The Indirect Effect of Investment-based Tax Policy on Innovation Efforts

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Abstract

This study examines how tax-induced temporary demand surges influence the *composition* of innovation efforts among capital-goods producing firms. Exploiting a difference-in-differences design around the initial wave of U.S. bonus depreciation, I find that affected firms that capitalize on the temporary demand surges induced by the investment-based tax policy (bonus depreciation) file fewer patents, increase incremental innovation, and reduce radical innovation relative to unaffected firms. Furthermore, the distortion is more pronounced among downstream firms, which shift toward incremental and away from radical innovation, whereas firms with greater product market power increase incremental innovation without reducing radical innovation efforts. The results provide novel evidence of an indirect channel through which investment-based tax policies shape knowledge accumulation and technological progress, underscoring the importance of considering innovation outcomes when evaluating such policies. These findings offer valuable insights for policymakers when considering the implications of government efforts to direct investment through tax or other policies.

Keywords: Investment-based tax policy; bonus depreciation; research and development; Innovation; radical innovation; incremental innovation

JEL Classification: D21, D22, D24, D25, G38, H23, H25, H32

Data availability: Data in this study are obtained from public sources as identified in the paper.

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1. Introduction

This paper studies an indirect effect of investment-based tax policy—designed to encourage taxpayers to increase capital investment—on the innovation efforts of capital-goods producing firms. Investment-based tax policies such as bonus depreciation, which allows eligible taxpayers to accelerate depreciation for tax purposes and thereby generate immediate or future cash flows upon purchasing qualified property, are commonly implemented during economic downturns to spur economic growth. However, the long-run growth effects of such tax policies are unclear, as they depend not only on the magnitude of tax savings but also on how firms reallocate resources in response to the tax break (Slemrod, 2003). By directly lowering the after-tax cost of qualified capital investments, bonus depreciation stimulates demand for these assets (Landis, 2004). As knowledge accumulation is a key source of sustained growth, understanding how and to what extent capital-goods producing firms reallocate their innovation efforts to meet this tax-induced demand surge has critical implications for economic growth. I investigate this dynamic by examining how capital-goods producing firms adjust the *composition* of innovation efforts in response to temporary demand surges induced by the initial bonus depreciation tax incentives.[1]

The introduction of bonus depreciation in the 2000s lowered the after-tax cost of capital property and substantially incentivized taxpayers to increase capital investment (Edgerton, 2010; House & Shapiro, 2008; Zwick & Mahon, 2017). This investment response increased demand for capital-goods producing firms that manufacture qualified property. Given the repeated adoption of bonus depreciation in the U.S. after the 2000s and the recent global implementation as a short-

[1] Bonus depreciation tax incentives were initially introduced as a temporary economic stimulus in the 2000s. Temporary bonus depreciation tax incentives likely induce short-term positive demand surges for qualified investments. Even though bonus depreciation incentives were extended several times in the 2010s, the temporary nature remained. OBBBA has now reinstated 100% bonus depreciation permanently. However, the focus of this study is on the initial wave of temporary incentives.

term economic stimulus during the COVID-19 pandemic, understanding the indirect link between capital-investment-oriented tax incentive policy and innovation is essential for evaluating the growth effects of these policies.

Drawing on Schmookler's (1966) view of invention as a profit-driven activity, I argue that the temporary demand surge induced by bonus depreciation could alter the balance of risk and reward for both short- and long-term innovation and, in turn, affect the *composition* of innovation efforts among capital-goods producing firms. I derive two testable predictions. I predict that the affected capital-goods producing firms are likely to allocate operating resources away from patented innovation to meet the temporary demand surge on existing products induced by bonus depreciation. This reduction in patented innovation should be more pronounced among resource-constrained firms, which face greater challenges in balancing the modification of existing products with the development of next-generation innovations. Moreover, I predict that the affected capital-goods producing firms are more likely to shift resources toward incremental innovation and away from radical innovation, as incremental innovation is better positioned to deliver immediate gains from the bonus-depreciation–induced sales surge of existing products. However, greater reliance on incremental innovation diverts resources from breakthrough-oriented radical innovation, thereby slowing the outward expansion of the knowledge frontier. Since radical innovation accounts for over half of economic growth, reallocating resources between these types of innovation profoundly impacts technological progress and long-run growth (Acemoglu et al., 2022; Akcigit & Kerr, 2018).

To empirically test these predictions, I identify capital-goods producing firms using the U.S. Bureau of Economic Analysis (BEA) National Income and Product Accounts (NIPA) tables. U.S. taxpayers who generate business income (primarily corporations), rather than individual consumers, are eligible to claim bonus depreciation upon the acquisition of qualified property when the bonus depreciation tax incentives are in effect. Capital-goods producing firms in industries with the highest value added to investment final demand are most likely to serve corporate customers that utilize such tax incentives.[2] Therefore, I assign firms in these industries to the treated group and label them as business-to-business (B2B) capital-goods producing firms. Firms in the rest of industries with a non-zero value added to the investment final demand that also appear in the personal consumption expenditure (PCE) final demand should be less exposed to the demand surge induced by bonus depreciation because individual consumers are unlikely to change purchase behavior during the incentive periods. I assign these firms to the control group and label them as business-to-consumer (B2C) capital-goods producing firms.[3]

To examine the indirect effect of bonus depreciation on the *composition* of innovation efforts, I focus on patent-based innovation measures and decompose patented innovation efforts into radical and incremental components (Balsmeier et al., 2017; Goldman et al., 2024; Hall et al., 2001). While both types of innovation efforts are vital to economic growth, radical innovation plays a particularly pivotal role by spawning new technological clusters and laying the groundwork for successive advancements (Acemoglu et al., 2022; Akcigit & Kerr, 2018). When confronted with an inelastic supply of innovation resources, firms may prioritize leveraging existing innovation capabilities over exploring new opportunities in response to a demand surge induced by bonus depreciation. I predict and find that B2B capital-goods producing firms are more likely to increase incremental and product innovation while reducing radical innovation. This pattern suggests that the distortion of innovation efforts toward the exploitation of existing capability

[2] Consistent with the post-1997 NIPA tables, I identify the related industry using the NAICS industry classification.
[3] For clarification and brevity, B2B capital-goods-producing firms (or B2B firms) and B2C capital-goods-producing firms (or B2C firms), as well as treated (control) firms, are used interchangeably. The identification strategy and its validation analysis are detailed in Section 4.1.

partially crowds out the exploration of new opportunities and potentially hinders long-term technological advancement.

Next, I explore the heterogeneity in the indirect effect of bonus depreciation on innovation efforts. The empirical evidence indicates that the distortion toward incremental innovation and away from radical innovation is closely linked to the degree of exposure to bonus-depreciation-induced demand surges. In particular, the distortion toward incremental innovation is more pronounced among B2B firms that operate closer to final demand along the supply chain and possess greater product market power. While the tax-induced demand surge generally incentivizes firms to allocate innovation efforts toward incremental innovation at the expense of radical innovation, the presence of greater product market power and the associated monopoly rights partially offset this disincentive to engage in radical innovation. Together, these findings help substantiate the mechanisms underlying the indirect effect of bonus depreciation on the reallocation of innovation efforts among capital-goods producing firms.

I perform a battery of additional tests centered on the initial wave of bonus depreciation. First, I provide additional insights into the reallocation of innovation efforts by employing a range of alternative innovation measures. To better understand the implications for technological progress, I conduct patent-level analyses that document a decline in scientific value associated with the distortion of innovation efforts away from radical innovation following the implementation of bonus depreciation. Second, I expand the U.S. sample to include global capital-goods producing firms and employ an alternative control group to alleviate concerns about divergent innovation trajectories between treated and control groups. Third, to rule out confounding effects driven by heterogeneous firm characteristics, I construct a within-industry matched sample. Finally, I include industry-wide import penetration and firm-specific tax loss status as additional controls for factors that may influence innovation efforts. Across all specifications, my primary inferences remain unchanged.

This paper makes several contributions. First, it contributes to the literature on the real effects of tax policy. Specifically, my study documents a change in the *composition* of innovation efforts among capital-goods producing firms following a temporary tax-induced demand surge. By highlighting the reallocation of innovation efforts toward incremental and away from radical innovation in response to demand surges induced by bonus depreciation, this study advances our understanding of the indirect channels through which capital-oriented investment-based tax policy influences the trajectory of commercial innovation. In doing so, this paper speaks directly to the existing research agenda by providing empirical evidence on the broader economic implications of tax policy (Blouin, 2025; Jacob, 2022; Lester & Olbert, 2025). Moreover, this study extends the literature on the indirect effects of tax policy by moving beyond the role of taxes in shaping competition (Donohoe et al., 2022; Glaeser et al., 2023; Kim et al., 2021).

Second, this study provides valuable insights for policymakers designing future tax policies and for global capital market participants dedicated to long-run value creation. By analyzing the compositional changes in innovation efforts, this study demonstrates that well-intentioned investment-based tax policies can inadvertently distort the technological paths of capital-goods producing firms and redirect innovation efforts away from frontier technological development. In addition, bonus depreciation is likely to be a popular pro-growth tax instrument under the upcoming OECD Pillar Two global minimum corporate tax regime, as such tax incentives are treated as a deferred tax liability without triggering an immediate minimum tax liability. Taken together, the results highlight how capital-oriented investment-based tax policies can shape the direction of technological change, emphasizing the critical need to incorporate technology dynamics when evaluating the growth effects of investment-based tax policies that aim to promote tangible capital investments (Acemoglu, 2009; Aghion & Howitt, 1992; Romer, 1990).

Finally, this paper connects to extensive work examining how changes in product demand influence investments in innovation (Acemoglu & Linn, 2004; Finkelstein, 2004; Krieger et al., 2022; Schmookler, 1966). My findings reveal a systematic shift toward exploitative (or incremental) innovation efforts and away from exploratory (or radical) innovation efforts within a group of capital-goods producing firms, a shift heavily influenced by investment-based tax policy. This study not only confirms the innovation distortions predicted by the endogenous technology growth model (Romer, 1990), but also underscores the need for a closer examination of how these distortions influence the direction of technological change (Acemoglu, 2023). The findings provide essential empirical evidence for assessing the welfare implications of investment-based tax policy, and reinforce the importance of government intervention in promoting socially desirable innovation (Arrow, 1962; Bryan & Williams, 2021; Howell, 2024; Nelson, 1959).

2. Background of Bonus Depreciation Tax Incentives

Bonus depreciation was first introduced in the U.S. in 2001. On March 9, 2002, President Bush signed the Job Creation and Worker Assistance Act (JCWAA 2002) into law. The first provision allows for an additional 30 percent depreciation allowance for tax purposes for certain types of business investments, primarily new equipment and machinery with a recovery period of 20 years or less. In 2003, the bonus depreciation rate was further increased from 30 to 50 percent by the Jobs and Growth Tax Relief Reconciliation Act (JGTRRA 2003). To be eligible for bonus depreciation, taxpayers must have purchased qualified property that was placed in service after September 11, 2001, and prior to January 1, 2005, for business purposes. This first wave of bonus depreciation was intended to be temporary, as the Bush Administration argued that the temporary deficits due to tax cuts could be offset by future budget surpluses (Gale & Orszag, 2004).

In subsequent years, bonus depreciation schemes were repeatedly implemented and extended under various presidential administrations. Although designed as a temporary tax instrument, these repeated extensions have likely led tax professionals to perceive later iterations of bonus depreciation as increasingly permanent (Jackson & Pippin, 2013). Appendix 2 illustrates the initial implementation and the associated extensions of bonus depreciation up to 2025. More recently, the One Big Beautiful Bill Act (OBBBA) permanently implemented 100% bonus depreciation for qualified property acquired after January 19, 2025.

