the states' conformity to Section 168(k) and Section 179. Our findings indicate that changes in bonus depreciation primarily drive the results of the capital reallocation analyses. Furthermore, during periods without bonus depreciation but with Section 179 limit changes, we do not observe any differential effects on the price of old equipment or the investment in old equipment for the treated firms. This suggests that Section 179, which subsidizes both new and old capital, may not result in spillover benefits via the lower price of used capital.

One of the challenges 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. We observe no difference in trends for treatment and control groups for the pre-period, which provides some validity to the natural experiment. To further address the concern that time-varying industry shocks overlap with the timing of bonus depreciation, we created tax benefit measures at the equipment level to use the variation based on the equipment purchased. We included industry-year fixed effects in our tests.[6] Further, we utilize the variation across states using the buying firm's state conformity to Section 168(k). This allows us to control for time-varying industry-level omitted variables.

Our paper contributes to the large literature on the impact of various corporate tax policies on investment (Campbell, Chyz, Dhaliwal, and Schwartz Jr, 2013; Ohrn, 2019; Giroud and Rauh, 2019; Lester, 2019; Fox, Jacob, Wilde, and Wilson, 2022). However, the evidence on the response of small businesses to such policies is limited (Zwick and Mahon, 2017; Tuzel and Zhang, 2021). Further, the lack of data on small business investment makes it difficult for researchers to precisely document the effects of tax policies

[6] One caveat with using the equipment level tax benefit measure is that it may introduce estimation bias in the analysis. Many small businesses do not invest regularly, and if they choose to invest, they may self-select themselves into treatment group by investing more in machines of longer duration based on the perceived benefit from bonus depreciation.

and the mechanisms behind them (Lisowsky and Minnis, 2020; Minnis, Sutherland, and Vetter, 2023). We provide the first empirical evidence on the spillover effect of tax-based economic stimulus, which often subsidizes the purchase of new capital. Our data allow us to observe various investment characteristics at a more granular level. We document that these tax incentives not only induce firms to invest in new capital but also reduce the price of old capital goods, enabling financially constrained small businesses to invest in old capital. This indirect investment tax elasticity is significant, at approximately 44% of the direct tax elasticity.[7] Furthermore, our results suggest that with these incentives, small businesses purchase used machines with upgraded technology from the secondary market. This means that investment-based incentives lower the cost of used capital while simultaneously helping small businesses adopt newer technology. We document a new mechanism through which governmental policies help alleviate financial constraints for small businesses and support growth. Our paper suggests that it is important to recognize these spillover effects of tax policies when comparing different governmental policies.

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. Darmouni and Sutherland (2023) show how small firms' investments change when old capital is hard to find. Our paper is closely related to the theoretical work by Lanteri and Rampini (2023) and provides empirical evidence for the capital reallocation effect of investment stimulus.

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).

[7] We provide back-of-the-envelope calculations on the magnitude of this indirect effect. Borrowing from Curtis, Garrett, Ohrn, Roberts, and Serrato (2023), a 7.8% increase in equipment investments leads to a relative increase in employment of 9.5% during the bonus period for large plants. Assuming a similar capital-to-labor ratio for small businesses in our data, our rough estimates suggest that an increase in investment in old capital by 9.2% (indirect effect) leads to an estimated increase in employment by 11.2%. This implies that one job is created every three years for a small business in our sample that employs three workers on average.

2 Conceptual Framework and Empirical Strategy

In this section, we first discuss the history of the bonus depreciation 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 Depreciation Allowance

In the United States, firms conventionally depreciate every 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 qualified *new* and *used* 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 has gradually increased in the past three decades.[8]

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 2010 and

[8] 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.

December 2011.[9] Later, 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.

Figure I plots bonus depreciation for qualified equipment during the bonus and non-bonus depreciation years.[10] 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 impact other small businesses by affecting 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, 1981), 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, 1998). 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, a particular tax incentive we use in our study, is *temporary* in nature and primarily implemented during recessions. Further, bonus depreciation incentives

[9] 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.

[10] 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.

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 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 investment in *new* equipment or *used* equipment.[11] 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. At the same time, it is possible that certain small businesses will increase investment in old capital goods (not eligible under bonus depreciation) as they *indirectly* benefit from tax incentives on new capital.

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.[12] 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 won't be any *indirect* benefit of tax incentives on new capital. However, if 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.