This study focuses on the first two waves of the bonus depreciation incentive periods. These two waves of implementation (2002–2004 and 2008–2012) were not accompanied by other major changes in innovation-related tax policies, allowing for sharper identification.[4] The temporary nature of the first bonus depreciation period likely generated a stronger demand surge for suppliers of qualified capital goods, while the relatively less temporary nature of the second bonus depreciation period provides an opportunity to examine whether the temporary aspect of bonus depreciation moderates its indirect effect on the innovation efforts of capital-goods producing firms. For these reasons, I focus the empirical analyses on the pre-2014 bonus depreciation periods to best isolate the indirect effect of bonus depreciation on innovation efforts among capital-goods producing firms.

While forms of bonus depreciation tax incentives have existed in Europe since the 1940s, the U.S. was a key innovator in formalizing them into modern tax policy.[5] What began as a U.S.

[4] Post-2014 extensions coincide with several confounding provisions, such as the 2015 PATH Act—which made R&D tax credits permanent and allowed them to offset alternative minimum tax (AMT) liabilities—and the 2017 TCJA's sweeping corporate tax cuts and international tax reforms. The overlap of these policies complicates efforts to isolate the effects of bonus depreciation alone in later periods.

[5] Some European countries had similar concepts earlier to encourage investment. For example, Germany implemented accelerated depreciation after the World War II. The UK also allowed accelerated depreciation in the 1940s. In addition, U.S. bonus depreciation is a broad-based tax incentive rather than an industrial policy: it applies uniformly

policy innovation has evolved into a global phenomenon, especially during the recent global pandemic.[6] In the international tax landscape, bonus depreciation is expected to be used increasingly as a pro-growth tax policy in the upcoming OECD Pillar Two Global Minimum Tax regimes. Since bonus depreciation triggers temporary book-to-tax differences, which are recognized as deferred tax liabilities under Pillar Two, it is unlikely to erode the tax base or trigger an immediate minimum tax liability for minimum tax purposes (KPMG, 2025). Consequently, this study also relates to a timely policy discussion around the rising global implementation of bonus depreciation tax incentives in response to the Pillar Two minimum tax regime (Baert, 2023; OECD, 2024).

3. Related Literature and Hypothesis Development

3.1. Investment-based Tax Policy: Bonus Depreciation

Since its introduction in the U.S., bonus depreciation has garnered significant attention from scholars and policymakers who are eager to understand its policy implications. House and Shapiro (2008) document a notable surge in capital investment in response to bonus depreciation. Importantly, they find no evidence that bonus depreciation incentives drive up the price of qualified property. Put differently, the surge in capital investments is driven by the quantity effect but not masked by the price effect. Edgerton (2010) finds that investment responses are stronger among firms with higher cash flows. Subsequently, Zwick and Mahon (2017) refine semi-elasticity estimates, uncover heterogeneity in investment responses to bonus depreciation based on the durability of qualified property, and document particularly strong investment responses among small firms. In contrast to earlier studies that utilize cross-industry variation, Ohrn (2019)

across industries and does not target specific sectors. Only bonus depreciation tax incentives that are not industry-specific fall within the scope of this study.

[6] For the summary of the implementation of bonus depreciation outside U.S., see tax summary website maintained by PWC at https://taxsummaries.pwc.com/united-states/corporate/taxes-on-corporate-income.

reinforces the significant impact of bonus depreciation on investment by exploiting the staggered adoption of bonus depreciation across states as a natural experiment.

Prior research on bonus depreciation provides reasons to believe that this tax incentive is likely to trigger demand surges among capital-goods producing firms. As such, these firms are well positioned to capture a substantial share of the associated economic gains. As Slemrod (2003) emphasizes, "*How government activity affects prosperity depends not only on the level of taxes, but also on what the money is used for.*" This insight highlights the need for further research on the growth effects of tax policy, particularly from the lens of the capital-goods producing firms that are in a favorable position to benefit economically from the bonus depreciation tax incentives.

Furthermore, the private sector, especially the capital-goods producing sector, plays a central role in shaping the trajectory of innovation.[7] Using U.S. Census Bureau microdata, Bessen and Wang (2024) demonstrate that R&D activity is highly concentrated within large firms employing more than 1,000 individuals, including capital-goods producing firms. These organizations function as primary vehicles for national technological advancement. In addition, the capital goods they manufacture serve as a conduit for technology transfer; by integrating sophisticated technology into physical equipment, they lower the barriers to technology adoption and stimulate productivity growth in downstream manufacturing industries.

3.2. Indirect Effect of Tax Policy

Firms' responses to tax policy can generate significant spillover effects. Prior research has attempted to explore the indirect effects of changes in tax burden among peer firms' financial performance through shifts in focal firms' competitive position (e.g., see the review by Lester &

[7] Commercial innovation is the backbone of U.S. R&D. According to the National Science Foundation, since 1964, federally funded R&D has declined, while total R&D expenditures as a share of GDP have risen over time. By 2020, U.S. business accounted for 73% of domestic R&D spending. See the full article at https://ncses.nsf.gov/pubs/nsf23339.

Olbert, 2025). Kim et al. (2021) find that U.S. domestic firms experience a decline in market power when foreign competitors benefit from tax cuts in their home countries. In response to heightened competition induced by foreign tax cuts, U.S. domestic firms increase R&D and capital investment to maintain their product market competitiveness. Conversely, Glaeser et al. (2023) show that import penetration driven by corporate income tax competition negatively affects domestic employment. In addition, Donohoe et al. (2022) find that heterogeneity in tax windfall due to the American Jobs Creation Act of 2004 (AJCA) repatriation tax holiday reshapes the competitive dynamics among product market rivals, with firms that do not benefit from the repatriation tax holiday more likely to be forced out of the market. While these studies highlight the competitive channel of indirect effects, our understanding of the full scope of the indirect impacts of tax policy remains limited.

Tax policy shapes the broader economy by shifting demand for goods and services, which in turn indirectly affects the suppliers' operational and investment behavior. In response to bonus depreciation incentives, corporate taxpayers increase capital expenditures, which in turn raises demand for suppliers of qualified property and induces additional investment by those suppliers. While the demand-side tax incentives on consumers are often temporary, their indirect impact on suppliers' future spending and resource allocation can have longer-term consequences. In addition, as innovation is viewed as the DNA of most firms, it is unclear how firms allocate innovation efforts (Aaker, 2007). This study examines an understudied dimension of tax policy: how bonus depreciation tax incentives affect demand for capital goods and, consequently, influence the *composition* of innovation efforts among capital-goods producing firms.

3.3. Indirect Effect of Tax Policy: Induced Innovation

As bonus depreciation promotes capital investment in qualified property, the resulting tax-induced demand surge indirectly increases the utilization of existing technologies and distorts incentives to innovate and develop new technologies. In his seminal work, Schmookler (1966) empirically demonstrates with evidence drawn from the railroad industry that market demand and profit orientation are critical drivers of innovation. His analysis reveals that patent filings for railroad technologies increase significantly following expansions in track mileage, strongly suggesting that innovation responds to market-driven needs. Empirical evidence consistently demonstrates the market-size effect on innovation, with particularly ample evidence in the healthcare sector. Public health insurance policies that expand vaccination programs and prescription drug coverage directly increase the demand for related medical products, creating strong innovation incentives (Acemoglu & Linn, 2004; Finkelstein, 2004; Krieger et al., 2022). On the one hand, unlike mission-driven healthcare policy that durably expands the drug market and influences future novel drugs and therapies, investment-based tax policy may trigger only transient demand surges for capital goods, without explicitly stated mission-oriented goals for directing technological trajectories. On the other hand, because pharmaceutical firms operate in markets where appropriability hinges on patent protection and regulatory exclusivity, they have strong incentives to seek patents immediately to deter future competition, whereas capital-goods producers—facing weaker appropriability and more customization—may prioritize incremental, often non-patented and non-technological product innovation. As a result, the effect of temporary tax-induced demand surges on patented innovation remains highly unpredictable.

As bonus depreciation increases demand for qualified property, the affected capital-goods producing firms temporarily reallocate resources to meet the surge in demand for existing products. Such transient tax incentives are likely to accelerate capital purchases during incentive periods and increase the utilization of incumbent machinery and equipment, thereby encouraging those capital-goods producing firms to address issues within their existing product portfolio. Consequently, the affected capital-goods producing firms have a stronger incentive to capitalize on the temporary demand surge by shifting innovation efforts toward incremental product improvements that enhance existing product quality. This reallocation of innovation efforts may temporarily dampen patented innovation efforts. This discussion leads to the first hypothesis in an alternative form.

H1: *Capital-goods producing firms that benefit from tax-induced demand surges are more likely to reduce patented innovation efforts than control firms following the implementation of bonus depreciation.*

Even when capital-goods producing firms divert resources to enhance the existing product portfolio, they may still maintain or even increase patented innovation efforts for two reasons. First, product innovation and patented innovation are not mutually exclusive; accordingly, capital-goods producing firms may continue to pursue patented innovation alongside efforts to improve existing products. Second, affected capital-goods producing firms may have strong incentives to secure patent protection for product innovation given that the risk of business stealing or appropriation following the key employee departures is high, as such downside risk can reduce the return from non-patented product innovation activity.

3.4. Indirect Effect of Tax Policy: Reallocation of Innovation Effort

While markets are commonly seen as the ideal mechanism for allocating resources, the persistent misalignment between private incentives and societal goals can systematically distort the direction of both cutting-edge innovation pathways and the trajectories of proven technologies (Acemoglu, 2023; Arrow, 1962). The transient nature of bonus depreciation tax incentives creates a compressed timeline (typically 1-2 years) during which for-profit business taxpayers can execute investments in qualified property. This temporal constraint inherently favors the utilization of existing, proven technologies rather than the development of breakthrough innovations. Since bonus-depreciation-induced purchases disproportionately reward incumbent solutions that can be rapidly deployed, the policy reinforces existing production networks, increases returns to scale for established technologies, and creates disincentives for developing alternative solutions. The reinforcing feedback loop may exacerbate path dependence and technological lock-in (David, 1985). While this distortion may generate short-term efficiency gains for capital-goods producing firms, it risks compromising long-term technological development and knowledge creation. The compressed investment window makes radical technologies requiring longer development cycles particularly disadvantaged, potentially stifling innovation in precisely those areas where breakthrough advances are most needed.

However, capital-goods producing firms may exhibit no inherent bias toward incremental innovation, even amid demand surges driven by bonus depreciation tax incentives. First, the bonus depreciation tax policy enhances and broadens capital-goods producing firms' sales network by stimulating capital equipment purchases. The resulting purchasing and bargaining processes provide valuable market intelligence, allowing those firms to gain deeper insights into their clients' operational requirements and production challenges, benchmark competitors' technological capabilities, and identify opportunities to upgrade existing solutions. Additionally, this demand stimulus creates incentives for capital-goods producing firms to develop novel solutions addressing previously unmet needs and tailor offerings to niche market segments. Therefore, whether the demand induced by bonus depreciation ultimately promotes radical or incremental innovation remains an empirical question.

Nevertheless, exposure to bonus-depreciation-induced demand surges likely shifts capital-goods-producing firms' innovation efforts toward incremental rather than radical innovation projects. This anticipated behavioral response leads to the following hypotheses, stated in an alternative form:

H2a: *Capital-goods producing firms that benefit from tax-induced demand surges are more likely to increase incremental innovation efforts than control firms following the implementation of bonus depreciation.*

H2b: *Capital-goods producing firms that benefit from tax-induced demand surges are more likely to reduce radical innovation efforts than control firms following the implementation of bonus depreciation.*

4. Research Design

4.1. Identification Strategy

My empirical analyses investigate how demand surges induced by bonus depreciation affect the innovation efforts within capital-goods producing firms supplying qualified property. Because bonus depreciation applies only to corporations—not individual consumers—firms serving business clients are likely to experience a stronger positive impact from the resulting sales surges than those oriented toward individual consumers. Following prior research (Gomes et al., 2009; Papanikolaou, 2011), I identify capital-goods producing firms using the U.S. BEA NIPA tables, which classify industries by their contribution to final demand based on the North American Industry Classification System (NAICS). Specifically, I use 2000-2001 NIPA for two years immediately preceding the first wave of the bonus depreciation incentive period to identify treated and control groups. To focus exclusively on capital-goods producing firms, I exclude industries that do not contribute to the investment final demand.[8]

[8]According to the NIPA table, the industries producing defense goods contribute to the government final demand. Therefore, my identification strategy targeting capital-goods producing firms should provide a clean measure for B2B capital-goods producing firms. The observed demand surge is likely attributable to bonus depreciation tax incentives, rather than government procurement of defense goods. This approach helps alleviate concerns that government

I classify firms in industries contributing the most value to investment final demand as business-to-business (B2B) capital-goods producing firms, and firms in the remaining industries that contribute non-zero value to personal consumption expenditure (PCE) final demand as business-to-consumer (B2C) capital-goods producing firms. Consistent with the existing literature, I exclude the retail and financial sectors from the empirical analysis (Gomes et al., 2009; Papanikolaou, 2011). Given the differential eligibility for bonus depreciation, I expect that B2B capital-goods producing firms benefit more from the tax-induced demand surges than B2C capital-goods producing firms. To further test the research question, I construct an indicator variable, $TREAT_i$, equal to 1 for firms classified as B2B capital-goods producing firms, and 0 for firms classified as B2C capital-goods producing firms.

If the identification strategy is valid, assuming the stock market is at least semi-efficient, the wealth effect of the bonus depreciation tax incentives should be reflected in the security price under the rational expectation hypothesis (Schwert, 1981). Given the relative stability of product portfolios in the short term, investors' foresight of the bonus-depreciation induced value implication is likely to be intensified during the legislative process of these related tax acts. If investors anticipate that capital-goods producing firms will benefit disproportionately from the demand surges induced by bonus depreciation tax incentives, I expect to observe positive market reactions to key legislative events that implement these tax provisions. Moreover, to the extent that bonus depreciation stimulates demand for qualifying property, capital-goods producers with greater exposure to these tax-induced demand surges should experience significantly higher sales, accompanied by corresponding increases in the cost of goods sold. While I expect all capital-goods producing firms to leverage the bonus depreciation tax incentive to increase their own capital

defense spending may confound the analysis, particularly given the post-bonus depreciation periods coinciding with the 9/11 terrorist attack.

expenditures, I do not anticipate systematic differences in investment behavior between B2B and B2C firms during the bonus depreciation incentive period. Accordingly, the demand surges—rather than idiosyncratic differences in tangible or intangible investment—should serve as the primary mechanism driving innovation efforts following the bonus depreciation period.

Although the investors' perceptions of the value implications of bonus depreciation among capital-goods producing firms are ex-ante unobservable, I analyze conference call transcripts from FactSet to identify discussions of bonus-depreciation-induced demand surges. Specifically, I search for the term "bonus depreciation" and manually review transcripts to determine whether managers or financial analysts mention or discuss the extent to which these tax incentives may affect future sales. Despite the limited availability of pre-2004 conference call transcripts in the existing commercial databases, the anecdotal evidence provides a clear signal: investors anticipated sales growth among capital-goods producing firms that benefit from bonus-depreciation-induced demand surges, although the affected firms lacked precise knowledge of the magnitude of this growth.[9]

Table 2, Panels A and B, present the empirical validation of the identification strategy. Specifically, for the market reaction validation test, I identify all the key legislative events leading up to the passage of each tax act that encompasses bonus depreciation provisions and calculate the 3-day cumulative abnormal return (CAR) around the two legislative events (JCWAA2002 and JGTRRA 2003) using firms' cumulative return less the value-weighted return of S&P 500 over the

[9] Coverage of conference call transcripts in existing commercial databases is very limited before 2004; I therefore present an illustrative example. According to the Raytheon Co.' conference call on April 29, 2004, George Shapiro (financial analyst) asked about the expectation of future sales, "And then one last one for Jim, Jim, is there any way for you to tell how much of a benefit the general aviation business is getting this year from the tax benefit, and in turn does that suggest that the next year is running a little weaker at this point, or it's kind of too early to tell or running about what you'd expect?" Raytheon's executive responded, "…so, it's a kind of mixed benefit and I, it's real, real hard to put math to it because when someday buys an airplane is it because they have the bonus depreciation or not, I really don't know, it's tough for anybody I think to say that, its having a great effect on any particular sale."

event window. Appendix 3 lists all related legislative events for each tax act encompassing bonus depreciation provisions. For brevity, I aggregate the 3-day CARs for each firm across all legislative events for each act.

Table 2, Panel A(a) presents the market response of B2B firms to all key legislative events for each legislated act. The results show significant positive abnormal returns of 2.4% and 4.5% for JCWAA2002 and JGTRRA2003, respectively (t-statistics =5.104 and 7.435). These findings suggest that investors anticipate the substantial value gain for B2B capital-goods producing firms upon the passage of the two acts. Panel A(b) reports the market reaction of B2C firms to the same legislative events. While the reaction is also positive (t-statistics = 1.745 and 3.210), the magnitude of the abnormal returns is smaller, at 0.9% and 2.7%, respectively. Panel A(c) shows the difference in market reaction between the two types of firms, with B2B firms exhibiting more positive market reaction in both acts than B2C firms (t-statistics =1.731 and 1.721). Overall, these results suggest that a larger share of the perceived value associated with the bonus depreciation is likely to accrue to B2B firms following the implementation of bonus depreciation.

Table 2, Panel B presents the validation tests for incremental sales, cost of goods sold, capital, and R&D expenditures during the initial bonus depreciation period. Consistent with my expectations, B2B firms exhibit significantly higher sales and cost of goods sold relative to control firms. Notably, however, there is no corresponding divergence in capital or R&D expenditures, suggesting that the observed treatment effects are driven by tax-induced demand surges.

4.2. Key Dependent Variable: Innovation Proxy

To ensure a robust assessment of innovation efforts, I focus on patent-based innovation measures supplemented with a variety of alternative output-based innovation measures.[10] I first

[10] This analysis relies on output-based innovation measures for three reasons. First, input-based metrics like R&D expenditure often mask the underlying shift in innovation efforts (e.g., inventors' time and effort) since many inputs

measure patented innovation efforts ($PAT_{i,t+1}$) by counting the total number of newly filed patents that are ultimately granted (Fang et al., 2014; He & Tian, 2013; Li et al., 2021; Williams & Williams, 2021).[11]

To measure the composition of innovation efforts, I further decompose patented innovation efforts by the degree of innovation novelty. This breakdown clarifies how firms shift their focus between improving existing technological capabilities and pursuing new technologies after the tax-induced demand surge. Following the established methodologies used in existing literature (Balsmeier et al., 2017; Goldman et al., 2024; Hall et al., 2001), I construct incremental patented innovation efforts ($Incr\_PAT_{i,t+1}$) by counting the number of newly filed patents containing at least one backward citation made by applicants. Incremental innovation reflects the extent to which firms refine and extend existing knowledge within established technological domains. I also construct radical patented innovation efforts ($Radi\_PAT_{i,t+1}$) by counting the number of newly filed patents without backward citation made by applicants. Radical innovation captures the extent to which firms engage in exploratory efforts that depart from existing knowledge trajectories.

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are not publicly observable. In addition, many firms may not report R&D expenses in the financial statements (Koh & Reeb, 2015). Output-based innovation measures, such as patent counts and citations, provide concrete ex-post evidence to evaluate a firm's ex-ante strategic focus. Second, existing research indicates that firms tend to smooth R&D expenditures over time despite the high political uncertainty and financial crisis (Aaker, 2007; Atanassov et al., 2024; Brown & Petersen, 2011; Mezzanotti & Simcoe, 2025). Given this inherent stickiness in R&D budgeting, I expect the effects of the tax-induced demand surge to manifest in the quality and direction of innovation outputs, rather than in aggregate R&D spending levels. Finally, as a central aim of this research is to trace the trajectory of knowledge accumulation, output-based metrics are appropriate for this context. These metrics provide the observable data required to measure how internal knowledge stocks grows over time and how that expertise eventually diffuses throughout the broader technological landscape. The additional innovation efforts measures are detailed in Section 7.1.

[11] I follow prior literature to count the number of newly filed utility patents that are ultimately granted. Typically, the United States Patent and Trademark Office (USPTO) accepts three types of patent applications: utility patents, design patents, and plant patents. Utility patents are typically known as "patents issued for the invention of a new and useful process, machine, manufacturing or composition of matter, or a new and useful improvement" (See detailed definition at https://www.law.cornell.edu/wex/patent). According to a U.S. Patent statistics chart for 1963-2020, utility patents typically constitute 92% of total patents granted each year (See USPTO patent statistics at https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm). I use firm-level patent application data from the University of Virginia Darden Global Corporate Patent Datasets (GCPD), which include USPTO patents of public companies from 1980 through 2017 (Bena et al., 2017).

4.3. Empirical Specification

The primary empirical analyses employ a difference-in-difference design around the implementation of bonus depreciation. The model specification is as follows:

$$Innovationproxy_{i,t+1} = \beta_1 TREAT_i \times POST_t + \gamma_1 X_{i,t} + \delta_i + \theta_t + u_{i,t} \tag{1}$$

The unit of observation is at firm *i* and year *t* level. I include firm (δ_i) and year (θ_t) fixed effects and report robust standard errors clustered by firm. Innovation proxy is one of the innovation measures discussed in Section 4.2. Following established empirical norms, I use one-year-ahead innovation measures to reflect the minimum one-year lag between R&D investment and patent applications (Kondo, 1999). For ease of interpretation, I apply the inverse hyperbolic sine (ihs) transformation to all count-like innovation measures (Glaeser & Lang, 2024).[12] $TREAT_i$ is as defined in Section 4.1. $POST_t$ is an indicator variable equal to 1 for years from 2002 to 2007 when the patent applications take place following the first wave of bonus depreciation incentive period.[13] The coefficient on the interaction term $TREAT_i \times POST_t$ (i.e., β_1) captures the incremental effect of bonus-depreciation-induced demand surges on the innovation efforts relative to control firms. Thus, I predict β_1 to be negative for patented innovation efforts, and positive (negative) for incremental (radical) innovation efforts.

Factors besides bonus-depreciation-induced demand surges can also affect the allocation of innovation efforts. Prior literature documents systematic differences in innovation intensity and

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[12] In untabulated analyses, I employ Poisson Pseudo Maximum Likelihood (PPML) specification for count-like, patent-based innovation effort variables. Despite the sample size being substantially reduced due to the zero-inflated patent filing data, the results hold for total patenting innovation efforts. However, the PPML may not be the optimal specification for other innovation proxies due to the highly zero-inflated patent data.

[13] The first wave of the bonus depreciation is in place from 2002 to 2004 during the Bush administration. The second wave of bonus depreciation is in place from 2008 to 2012. To reduce the political uncertainty induced by the presidential election, the year 2008 is excluded. I focus on the second wave of bonus depreciation during the Obama administration from 2009 to 2012. For empirical purposes, to account for patent application, I examine the post-period from 2009 to 2014 to allow more flexibility in lag between innovation investment and patent application. See Section 7.5 for the empirical analysis of the second wave of bonus depreciation.