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

[12]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 *used* equipment it can only take 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 subsidized new capital and sell their old capital.[13] 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 take-up, Kitchen and Knittel (2016) show a positive relationship between the use of bonus 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.[14]

[13] Lanteri and Rampini (2023) show that any subsidy on old capital may increase the price of the old capital. This may increase the constraints of the potential buyers of the old capital who are already capital constrained and may exclude them from the market.

[14] During the period 2002–2011, the net total Section 179 deductions account for \$500.7 billion, while total bonus amount claimed was \$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

Following literature, (Zwick and Mahon, 2017; Garrett, Ohrn, and Suárez Serrato, 2020; Curtis, Garrett, Ohrn, Roberts, and Serrato, 2023) we 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_j^0 from Zwick and Mahon (2017) for industry variation.[15] The variation in z_j^0 across industries provides the basis for a difference-in-differences research design with continuous treatment, that is,

$$z_{j,t}^\theta = \theta_t + (1-\theta_t)\, z_j^0,$$

where $z_{j,t}^\theta$ varies between zero and one across industries before tax changes, and equal to one when bonus deprecation is 100%. Thus, industries with lower z_j^0 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_j^0. The most affected industries at the three-digit industry code level in our data are crop production (111), animal production

[15] 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_j^0, which measures the present value of depreciation deductions for the average asset in which industry j invests.

and aquaculture (112), and fabricated metal manufacturing (327). The least affected industries include specialty trade contractors (238), construction of buildings (236), and heavy and civil engineering construction (237). Consistent with Zwick and Mahon (2017), we use variation in the four-digit NAICS codes in our regression analyses.

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. We also use the price of old and new equipment as dependent variables that are defined in Section 4.2.

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 is 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 in the agriculture, construction, copier, lift truck, logging, machine tool, printing, trucking, and woodworking industries are processed.[16]

[16] 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.

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* 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 Section 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. 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 to show how equipment manufacturers use captive finance to maintain higher resale prices 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. Darmouni and Sutherland (2023) use EDA data to show how during COVID-pandemic the supply of fixed capital affects firm investment.

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 average (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 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 are \$4.383 million and \$2.463 million, respectively. The 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). Thereafter, we rule out alternative mechanisms using state-level variation in Section 179 (Section 4.5). After that, we document 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 access to small business credit and the market power of the equipment manufacturers (Section 4.3).

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

We start by providing 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 document the results for our baseline regression model (Section 4.1.2).

4.1.1 Graphical Evidence

We begin with a simplified setup to provide graphical intuition on the main results at the aggregated four-digit NAICS industry, county, and year levels. 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 equipment investment. This finding suggests that the industries in the treatment and control groups followed patterns consistent with parallel trends before the bonus depreciation schedule change. Next, we see a greater increase in new equipment investment for treated industries compared with the control group during the initial phase of bonus depreciation. However, surprisingly, we also notice 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 negligible increases 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 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 on 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). We can measure the change in investment composition with our data. 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)*). 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 (0.045×8.881). 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)–(4). We also include buyer fixed effects and buyer size-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 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.[17]

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.

b) Indirect Effect on 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.

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).

Notice that bonus depreciation is available only on new equipment during our sample period. Hence, one possible explanation for the spillover effect may arise due to a reduction in the price of old equipment. We discuss this mechanism in Section 4.2. Another

[17] This intensive margin semi-elasticity of investment is comparable and in fact larger compared to Zwick and Mahon (2017).

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 the states are more likely to adopt federal bonus depreciation policies (Section 4.5). Further, in Section 4.5, we exploit the state's conformity to Section 179 to provide additional insights on the alternative explanations.

4.2 Mechanism: Price of Old and New Equipment

So far, we observe a positive effect on new capital (direct effect) and used capital (indirect effect) investment with the introduction of tax subsidies on the purchase of 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 the 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.[18] For example, consider a 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,

[18] 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 the 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 Internet Appendix Section IA.1 for details.

they are not directly comparable. For example, we observe a strong negative relationship between equipment value and machine age (See Figure IA.I). 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 in a given county during each year We define *New Price Residual* and *Old Price Residual* 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 *New Price Residual* and *Old Price Residual* 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 long-duration treatment industries, compared to short-duration industries when bonus depreciation increases from zero 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,

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

where *Price* refers to *New Price Residual* or *Old Price Residual*. 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 3.8% (column (1): 0.045×0.838). 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.