R&D productivity across firms of different size (Cohen & Klepper, 1996a, 1996b; Ciftci & Cready, 2011), growth opportunity (Kogan & Papanikolaou, 2010), R&D stock (Hirshleifer et al., 2013) and product market competition (Aghion et al., 2005). Financial constraints constitute another important, yet nuanced, determinant of innovation efforts, as young firms heavily rely on external financing while mature firms tend to deploy cash reserves and smooth innovation spending (Brown et al., 2009; Brown & Petersen, 2011; Mezzanotti & Simcoe, 2025). Accordingly, I include a set of control variables that capture firm size ($Size_{i,t}$), profitability ($ROA_{i,t}$), growth opportunity ($MTB_{i,t},$), leverage ($LEV_{i,t}$), tangible intensity ($PPE_{i,t}$), R&D stock ($RDC_{i,t}$), product market competition ($HHI_{f,t}$), external information environment ($Numest_{i,t}$), firm age ($Age_{i,t}$), and operating cash flow ($OCF_{i,t}$).

5. Main Results

5.1. Descriptive Statistics

Table 3, Panel A, presents descriptive statistics for sample period around the first wave of bonus depreciation (1996 – 2007), including the main dependent and control variables. Detailed definitions of all variables are provided in Appendix 1. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. While raw patent counts are shown in the descriptive statistics, subsequent analyses use inverse hyperbolic sine (ihs) transformed values for the related count-like innovation measures. On average, the sample firms file 17 patents per year, are 15 years old, and have a mean asset size of 121 million.[14]

5.2. Regression Analysis: Test of H1

Table 4, Column (1) presents the regression results for patented innovation efforts. For the

[14] As shown in Table 3, Panel A, the mean log firm age is 2.8, corresponding to 15 years, and the mean log asset size is 4.8, corresponding to 121 million in total assets when converted back to the original scale.

first wave of bonus depreciation, the coefficient on $TREAT_i \times POST_t$ is significantly negative for the number of 1-year-ahead newly filed patents (t-statistic = -1.992), indicating that B2B firms file 5.9 percentage points fewer patents following the tax-induced demand surge. In terms of economic magnitude, the reduction corresponds to approximately one fewer newly filed patent per year.[15]

Regarding the control variables, I find that the number of 1-year-ahead newly filed patents is positively associated with firm size, growth opportunity, tangibility, and analyst following. These results are consistent with prior studies (He & Tian, 2013; Williams & Williams, 2021). Furthermore, the high adjusted R-squared suggests that the model fits well overall.

Collectively, the above results support H1. In particular, B2B capital-producing firms are more likely than control firms to reduce patented innovation efforts in response to the demand surge induced by temporary bonus depreciation.

5.3. Regression Analysis: Test of H2

Table 4, Column (2) presents the regression results for the incremental patented innovation efforts. For the first wave of bonus depreciation, the coefficient on the interaction term ($TREAT_i \times POST_t$) is positive and statistically significant for the number of 1-year-ahead newly filed incremental patents (t-statistic = 3.617). The results indicate that B2B firms file more incremental patents than control firms following tax-induced demand surges, with an economic magnitude of 8.8 percentage points higher than that of control firms. Although the baseline incremental patenting activity among B2B firms during this period is low, this effect may accumulate over time.

Table 4, Column (3) presents the regression results for radical patented innovation efforts. For the first wave of bonus depreciation, the coefficient on $TREAT_i \times POST_t$ is negative and

[15] The point estimate is 0.059*17.194=1.0.

statistically significant for the number of 1-year-ahead newly filed radical patents (t-statistic = -2.341), indicating that the B2B firms file significantly fewer radical patents than control firms. In terms of economic magnitude, this result translates into a reduction of one radical patents.[16]

Overall, the results support H2, confirming that B2B capital-goods producing firms increase (decrease) incremental (radical) innovation efforts relative to control firms in response to the demand surge induced by temporary bonus depreciation.

5.4. Parallel Trend Assumption

A key identifying assumption for the main tests is parallel trends: treated and control firms must exhibit similar trajectories in the outcome variables during the pre-treatment period, and this parallel evolution would be expected to persist in the absence of the treatment. To estimate the dynamic effects, I employ a regression of innovation proxies on year indicators (omitting 2001 as base year), include the full set of controls and firm fixed effects, and perform this estimation separately for the treatment and control groups. Panel A of Figures 1-3 plots coefficient estimates (in dot for B2B capital-producing firms and triangles for B2C capital-goods producing firms) together with the 95% confidence interval (orange bars for B2B capital-goods producing firms and blue bars for B2C capital-goods producing firms) for three patent-based innovation efforts proxies. The graph not only suggests a shift in these innovation efforts for B2B firms with a higher exposure to tax-induced demand surges but also the absence of such an effect for B2C firms.

Panel B of Figures 1-3 plot the incremental effect for B2B firms relative to B2C firms by year. The visual evidence demonstrates statistically indistinguishable pre-trends between groups with a few exceptions. I maximize the pre-test power by having a 5-year pre-treatment window. The spike in 1998 for the radical innovation efforts is unlikely to violate the parallel trend

[16] The point estimate is 0.69*16.445=1.14.

assumption because the treatment effect is incremental to the extrapolation of the pre-trend (Hribar et al., 2025). Importantly, the statistically significant divergences emerge only in the post-implementation period, mitigating concerns regarding a violation of the parallel trend assumption.

6. Heterogeneity Analyses

The main results suggest that relative to B2C firms, the demand surges due to bonus depreciation dampen the patented innovation efforts, stimulate incremental innovation, and reduces radical innovation among B2B firms. In the next sets of analyses, I investigate the mechanisms through which B2B firms are more or less sensitive to the tax-induced demand surges in reallocating their innovation efforts. I derive two predictions. First, as the tax-induced demand surge may potentially increase the market size for qualified property, I expect that the B2B firms positioned closer to the final demand along the supply chain experience greater exposure to the tax-induced demand surges, amplifying the incentive to shift innovation efforts toward incremental innovation to address existing customer needs while scaling back patented and radical innovation efforts. Second, I investigate the potential moderating effect of product market power, which is widely recognized as an impetus for creative innovation and economic progress (Aghion & Howitt, 1992; Romer, 1990; Schumpeter, 1942). I predict that the B2B capital-goods producing firms with high product market power are more likely to sustain radical innovation to reap the monopoly profits from innovation in the future while also increasing incremental innovation efforts. Conceptually, I partition the treated group ($TREAT_i$) with above-median ($HighTREAT_i$) and below-median ($LowTREAT_i$) values of the cross-sectional variation. Then, I interact each of these indicators with $POST_t$ to examine the heterogeneous treatment effects among B2B capital-goods producing firms.

6.1. Heterogenous Effects: Proximity to Final Demand

I investigate whether the degree of exposure to the tax-induced demand surge distorts the incentive to reallocate innovation efforts among B2B firms. I predict that B2B firms are more likely to reduce patented innovation efforts and prioritize incremental innovation over radical innovation when they face an immediate increase in demand following the implementation of bonus depreciation. Empirically, I proxy for the degree of exposure to tax-incentive induced demand surges by measuring proximity to final demand along the supply chain. I employ the inverse of industry upstreamness measure from Antràs et al., (2012), where lower values indicate greater distance from end users (e.g., raw materials) and higher values denote proximity to final consumers (e.g., finished equipment).[17] I partition the B2B firms based on this measure and construct an indicator variable equal to 1 if B2B firms with above-median industry inverse upstreamness ($HighTREAT_i$) and above-median industry inverse upstreamness ($LowTREAT_i$). I predict that the reduction of patented innovation and the distortion toward incremental innovation and away from radical innovation should be more pronounced among B2B firms operating closer to final demand.

Table 5, Panel A presents the results for heterogeneity in proximity to final demand. Consistent with my prediction, I find that B2B firms operating closer to final demand are more likely to curtail patented innovation efforts and prioritize incremental innovation over radical innovation following the tax-induced demand surges. The coefficients on $HighTREAT_i \times POST_t$ are negative and statistically significant for patented innovation efforts and radical innovation, and positive for incremental innovation efforts (t-statistics = -2.446, -2.896, and 3.857). In contrast, the coefficients on $LowTREAT_i \times POST_t$ are smaller in magnitude and generally insignificant or marginally significant (t-statistics = -1.107, -1.201, and 1.985). The difference in the two

[17] I use the inverse upstreamness measure for the year of 2000 to partition the treated group.

coefficients is significant at the 10% level for incremental and radical innovation efforts.

Overall, these results suggest that B2B firms operating closer to final demand along the supply chain are more likely to prioritize incremental innovation over radical innovation in response to tax-induced demand surge associated with bonus depreciation.

6.2. Heterogenous Effects: Product Market Power

Although B2B firms with higher product market power are more likely to capitalize on the demand surges induced by bonus depreciation, higher market power also increases the monopoly profits associated with future innovation. As a result, B2B firms have stronger incentives to allocate innovation efforts toward projects with longer-term payoffs that are not directly tied to the immediate demand surges generated by temporary bonus depreciation. Specifically, I measure product market power by calculating the industry-adjusted, firm-specific price-cost margin.[18] I then partition the B2B firms and construct an indicator variable equal to 1 if B2B firms with above-median product market power ($HighTREAT_i$) and below-median product market power ($LowTREAT_i$). Accordingly, I predict that both high- and low-market power B2B capital-goods producing firms reallocate innovation efforts toward incremental innovation efforts following the tax-induced demand surge, while B2B firms with high (low) product market power are more likely to sustain (reduce) patented and radical innovation efforts.

Table 5, Panel B, presents the results for heterogeneity in product market power. Consistent with my predictions, both types of B2B firms exhibit a shift toward incremental innovation following the tax-induced demand surge. Specifically, the coefficients on $HighTREAT_i \times POST_t$ and $LowTREAT_i \times POST_t$ are both positive and statistically significant (t-statistics = 5.191 and

[18] Following Kubick et al., (2015) and Peress (2010), I calculate the price-cost margin as the ratio of a firm's sales less cost of goods sold less selling, general, and administrative expense to sales. I then adjust each firm-level price-cost margin by the average price-cost margin of a given industry-year (two-digit SIC code). I use the price-cost cost margin for the year of 2000 to partition the treated group.

2.684). However, the magnitude of the coefficient on $HighTREAT_i \times POST_t$ is larger than that on $LowTREAT_i \times POST_t$, with the difference significant at 10% level. In contrast, the coefficients on $HighTREAT_i \times POST_t$ are insignificant for patented efforts and radical innovation efforts (t-statistics = -0.0892 and -1.390), whereas the coefficients on $LowTREAT_i \times POST_t$ are significantly negative (t-statistics = -3.670 and -3.866). The difference in these two coefficients is significant at the 1% level for patented innovation and radical innovation efforts.

Taken together, the findings suggest that high product market power partially mitigates the disincentive in engaging patented and radical innovation following the tax-induced demand surge. While all B2B firms have incentives to exploit existing product portfolios through incremental innovation, firms with greater market power appear better able to resist this distortion, sustaining their investment in both patented and radical innovation. In contrast, heightened competition and tighter resource constraints among low-market-power firms exacerbate the trade-off between pursuing short-run gains and sustaining longer-term innovative activity.

7. Supplementary Analyses

7.1. Additional Innovation Outcomes Analyses

To provide additional insights into the indirect effect of bonus depreciation on innovation efforts, I exploit a suite of additional outcome measures related to innovation efforts. This approach provides a richer depiction of how innovation efforts are altered following the tax-induced demand surge.