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 prices.

4.3 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 4.3.1). Further, we test the impact of the market power of the equipment manufacturers on baseline results (Section 4.3.2).

4.3.1 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 Further, columns (1) and (2) of Table IV 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 $z^{\theta}_{j,t}\times$ *High SBA Loan*. 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.

4.3.2 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 V documents that there is a smaller decline in old equipment prices (Panel A) for industries where 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. Untabulated results documents that reallocation is more likely to occur within the same industry, between larger sellers and smaller buyers and between closely located buyers and sellers

4.4 Real Effects of Physical Capital Reallocation

Our results suggest that some firms increase investment in used equipment as a response to tax incentives on new equipment. However, given the granularity of our data, we can investigate if the used equipment purchases lead to the adoption of newer or older technology. It is important to know this because capital of older technology can adversely affect firm productivity and growth (Benhabib and Rustichini, 1991; Hsieh, 2001). We investigate for firms buying used machines, whether, there is any change in the used equipment's average machine age and technological (model) age (Section 4.4.1). Next, we test its real implication by testing if buying used equipment from the secondary market impacts small businesses' growth (Section 4.4.2). After that, we test in aggregate if the decline in the price of old equipment helps increase the small business entry rate (Section

4.4.3).

4.4.1 Do tax incentives help small businesses buy used machines with new technology?

One possible consequence of tax incentives can be that direct beneficiaries would sell existing machines that are relatively less dated. This will result in a steady increase in the supply of relatively newer vintage used machines. However this may not be the most obvious outcome. If the sellers are more likely to sell their most dated and old technology machines, we may observe an increase in the supply of older technology used equipment to be purchased by other small businesses. Hence, 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 $(= -3.554 \times 0.045)$ log points. 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 $(= -1.261 \times 0.045)$ log points. 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 to 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. Next, we examine the consequences of buying newer vintage machines on small business growth.

4.4.2 How does buying used machines with new technology impact firm growth?

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 Machine* (based on machine age) and *Newer Model* (based on model age) 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% ($e^{3.904\times0.045} = 1.192$). 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 How does the price of old equipment impact small business entry?

In the following analysis, we examine whether the reallocation of old capital via bonus depreciation would encourage the 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 entries 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 columns (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 10–19 employees by approximately 1.4% ($e^{0.307\times0.045} = 1.014$). 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, the machine age, and the 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 incremental effect of $z^{\theta}_{j,t}$ on *est5_9* (1% increase) and *est10_19* (1% increase) when ex-ante old equipment prices are above the median. The results are consistent with our expectations that tax incentives help new business entry, especially in industries and locations with a higher ex-ante relative price of old equipment.

4.5 Alternative Mechanism: 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.[19]

In the United States, firms file corporate taxes both at the federal and state level. When federal depreciation incentives are implemented, some states 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).[20] In this section, we test how our results vary based on states' conformity to bonus depreciation and Section 179. In addition, it also allows us to use industry-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 an indicator *Bonus State Conformity* 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* and $z^{\theta}_{j,t}$. Firstly, we find that the interaction effect of *Bonus State Conformity* and $z^{\theta}_{j,t}$ on new equipment purchase is positive and significant Table IX 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

[19] 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.

[20] For example, when bonus depreciation was first initiated, only 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, only 12 states fully adopted when bonus depreciation was reintroduced while five partially adopted the 50% rate (Ohrn, 2019).

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 of investment elasticity on used equipment in column (5) is 25.5% (= 0.53/2.08) for conformity states. This effect remains equally strong after adding industry-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* 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 X, Panel A. We see that the main effect on $z^{\theta}_{j,t}$ is negative and statistically significant. The coefficient on interaction term with *Sec179 State Conformity* 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 of $z^{\theta}_{j,t}$ on old equipment investment is positive and significant. However, the incremental effect of *Sec179 State Conformity* is very small and statistically insignificant.

These results from IX and Table X suggest that our main results are more likely to be driven by changes in bonus depreciation policies. We did additional robustness tests to further examine this alternate channel. 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 These results collectively suggest the importance of bonus depreciation in capital reallocation triggered by subsidizing new equipment purchases.

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 help reallocate old capital? For the two waves of bonus depreciation from 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 a novel mechanism through which depreciation policies benefit small businesses and help us uncover a more complete picture of such investment stimulus.

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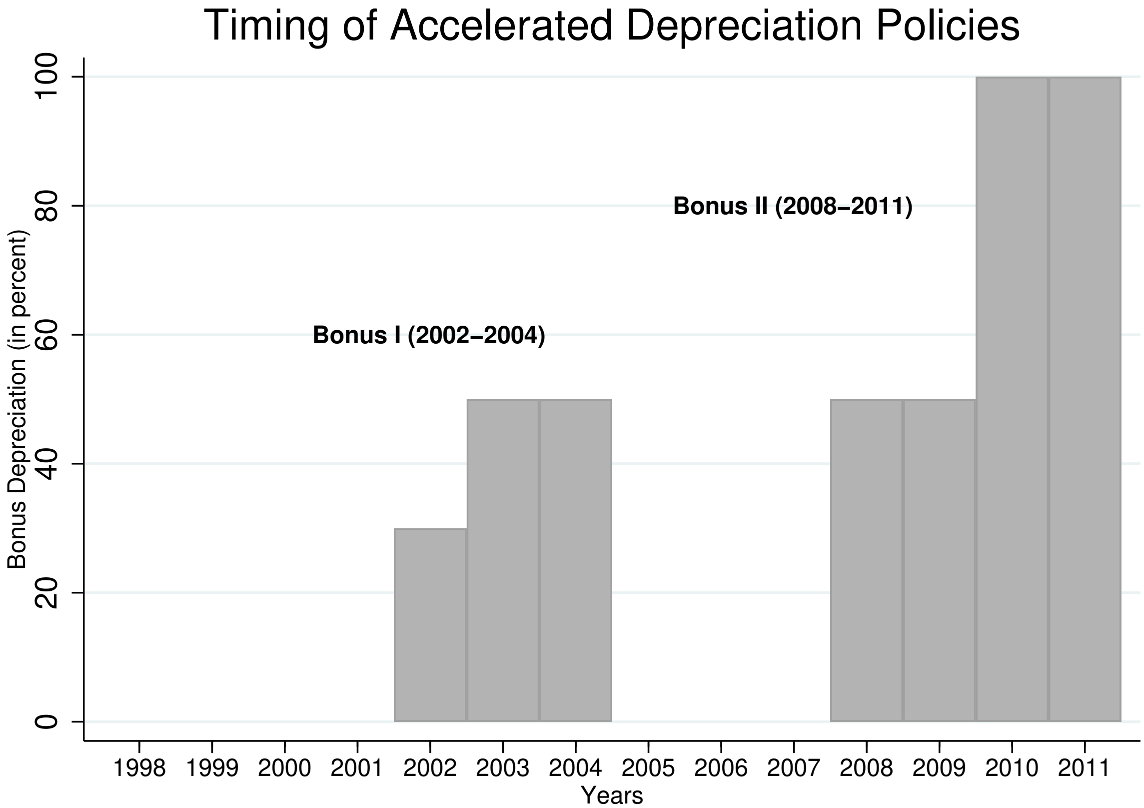

Figure I: This figure plots the depreciation deductions that are accelerated into the first year of the investment for the two episodes of bonus depreciation from 2001 to 2004 and 2008 to 2011. Starting in 2002, firms could immediately deduct 30% of the cost of qualifying investments. This was later 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.