To capitalize on the temporary demand surges induced by bonus depreciation, I expect affected B2B firms to increase their efforts toward incremental product innovation more than control firms. In particular, prior studies provide both conceptual frameworks and empirical evidence supporting the use of trademarks as indicators of incremental innovation (Davis, 2006;

Sandner, 2010).[19] In addition, service innovation, a form of non-technological innovation associated with underlying products, is generally not patentable, yet it is often protected through trademarks (Millot, 2009). Given the compressed timeline of the tax-induced demand surge, I expect affected B2B firms to allocate more innovation efforts to non-technological innovation associated with their existing product portfolios. Accordingly, I expect an increase in the number of newly filed services trademarks for the B2B firms following bonus depreciation.

Conversely, as a natural strategy for firms to flag product innovation or technological advances, firms may create new brands to highlight the distinctness of their new product offerings (Aaker, 2007; Flikkema et al., 2019). If the B2B firms are more likely to reallocate innovation efforts to upgrade existing product portfolios, I expect that B2B firms will be less likely to create new brands. Using the USPTO Trademark Case File Dataset, I construct two trademark-based proxies to measure incremental product innovation. Specifically, I measure the number of 1-year-ahead newly filed service trademarks ($TM\_Service_{i,t+1}$) and the number of 1-year-ahead newly filed product trademark families ($TM\_Family_{i,t+1}$).[20] I expect that, relative to control firms, B2B

[19] Lee N. Davis, a faculty member at Copenhagen Business School, offers the intuition for the linkage between firm-level strategies behind trademark application and incremental innovation: "Most incremental innovations represent only very small changes over existing goods, or new combination of existing goods, neither of which represent the kind of 'inventive step' necessary to qualify for patent protection." (Davis, 2006, p.11). Therefore, firms have incentives to apply for trademarks to signal the newness of their products. Though trademarks can signal the product or service innovation, existing marketing literature also finds that trademarks may indicate various branding strategies. In other words, only a limited share of trademarks is directly related to innovation. Given the absence of rules of thumb to measure innovation using trademarks, Flikkema et al. (2019) caution researchers against using raw trademark counts as measures of innovation.

[20] According to USPTO, the definition of trademarks is "any word, phrase, symbol, design, or a combination of these things that identifies your goods or service" (See USPTO website at https://www.uspto.gov/trademarks/basics/what-trademark). Typically, firms apply for new trademarks. After the trademarks are registered, the firms can cancel, abandon, or renew existing active trademarks if needed (Graham et al., 2013). For empirical purposes, I focus on newly filed trademarks which are ultimate registered, regardless of future cancellation or abandonment. In addition, given that I am not able to identify the graphical or sound features, I rely on word marks to identify trademark families for empirical purposes. Furthermore, to better account for product innovation using trademarks, I focus on product trademarks to construct the trademark family measure following Faurel et al., (2024). The product trademarks should be more closely related to product innovation efforts, while marketing trademark should be more closely linked to marketing efforts.

firms file more service trademarks but fewer trademarks classified as new trademark families.

While the distinction between radical and incremental innovation is often nuanced, extant literature defines radical innovation by its outsized potential to catalyze subsequent technological progress and spawn future generations of discovery (Acemoglu et al., 2022; Kelly et al., 2021). Utilizing forward citations to proxy for knowledge creation and diffusion, I construct alternative measures of incremental and radical innovation efforts, respectively. I define alternative incremental innovation as patents that receive zero citations within five years of patent application and construct the number of 1-year-ahead newly filed patents that receive zero forward citations ($NoFC\_PAT_{i,t+1}$). In addition, I define alternative radical innovation as patents that rank in the top 10% of the non-self forward citations within 10 years following patent application and construct the number of 1-year-ahead newly filed patents that receive top 10% non-self forward citations ($TOP10NSFC\_PAT_{i,t+1}$).[21]

Furthermore, I measure 1-year-ahead product differentiation ($ProdDiff_{i,t+1}$), which reflects improvements in product quality and differentiation induced by an increase in incremental innovation efforts following the bonus depreciation (Hoberg & Phillips, 2016). Finally, to capture the extreme radical innovation efforts, I identify breakthrough patents using the text-based classification method developed by Kelly et al. (2021). I then measure the incidence of breakthrough patenting efforts by constructing an indicator variable, $Bkt\_PAT_{i,t+1}$.

Table 6, Panels A-C report the results for alternative measures of innovation efforts. Consistent with expectations, in Table 6, Panel A, I find that B2B firms file more service trademarks but fewer trademarks that spawn new brand portfolios than control firms following the

[21] Given that the majority of forward citations typically accrue within ten years of a patent's application (Graham & Hegde, 2015), I use a 10-year period following the patent application to count the forward citations.

bonus depreciation. In Table 6 Panel B, I find that B2B firms exhibit higher product differentiation and file more patents without any forward citations relative to their B2C counterparts following the tax-induced demand surge. Table 6, Panel C demonstrates that, after the tax-induced demand surge, B2B firms are less likely to file breakthrough patents and file fewer patents that fall in the top decile of non-self forward citations within ten years of application than control firms. Taken together, these results provide additional insights into the compositional change in innovation efforts and help confirm that the bonus-depreciation-induced demand surge consistently shifts innovation efforts toward product and incremental innovation, while reducing patented and radical innovation among B2B capital-goods producing firms.

7.2. Robustness Tests

While the difference-in-difference design with firm- and year-fixed effects mitigates the influence of unobservable firm-specific and time-varying confounders, the difference in firm characteristics across the treated and control groups may still impact the inferences drawn from the main findings. To alleviate these concerns, I implement within-industry (four-digit NAICS) propensity score matching procedures.[22] The results from the matched sample remain qualitatively consistent with the main findings. Table 7, Panel A reports results. The evidence from matched sample suggests that the main results are unlikely to be driven by differences in observable firm characteristics, although the matching procedures reduces the sample size.

Furthermore, recognizing the U.S. operates within an open global economy, non-U.S. capital-producing firms also play a vital role in serving U.S. markets.[23] To account for this, I

[22] Given that the existing identification strategy relies on industries that contribute to final demand per NIPA table, within-industry propensity score matching is more appropriate than alternative procedures such as entropy balancing, which does not preserve industry-level matching. Despite this limitation of entropy balancing, I find that the inferences remain unchanged when using the entropy balancing procedure (results untabulated).

[23] As U.S. firms claim bonus depreciation on qualifying property, demand for such property accrues to all capital-goods producers supplying qualifying assets, regardless of whether those capital-goods producing firms are U.S. or foreign firms.

expand the sample by including non-U.S. capital-producing firms with significant U.S. sales exposure. Specifically, I identify such firms as those operating in the same industries as U.S. capital-goods producing firms and generating at least 30% of their sales from U.S. markets before the implementation of bonus depreciation. Table 7, Panel B presents the results. The results are consistent with the main findings and indicate that the impact of bonus depreciation tax policy on composition of innovation efforts can extend beyond national borders.

In addition, I conduct several untabulated robustness tests. First, I construct an alternative control group consisting of non-U.S. B2B capital-goods producing firms.[24] In the main tests, some B2C control firms may also experience demand surges because they serve both corporate and individual customers, which would bias the estimates against finding results. Nonetheless, the non-U.S. B2B firms are likely similar to the treated B2B firms along many dimensions, and thus help rule out alternative explanations. The results using the alternative control group are consistent with my main findings. Second, to account for the influx of Chinese goods during the sample period (1996-2007) around the implementation of the initial wave of bonus depreciation, I control for industry-level import penetration, and the results continue to hold.[25] In addition, prior studies show that tax loss utilization could distort future risk-taking, thereby influencing future innovation efforts (Domar & Musgrave, 1944; Langenmayr & Lester, 2018; Ljungqvist et al., 2017). To account for this, I include an indicator variable for firms with negative beginning retained earnings (Christensen et al., 2022).[26] Collectively, the results remain unchanged.

7.3. Composition of R&D Investment: Financial Constraints Puzzle

[24] Non-U.S. B2B capital-goods–producing firms are defined as firms incorporated outside the United States, operating in industries whose final products contribute to the investment categories in the NIPA tables, and with less than 10% of sales in the U.S, based on geographical segment disclosures from Refinitiv Eikon.

[25] Import penetration is defined as the ratio of imports to [imports+ domestic production-exports] at the 3-digit NAICS level constructed based on NIPA table.

[26] Given the low data quality for tax loss carry forward (TLCF) in Compustat (Heitzman & Lester, 2021, 2022), I follow Christensen et al. (2022) and use the negative retained earnings as a proxy for tax loss status.

In a recent study, Mezzanotti and Simcoe (2025) provide evidence that, using US Census data, the global financial crisis only partially explains the decline in research activities associated with knowledge creation.[27] They explore a range of potential factors, such as risk preferences, adjustment costs, and strategic considerations, yet the specific compositional shifts within R&D activities in response to financial constraints remain an open question.

In untabulated analyses, I find that B2B firms facing lower (higher) refinancing risks are more likely to increase (reduce) their incremental innovation efforts following a tax-induced demand surge than control firms.[28] In contrast, refinancing risk does not differentially influence patented and radical innovation efforts between B2B and B2C firms following the tax-induced demand surge. These findings indicate that tax-induced demand surges amplify incremental innovation efforts among less financially constrained firms while mitigating the adverse effects on patented and radical innovation among more financially constrained firms. Taken together, this study offers a plausible explanation for the 'financial constraints puzzle' by identifying a tax-induced demand channel that influences the relationship between financial constraints and the composition of R&D investment.

7.4. Patent-level Analyses

To gain deeper insights into the compositional change in patented innovation, I conduct patent-level analyses, which allow for a more precise assessment of the long-run consequences of patent-based innovation efforts. Specifically, I focus on a restricted sample of capital-goods

[27] Mezzanotti and Simcoe (2025) find that U.S. firms have reduced their investment in basic and applied research ('R') compared to development ('D') over the past thirty years, however, the reduction in R cannot be solely explained by short-term financial pressures. Though the classification of the composition of R&D based on their paper is slightly different from my study, the underlying concepts of the R in their study and radical innovation in mine are similar. Both studies frame the distinction between R (radical innovation) and D (incremental innovation) in terms of knowledge creation.

[28] Consistent with Mezzanotti and Simcoe (2025), refinancing risk is measured the ratio of long-term debt due within one year to its cash and other liquid holdings. B2B (Treated) firms above the median refinancing risk measure (for the year of 2000) are classified as high-refinancing-risk treated firms; otherwise, low-refinancing-risk treated firms.

producing firms with at least one 1-year-ahead patent application in both the pre- and post-treatment periods.[29]

I focus on uncovering the private economic value and social value associated with patent applications, while also examining how the quality of patents reflects underlying innovation efforts and their potential impact on the broader economy. As firms that engage in commercial innovation cannot capture all the returns from innovation, the private sector tends to underinvest relative to the socially desirable level (Glaeser & Lang, 2024; Howell, 2024; Nelson, 1959). The aforementioned firm-level analyses suggest that the tax-induced demand surge prompts capital-goods producing firms to shift their innovation efforts toward incremental product innovation while reducing radical innovation. Consequently, I predict that these affected firms are more likely to allocate innovation efforts to patents that maximize private economic value while underinvesting in socially valuable innovations with higher scientific value and broader social impact. To empirically test this prediction, I construct the private economic value ($MKTVal_{i,t+1}$), measured as 1-year-ahead newly filed patents based on the patent's grant-day announcement stock return, following Kogan et al.(2017), and construct the scientific value ($FNSCitation\_10Y_{i,t+1}$), measured as 1-year-ahead newly filed patents by calculating the number of non-self forward citations received within 10 years following the patent application day. To further measure the social impact of patents, I measure patent scope by constructing the number of allowed claims per patent ($Claim_{i,t+1}$), and calculating the average number of words per each claim ($Claim\_WC_{i,t+1}$) (Hegde et al., 2023; Kuhn & Thompson, 2019).[30]

Table 8 presents the results. Consistent with my prediction, Table 8, Panel A demonstrates

[29] For patent-level analysis, the specification is on patent-firm-year level. The model specification includes firm and industry (2-digit NAICS)-year fixed effect. The standard errors are clustered by firm.
[30] Following the existing literature, a higher number of claims reflects broad scope, while a greater number of words per each claim is associated with narrower scope.

that the coefficient on $TREAT_i \times POST_t$ is negative and statistically significant for the scientific value of patents, while the corresponding coefficient is not statistically significant for the private economic value of patents. These results suggest that the reallocation of innovation efforts induced by the tax-induced demand surge does not impact private economic value of innovation, but it does diminish the scientific value of innovation, making the distortion socially undesirable. Table 8, Panel B reports the results for patent scope. The estimates show that B2B firms file patents with a significantly narrower scope relative to control firms following the tax-induced demand surge.