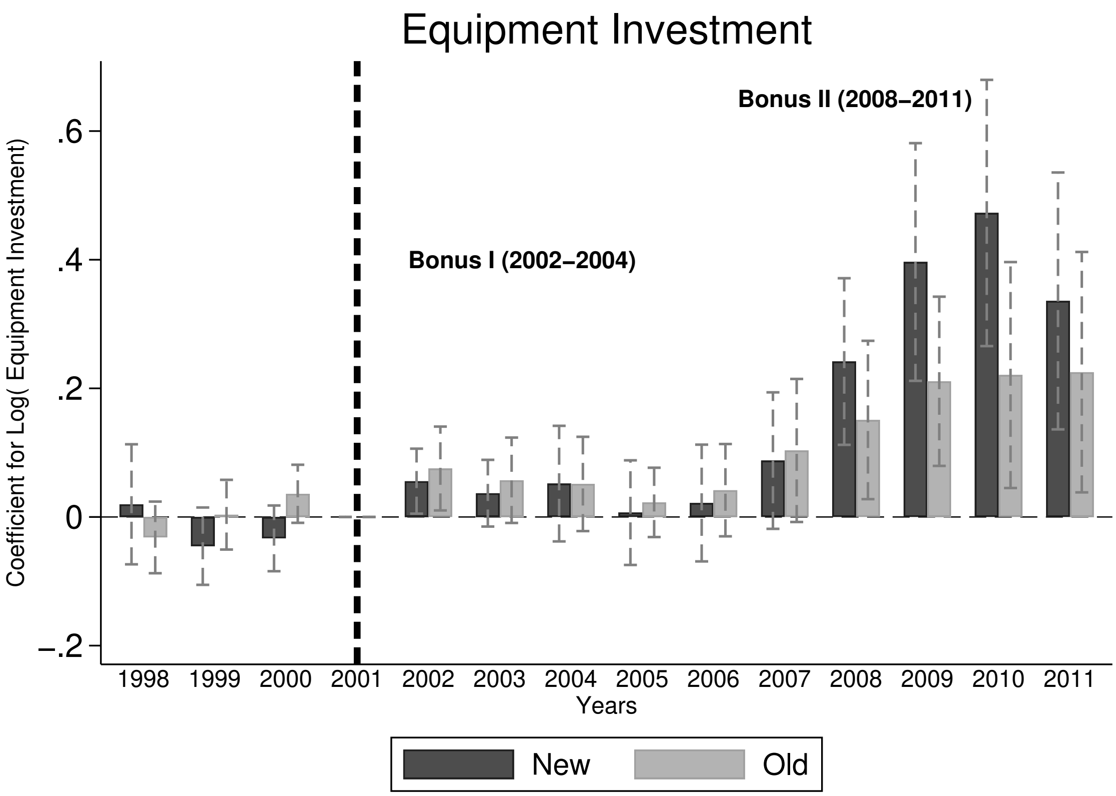

Figure II: New and Old Equipment Investment Elasticity: This figure plots regression estimates of difference-in-differences coefficients with their 95% confidence intervals for data aggregated at the four-digit NAICS industry-county-year level. We define the treatment indicator variable, $Treatment_j$, 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-year fixed effects ($\omega_{s,t}$), and state-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. Standard errors are clustered at the four-digit NAICS industry level.

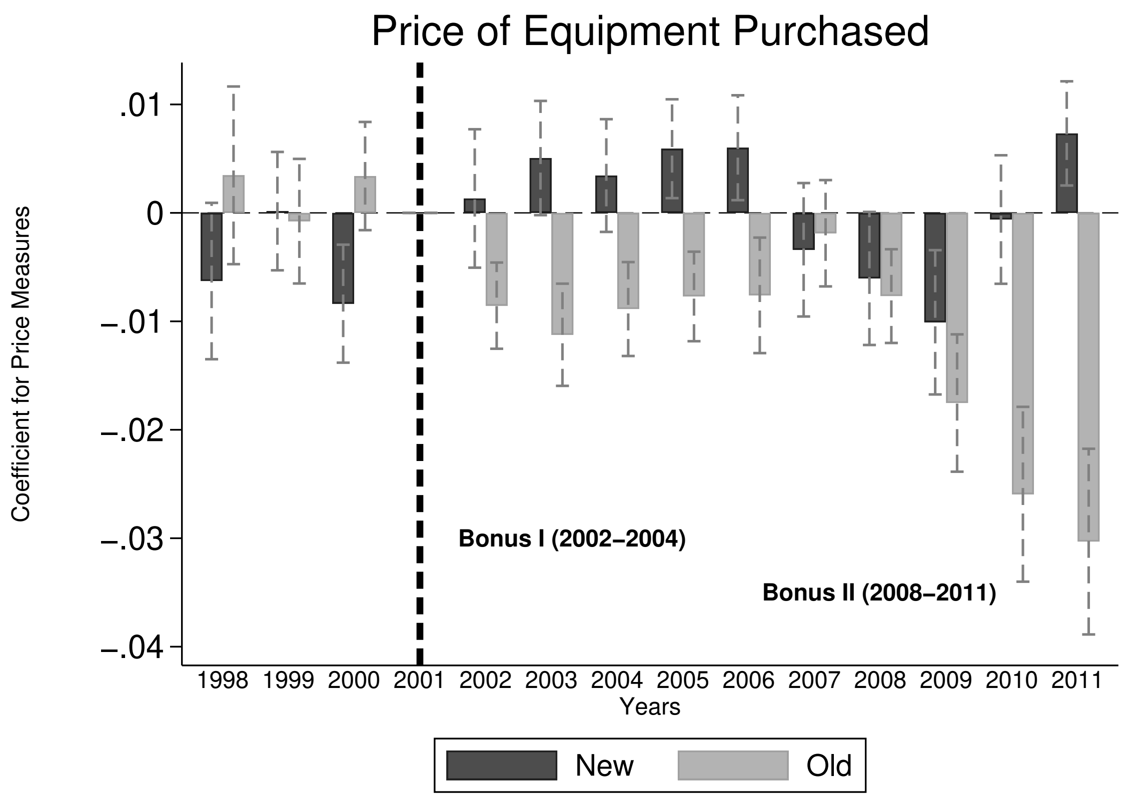

Figure III: **Price of Equipment Purchased:** This figure plots regression estimates of difference-in-differences coefficients with their 95% confidence intervals. The dependent variable is *New* (*Old*) *Price Residual*. We calculate the variable *New* (*Old*) *Price Residual* as the average residual 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. Standard errors are clustered at the four-digit NAICS industry level.

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: Investment Response to Bonus Depreciation

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) include buyer fixed effects. In all columns except column (4), we include buyer-level controls such as logged sales and logged employees. In column (4), we replace buyer controls with non-linear buyer size-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 by 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 × 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: Role of Access to Small Business Credit

This table reports the heterogeneity based on a buyer's access to small business finance. 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) 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 V: Market Power of Equipment Manufacturer

This table reports the heterogeneity based on a seller's market power. Market power is measured using *High HHI* 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* on the price of old equipment. All regressions include group fixed effects that consist of the *High HHI* dummy. Column (1) includes equipment, industry, and year fixed effects, column (2) adds county fixed effects, and column (3) adds sector trends. Panel B documents the cross-section effect on the elasticity of old equipment purchase. Column (1) includes industry and buyer size-year fixed effects. Column (2) adds sector trends and column (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)
$z^{\theta}_{j,t} \times$ *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)
$z^{\theta}_{j,t} \times$ *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 $\times$ Year Fixed Effects	Y	Y	Y
Industry Fixed Effects	Y	Y	
Sector Trends		Y	Y
Buyer Fixed Effects			Y

Table VI: Real Effect on Machine Age and Technology Adoption

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) include 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 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 Machine* (based on machine age) and *Newer Model* (based on model age) 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 Machine*. 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 Machine* (*Newer Model*) fixed effects. We also include buyer-level controls such as logged sales and logged employees in all columns. 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* $_{i,t+1}$	*Employment Growth* $_{i,t+1}$	*Sales Growth* $_{i,t+1}$	*Employment Growth* $_{i,t+1}$
Level: Buyer-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t} \times$ *Newer Machine*$_{i,t}$	1.630***	0.712***		
	(3.723)	(3.053)		
$z^{\theta}_{j,t} \times$ *Newer Model*$_{i,t}$			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 $\times$ 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 Num of Establishments with*			
	(5-9 Employees)		*(10-19 Employees)*	
Level: Industry-County-Year	(1)	(2)	(3)	(4)
$z^{\theta}_{j,t} \times$ *High Old Price Pre*		0.213**		0.210**
		(2.067)		(2.271)
High Old Price Pre		-0.184**		-0.181**
		(-2.024)		(-2.163)
$z^{\theta}_{j,t}$	0.298***	0.211*	0.307***	0.227*
	(2.751)	(1.860)	(2.717)	(1.947)
Observations	440,585	421,844	440,585	421,844
Clusters (Industry)	228	226	228	226
R^2	0.75	0.75	0.72	0.73
Sector Trends	Y	Y	Y	Y
Industry Fixed Effects	Y	Y	Y	Y
County $\times$ Year Fixed Effects	Y	Y	Y	Y

Table IX: State Conformity to Bonus Depreciation

This table reports the heterogeneity based on state adoption of bonus depreciation. *Bonus State Conformity* 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-year fixed effects. Column (3) adds buyer fixed effects while column (4) adds industry-year fixed effects in addition to the fixed effects in column (3). Finally, column (5) includes buyer fixed effects, buyer size-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-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			
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 X: State Conformity to Section 179 deduction