Taken together, the evidence highlights a pronounced decline in the scientific value of patented innovations, consistent with a shift toward more incremental innovation that generates limited spillover benefits for knowledge creation and diffusion.

7.5. Secondary Setting: Analyses of the Second Wave of Bonus Depreciation

Finally, while the initial bonus depreciation (2002–2004) was perceived as a purely temporary economic stimulus, the later implementation with multiple extensions of bonus depreciation after 2008 attenuated the temporary perception of such short-term economic stimuli (Gale & Orszag, 2004). A survey of tax professionals confirms that these subsequent implementations were viewed as less temporary in nature (Jackson & Pippin, 2013). I exploit this nuanced shift in perceptions to examine whether the temporary nature of the tax incentive moderates its distortionary effect on innovation efforts. Specifically, I test whether the attenuated demand surges induced by bonus depreciation cause a smaller misallocation of innovation when the tax incentives are perceived as less temporary. I estimate Equation (1) for the years 2005 through 2014 across the Bush and Obama administrations. I exclude the year 2008 to mitigate confounding effects arising from the political uncertainty of the election year and the immediate reintroduction of the policy under the Economic Stimulus Act of 2008 due to the Global Financial

Crisis (Atanassov et al., 2024). I again employ the identification strategy for B2B and B2C firms from the main tests, as these firms are most directly affected, allowing me to best observe the reallocation of innovation efforts under a bonus depreciation tax incentive perceived as less temporary. If the second wave of bonus depreciation is viewed as less temporary in nature, I expect a weaker demand surge for B2B firms.

Table 9 presents the results. Table 9, Panel A provides results from a market reaction test validating the identification strategy for the second wave of bonus depreciation. While B2B firms react positively to the Economic Stimulus Act of 2008 (ESA2008) and the American Recovery and Reinvestment Act of 2009 (ARRA2009), their market reaction is not significantly more positive than that of control firms. Panel B substantiates this prediction, as I find no evidence of a significant demand surge among B2B firms during the second wave of the bonus depreciation period. Table 9, Panel C presents the multivariate regression results of innovation efforts. I observe an immediate increase in incremental innovation efforts, accompanied by a significant decline in patented and radical innovation following the implementation of the second wave of bonus depreciation. While I cannot rule out lingering effects from the earlier distortions in innovation efforts, the results from the second wave of bonus depreciation indicate that the attenuation in the demand surge induced by less temporary bonus depreciation still distort the allocation of innovation efforts away from patented and radical innovation.

8. Conclusion

This study explores whether and to what extent bonus depreciation indirectly affects the *composition* of innovation efforts among capital-goods producing firms. Despite claims that investment-based tax policy is intended to promote economic growth, there is limited empirical evidence regarding its efficacy in promoting long-run growth. This study fills this void in the literature by providing novel evidence of the reallocation of innovation efforts toward incremental and away from radical innovation following the implementation of bonus depreciation.

Exploiting variation in customers' eligibility for bonus depreciation, I find that B2B capital-goods producing firms are more likely to divert innovation efforts toward non-patented product innovation. Simultaneously, demand surges on existing products incentivize these firms to shift toward incremental innovation and away from radical innovation. I further demonstrate that the distortion of innovation efforts due to bonus depreciation varies across a variety of firm attributes. Specifically, the shift toward incremental and away from radical innovation is more pronounced among B2B capital-goods producing firms that operate closer to final demand along the supply chain, whereas B2B capital-goods producing firms with greater product market power selectively increase incremental innovation without a corresponding reduction in radical innovation.

Taken together, this study provides preliminary evidence for an indirect effect of investment-based tax policy on future innovation efforts and technological progress among capital-goods producing firms. This evidence should be of particular interest to academics, capital market participants, regulators, and policymakers. Against the backdrop of the OECD Pillar Two Global Minimum Tax regime, bonus depreciation tax incentives are expected to be frequently implemented to spur investment without triggering an immediate minimum tax liability. This study underscores the importance of integrating the possible impact on innovation into the timely discussion concerning investment-based tax policy. While it is impossible to generalize my findings beyond the bonus depreciation setting, the findings of this study also raise questions about how government efforts to direct tangible investment in the economy may impact the *composition* of innovation investments.

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Appendix 1: Variable Definition

Variable	Definition	Source
$PAT_{i,t+1}$	The number of newly filed utility patents which are ultimately granted. The data are requested and obtained from GCPD data portal (https://patents.darden.virginia.edu/get-data) (Bena et al., 2017)	GCPD
$Radi\_PAT_{i,t+1}$	The number of newly filed utility patents that are ultimately granted without backward citations. The scope of backward citations is limited to those made by applicants.	PatentsView
$Incr\_PAT_{i,t+1}$	The number of newly filed utility patents which are ultimately granted, with at least one backward citation. The scope of backward citations is limited to those made by applicants.	PatentsView
$TREAT_i$	An indicator variable equal to 1 for B2B capital-goods producing firms primarily serving company customers, 0 for B2C capital-goods producing firms serving individual consumers.	BEA NIPA
$POST_t$	For the first wave of the bonus depreciation, an indicator variable equal to 1 for fiscal years from 2002 to 2007, 0 for fiscal years from 1996 to 2001. For the second wave of the bonus depreciation, an indicator variable equal to 1 for fiscal years from 2009 to 2014, 0 for fiscal years from 2005 to 2007.	
BD_0204_t	An indicator variable equal to 1 for fiscal years from 2002 to 2004 when bonus depreciation tax incentives are implemented in U.S., 0 for fiscal years from 1996 to 2001.	
BD_0912_t	An indicator variable equal to 1 for fiscal years between 2009 and 2012 when bonus depreciation tax incentives are implemented in U.S., 0 for fiscal years from 2005 to 2007.	
$SALES_{i,t}$	Sales (SALE) in year t scaled by total assets (AT) at the beginning of year t.	Compustat
$COGS_{i,t}$	Cost of goods sold (COGS) in year t scaled by total assets (AT) at the beginning of year t.	Compustat
$CAPX_{i,t}$	Capital expenditure (CAPX) in year t scaled by total assets (AT) at the beginning of year t.	Compustat
$RD_{i,t}$	R&D expenditures (XRD) in year t scaled by total assets at the beginning of year t. Missing R&D expenses are set to 0.	Compustat
$Size_{i,t}$	The natural logarithm of total assets in USD.	Compustat
$ROA_{i,t}$	Return on assets, computed as income before extraordinary items (IBC) scaled by total assets (AT) at the beginning of year t.	Compustat
$MTB_{i,t}$	The ratio of market value of equity (PRCC_F*CSHO) to book value of equity (CEQ).	Compustat
$LEV_{i,t}$	The ratio of total debt (DLTT+DLC) to book value of equity (CEQ)	Compustat
$PPE_{i,t}$	Property, plant, and equipment (PPENT) in year t scaled by total assets (AT) at the beginning of year t. Set to 0 if missing.	Compustat
$RDC_{i,t}$	R&D capital, computed as 5-year cumulative R&D expenses (XRD) with a 20% annual depreciation by following Hirshleifer et al. (2013). Missing R&D expense (XRD) is set to 0.	Compustat
$HHI_{f,t}$	The sales Herfindahl-Hirschman Index calculated at the three-digit NAICS level.	Compustat
$Numest_{i,t}$	The natural logarithm of the number of analysts following in year t.	IBES
$Age_{i,t}$	The natural logarithm of firm age in year t since IPO date. Missing IPO dates are replaced with the first fiscal year appearing in Compustat database.	Compustat
$OCF_{i,t}$	Cash flow from operations (CFO) in year t scaled by total assets (AT) at the beginning of year t.	Compustat
$INVT_{i,t}$	The inventory (INVT) on hand at the end of year t scaled by total assets at the beginning of year t	Compustat

$ProdDiff_{i,t+1}$	Hoberg and Phillips' (2016) text-based measure of product similarity multiplied by -1. Data is obtained from https://hobergphillips.tuck.dartmouth.edu/tnic_competition.html.	Hoberg & Phillips (2016)
$NoFC\_PAT_{i,t+1}$	The number of newly filed utility patents that receive zero forward citations within 5 years following the patents' application date.	PatentsView
$Bkt\_PAT_{i,t+1}$	An indicator variable equal to 1 for a firm-year file at least 1 breakthrough patent, 0 otherwise, based on the patent importance measures (including forward citation, text-based similarity, et al.). Specifics are provided by Kelly et al. (2021). The breakthrough patent data are obtained from https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Replication-Kit	Kelly et al. (2021)
$TM\_Service_{i,t+1}$	The number of newly filed service trademarks which are ultimately registered.	USPTO Trademark Case File Dataset
$TM\_Family_{i,t+1}$	The number of newly filed product trademark family which are ultimately registered. Trademarks with three words or fewer in the word mark are classified as product trademarks; otherwise, they are marketing trademarks (Faurel et al., 2024). A trademark family is defined as a set of product trademarks of which within-firm similarity exceeds 0.7, where similarity is measured using the Jaccard index computed on 2-grams.	USPTO Trademark Case File Dataset
$TOP10NSFC\_PAT_{i,t+1}$	The number of newly filed utility patents that fall in the top decile of non-self forward citations within ten years of application, relative to patents filed in the same year.	PatentsView
$MKTVal_{i,t+1}$	The natural log of one plus the private economic value of newly filed patents in year t+1 estimated based on the patent's grant day announcement returns. The private economic value of patents is estimated based on the method specified in Kogan et al. (2017). Given the short sample period, patent values are expressed in nominal value.	PatentsView
$FNSCitation\_10Y_{i,t+1}$	The number of non-self forward citations received within 10 years following the patent application day.	PatentsView
$Claim_{i,t+1}$	Total number of claims allowed at grant for a given patent filed in year t+1.	PatentsView
$Claim\_WC_{i,t+1}$	The average number of words per each claim for a given patent filed in year t+1.	PatentsView

Appendix 2: Timelines of the Implementation of Bonus Depreciation-Related Tax Policy in the U.S. since 2000

First bonus depreciation period: 2002-2004

- 2002: The JCWAA 2002 introduces 30% bonus depreciation for qualified property placed in service after Sep 10, 2001 and before September 2004
- 2003: JGTRRA 2003 increases bonus depreciation to 50% for eligible equipment placed in service after May 5, 2003 and extends the bonus depreciation period to December 31, 2004

Third bonus depreciation period: 2013-2017

- 2013: ATRA 2012 extends 50% bonus depreciation for eligible equipment placed in service between Jan 1, 2013 and Dec 31, 2013
- 2014: TIPA 2014 extends 50% bonus depreciation for eligible equipment placed in service between Jan 1, 2014 and Dec 31, 2014
- 2015: PATH 2015 initially extends 50% bonus depreciation for eligible equipment placed in service between Jan 1, 2015 and Dec 31, 2017, 40% between Jan 1, 2018 and Dec 31, 2018, and 30% between Jan 1, 2019 and Dec 31, 2019.