This table reports the heterogeneity based on state adoption of Section 179. *Sec179 State Conformity* 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 the states' Section 179 conformity on the price of old equipment. All regressions include group fixed effects that consist of the Section 179 state conformity dummy. Column (1) reports the effect on old equipment price with group fixed effects, 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 the 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-year fixed effects. Column (3) adds buyer fixed effects while column (4) adds industry-year fixed effects in addition to the fixed effects in column (3). Finally, column (5) includes buyer fixed effects, buyer size-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-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			
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

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 equipment value with respect to the machine age in Figure IA.I. We observe a negative relationship between equipment value and machine 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. We find similar trends over time across both data, which suggests that equipment transactions covered in EDA data do not substantially bias our results.

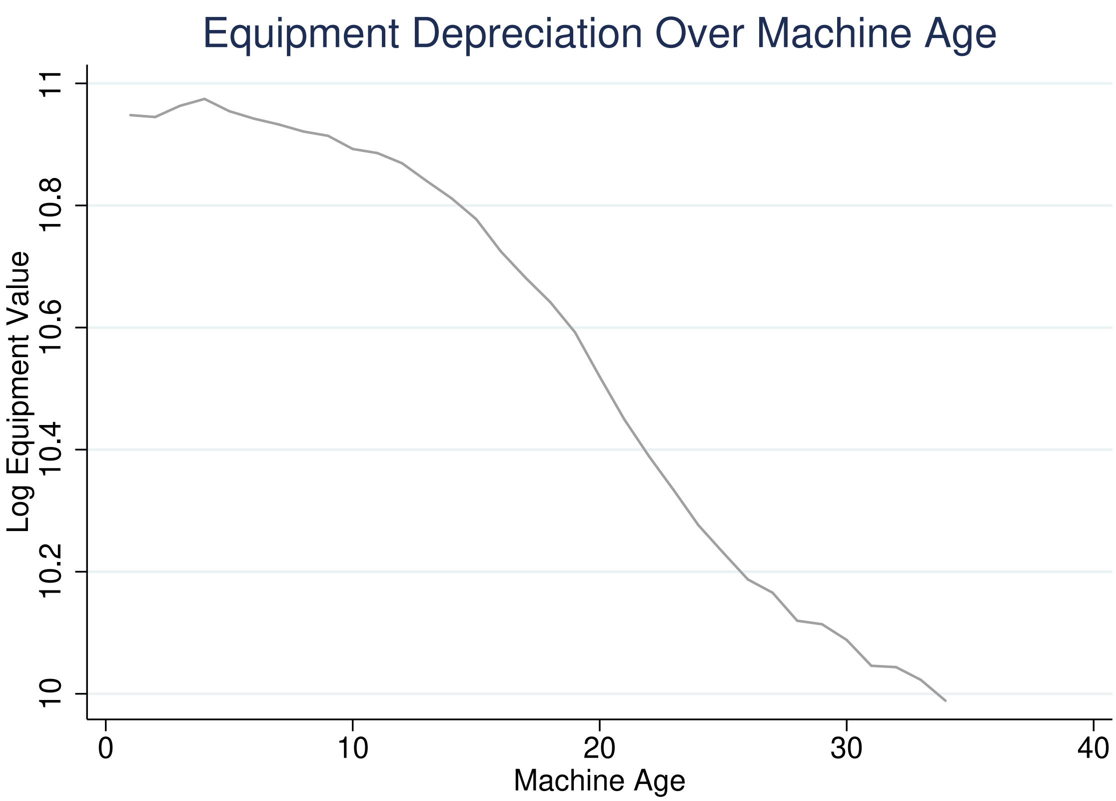

Figure IA.I: Equipment Depreciation: This figure plots the relationship between the logarithm of equipment value and the machine age.

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
424	Merchant Wholesalers, Non-durable Goods
	Less Affected
238	Specialty Trade Contractors
236	Construction of Buildings
237	Heavy and Civil Engineering Construction
561	Administrative and Support Services
541	Professional, Scientific, and Technical 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 the state that conforms 100% to federal Section 179 policy	Constructed
$\mathbb{1}\,(New)$	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 the 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 Machine (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 Num 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
$\mathbb{1}\,(New)$	0.449	0.497	0