2002-2004 | 2008-2012 | 2013-2017 | Post 2017

Second bonus depreciation period: 2008-2012

- 2008: ESA2008 introduces 50% bonus depreciation for eligible equipment placed in service between Jan 1, 2008 and Dec 31, 2008.
- 2009: ARRA 2009 extends the 50% bonus depreciation for eligible equipment placed in service to Dec 31, 2010
- 2010: TRA 2010 extends the 50% bonus depreciation to Dec 31, 2012, and allows 100% bonus depreciation for eligible equipment placed in service between Sep 9, 2010 and Dec 31, 2011.

Fourth bonus depreciation period: post 2017 TCJA

- 2017: TCJA 2017 reinstates bonus depreciation for eligible equipment placed in service between 2017 and 2027, and expands the scope of eligible eqiupment by including used as well as new capital equipment. 100% bonus depreciation applies to eligible equipment placed in service between Sept 27, 2017 and Dec 31, 2022, and bonus depreciation will be phased out by 2028.
- 2025: OBBBA permanently reinstates bonus depreciation.

This paper focuses on the first two bonus depreciation periods.

Appendix 3: Legislative Progress for the First Two Waves of Bonus Depreciation Policies in the U.S.

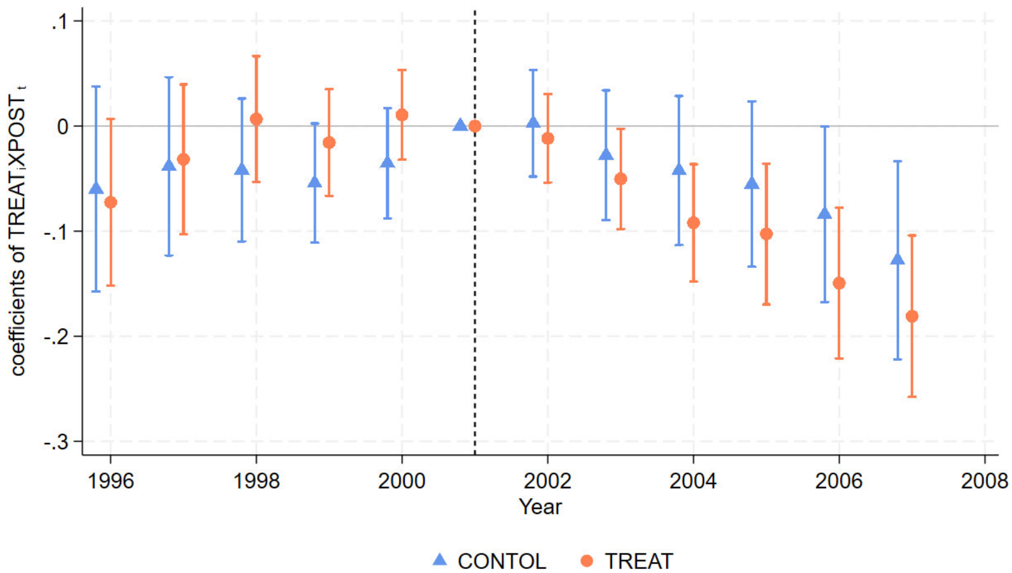
Event	Date	Description	Expected market reaction by capital-producing firms
		JCWAA2002	
E1	October 11, 2001	The Job Creation and Worker Assistance Act of 2002 (JCWAA2002) is first introduced. The bonus depreciation is the first items in the bill.	Positive
E2	October 24, 2001	The House passes the bill including bonus depreciation.	Positive
E3	February 14, 2002	The Senate passes the bill including bonus depreciation.	Positive
E4	March 7, 2002	The House passes House amendment to Senate Amendment.	Positive
E5	March 9, 2002	The JCWAA 2002 is written into law as Public Law 107-147. JCWAA 2002 gives an extra depreciation deduction equal to 30% of the adjusted basis of the qualified property placed in service after Sept 10, 2011, and before Sept 11, 2004.	Positive
		JGTRRA2003	
E6	February 27, 2003	The Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA2003) is first introduced in the House as H.R. 2 sponsored by Bill Thomas. Bonus depreciation is the second item in the bill.	Positive
E7	May 9, 2003	The House passes the bill.	Positive
E8	May 15, 2003	The Senate passes the bill.	Positive
E9	May 23, 2003	A conference committee forms. Both House and Senate agree to the conference report.	Positive
E10	May 28, 2003	JGTRRA 2003 is written into law as Public Law 108-27. The JGTRRA 2003 increases first-year bonus depreciation to 50% for eligible equipment acquired after May 5, 2003 and extends bonus depreciation to property acquired before January 1, 2005.	Positive
		ESA2008	
E11	January 28, 2008	The Economic Stimulus Act of 2008 (ESA2008) is first introduced and sponsored by Rep Nancy Pelosi.	Positive
E12	January 29, 2008	The House passes the bill.	Positive
E13	February 8, 2008	The Senate passes the bill.	Positive
E14	February 13, 2008	The ESA 2008 is written into law as Public Law 110-185. To qualify for the 50% special depreciation allowance under the new law, property must be placed in service after Dec 31, 2007, and before Jan 1, 2009.	Positive
		ARRA 2009	
E15	January 26, 2009	The American Recovery and Reinvestment Act (ARRA) is introduced in the House by Rep. Dave Obey.	Positive
E16	January 28, 2009	The House passes the bill.	Positive
E17	February 10, 2009	The Senate passes the bill.	Positive
E18	February 13, 2009	The Senate agrees to the report by a joint conference committee resolving the differences between the House and Senate versions.	Positive
E19	February 17, 2009	President Barack Obama signs H.R. 1, the ARRA 2009, into law as P.L. 111-5. The ARRA extends the 50% bonus depreciation benefit to property first placed in service prior to January 1, 2011.	Positive
		TRA2010	
E20	March 17, 2010	The Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 (TRA2010) is introduced into the House, sponsored by Rep James Oberstar.	Positive
E21	September 23, 2010	The Senate passes the bill with amendment.	Positive
E22	December 2, 2010	The House passes the bill with amendment.	Positive
E23	December 15, 2010	The Senate passes the bill with amendment.	Positive
E24	December 17, 2010	The TRA2010 is signed into law as Public Law 111-312. The Act extends the 50% bonus depreciation deduction to qualifying property placed in service through 2012. It allows 100% bonus depreciation for qualified property placed in service between September 9, 2010, and December 31, 2011.	Positive

Figure 1

Time Trends for Patented Innovation Efforts

Figure 1 displays the time trends for patented innovation efforts. The x-axis denotes the year. The y-axis plots the 1-year-ahead patented innovation efforts (ihs($PAT_{i,t+1}$)) coefficients for each event-year estimated separately for B2B capital-goods producing firms (treated firms) and B2C capital-goods producing firms (control firms) in Panel A. Panel B plots the incremental effect for B2B capital-goods producing firms. The dots (bars) represent coefficient estimates (95% confidence interval).

Panel A: Total Patents for B2B Capital-Goods Producing Firms and B2C Capital-Goods Producing Firms by Event Time



Panel B: Incremental Effect for B2B Capital-Goods Producing Firms by Event Time

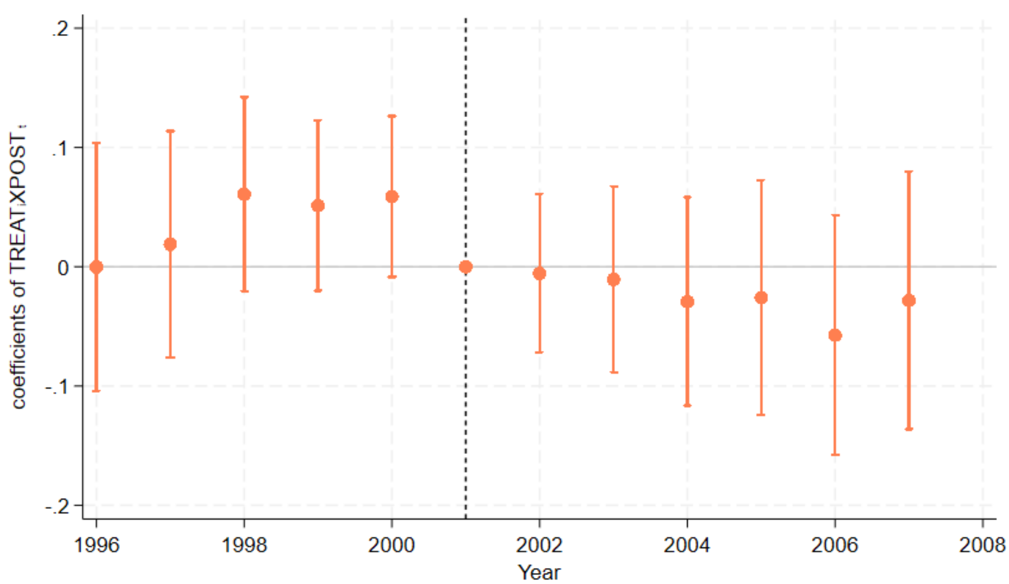
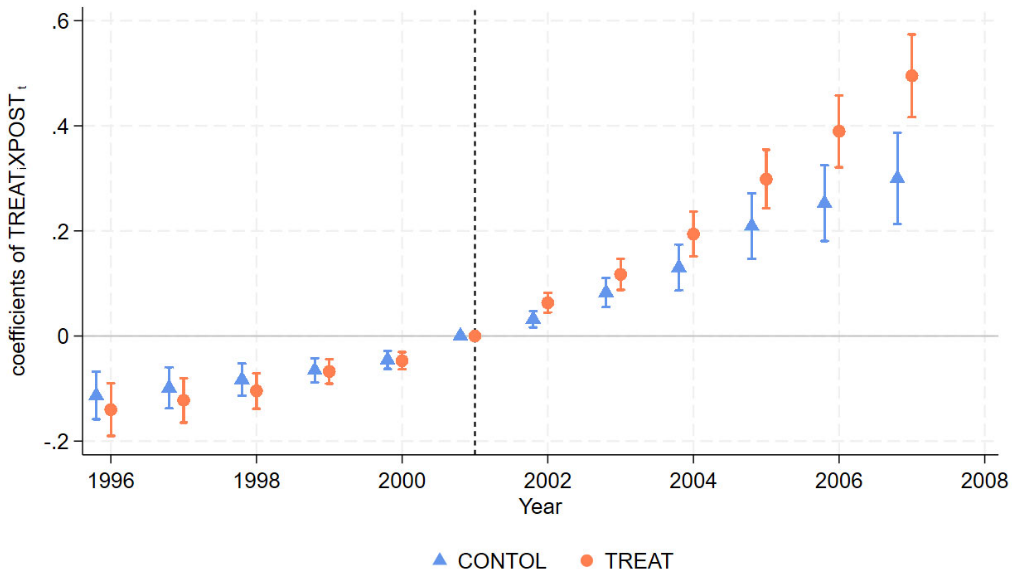


Figure 2

Time Trends for Incremental Innovation Efforts

Figure 2 displays the time trends for incremental patented innovation efforts. The x-axis denotes the year. The y-axis plots the 1-year-ahead incremental innovation efforts (ihs($IncrPAT_{i,t+1}$)) coefficients for each event-year estimated separately for B2B capital-goods producing firms (treated firms) and B2C capital-goods producing firms (control firms) in Panel A. Panel B plots the incremental effect for B2B capital-goods producing firms. The dots (bars) represent coefficient estimates (95% confidence interval).

Panel A: Incremental Patents for B2B Capital-Goods Producing Firms and B2C Capital-Goods Producing Firms by Event Time



Panel B: Incremental Effect for B2B Capital-Goods Producing Firms by Event Time

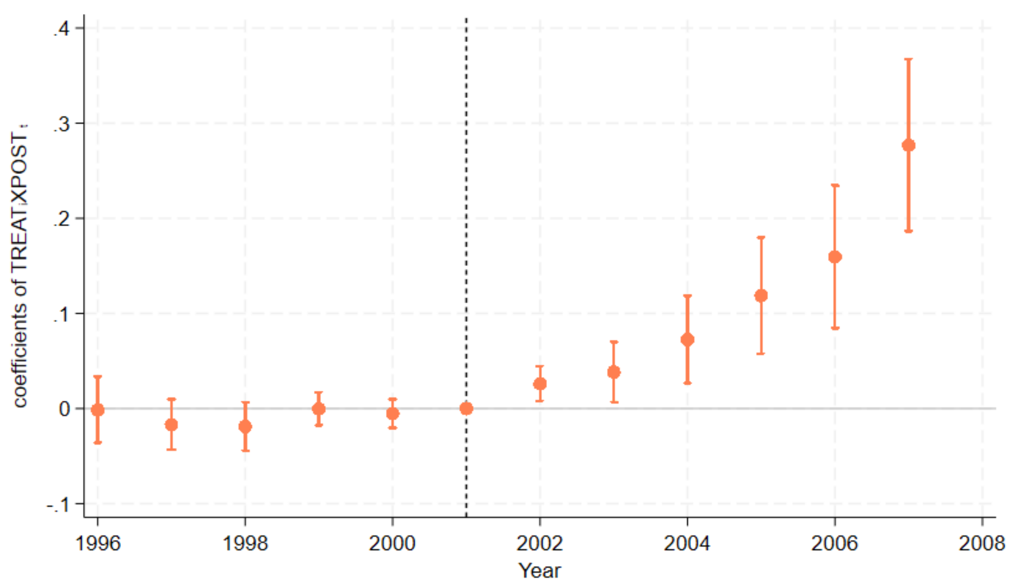
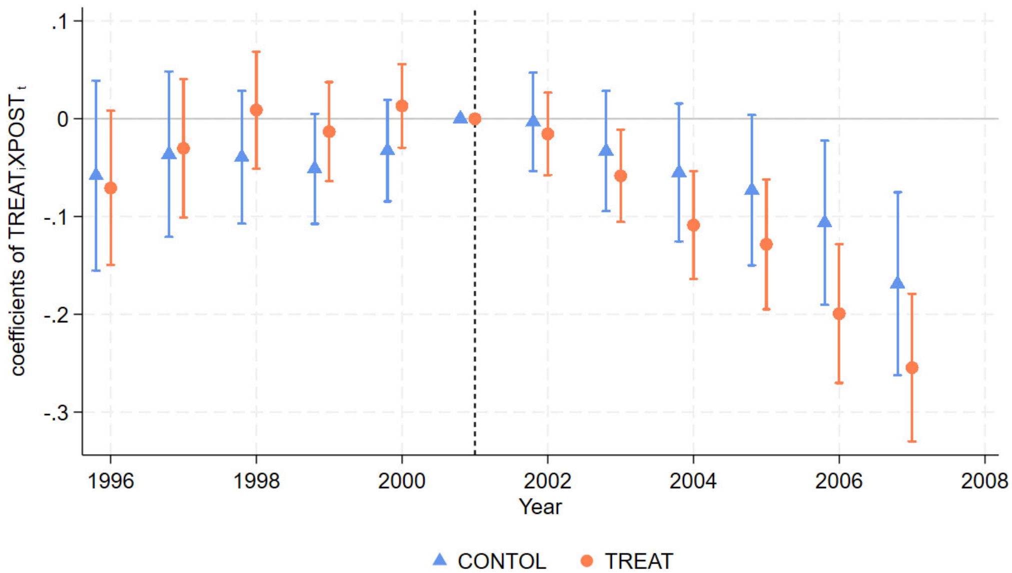


Figure 3

Time Trends for Radical Innovation Efforts

Figure 3 display the time trends for radical patented innovation efforts. The x-axis denotes the year. The y-axis plots the 1-year-ahead radical innovation efforts (ihs($RadiPAT_{i,t+1}$)) coefficients for each event-year estimated separately for B2B capital-goods producing firms (treated firms) and B2C capital-goods producing firms (control firms) in Panel A. Panel B plots the incremental effect for B2B capital-goods producing firms. The dots (bars) represent coefficient estimates (95% confidence interval).

Panel A: Radical Patents for B2B Capital-Goods Producing Firms and B2C Capital-Goods Producing Firms by Event Time



Panel B: Incremental Effect for B2B Capital-Goods Producing Firms by Event Time

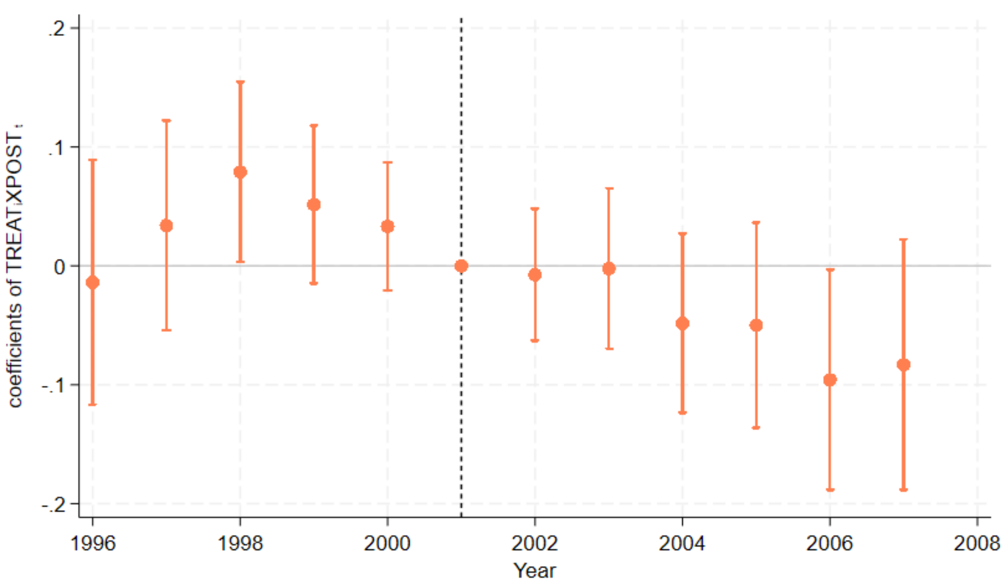


Table 1

Sample Composition

Panel A: Sample Selection
Table 1, Panel A presents the sample selection.

Sample period	**1996-2007**
	Firm-Years
U.S.-incorporated firm-year firms in Compustat belong to industries (identified by NAICS) that contribute to the investment final demand as B2B and B2C firms, detailed in Section 4.1, based on 2000-2001 NIPA tables.	18,466
Delete firm-years without at least two observations in both pre- and post-period.	(1,769)
Delete firm-years in retail (NAICS sector 44-45) and finance (NAICS sector 52) industries.	(1,929)
Main Sample	**14,768**

Panel B: Industry Distribution
Table 1, Panel B presents the sample industry distribution.

	Sample period: 1996-2007		
Industry Sector	**Firm-Years**		
	Treated	**Control**	**Total**
Administrative and Support and Waste Management and Remediation Services	44	31	75
Accommodation and Food Services	16	0	16
Construction	19	0	19
Health Care and Social Assistance	39	12	51
Information	191	99	290
Manufacturing	8,008	2,312	10,320
Mining, Quarrying, and Oil and Gas Extraction	261	10	271
Professional, Scientific, and Technical Services	1,504	40	1,544
Real Estate and Rental and Leasing	30	0	30
Transportation and Warehousing	0	295	295
Utilities	12	69	81
Wholesale Trade	31	1,733	1,764
Arts, Entertainment, and Recreation	0	12	12
Total	**10,155**	**4,613**	**14,768**

Table 2

Identification Validation

Panel A: Cumulative Abnormal return (CAR) Around the Critical Events during the First Wave of Bonus Depreciation Legislative Process

Table 2, Panel A reports the CAR for B2B capital-goods producing firms (treated group) and B2C capital-goods producing firms (control group), and the difference between the treated group and control group. CAR = cumulative abnormal value weighted return for all 3-day events around each legislative event day. See Appendix 3 for details of the legislative progress. To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

(a): CAR for B2B capital-producing firms (Treated Group)			
Legislation	#Event Days	CAR	t-Statistics
JCWAA2002	5	0.024***	5.104
JGTRRA2003	5	0.045***	7.435
(b): CAR for B2C capital-producing firms (Control Group)			
Legislation	#Event Days	CAR	t-Statistics
JCWAA2002	5	0.009*	1.745
JGTRRA2003	5	0.027***	3.210
(c): Sample Differences Between Treated and Control Groups			
Legislation	#Event Days	CAR	t-Statistics
JCWAA2002	5	0.014*	1.731
JGTRRA2003	5	0.017*	1.721

Panel B: Change in Production Activities During the Bonus Depreciation Period

Table 2, Panel B reports the results from regression of incremental sales ($SALES_{i,t}$), cost of goods sold ($COGS_{i,t}$), Capital expenditure ($CAPX_{i,t}$), and R&D expenditure ($RD_{i,t}$) for the first wave of bonus depreciation (1996 - 2004). Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Pred. Sign	(1) $SALES_{i,t}$	(2) $COGS_{i,t}$	(3) $CAPX_{i,t}$	(4) $RD_{i,t}$
$TREAT_i \times BD\_0204_t$	+/+/0/0	0.158***	0.142**	-0.004	0.007
		(2.770)	(2.337)	(-1.348)	(0.387)
$Size_{i,t}$		-0.018	0.013	0.012***	-0.005
		(-0.440)	(0.277)	(5.614)	(-0.302)
$MTB_{i,t}$		0.041***	0.053	0.004***	0.022
		(4.948)	(1.588)	(5.109)	(1.457)
$LEV_{i,t}$		-0.051	-0.320	-0.020***	-0.165
		(-0.486)	(-0.995)	(-2.761)	(-1.068)
$PPE_{i,t}$		-0.817***	-0.693***	0.178***	-0.095
		(-3.423)	(-3.044)	(6.209)	(-1.555)
$Age_{i,t}$		0.173	0.334**	-0.033***	0.078
		(1.500)	(2.532)	(-4.941)	(1.629)
$OCF_{i,t}$		0.480*	-0.269	-0.005	-0.198***
		(1.658)	(-0.996)	(-0.442)	(-3.335)
$INVT_{i,t}$		5.265***	3.479***	0.158***	0.138***
		(6.994)	(5.717)	(8.655)	(2.691)
Observations		11,492	11,492	11,492	11,492
Fixed Effects		Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.473	0.464	0.357	0.289

Table 3

Descriptive Statistics

Panel A: Summary Statistics for Both Waves of Bonus Depreciation

Table 3, Panel A reports descriptive statistics based on the firm-years observations for the first wave of bonus depreciation sample period. Detailed definitions of all variables are provided in Appendix 1. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Sample Period: 1996-2007							
	N	Mean	SD	P5	P25	P50	P75	P95
$PAT_{i,t+1}$	14,768	17.194	160.768	0.000	0.000	0.000	2.000	48.000
$Incr\_PAT_{i,t+1}$	14,768	0.749	14.130	0.000	0.000	0.000	0.000	1.000
$Radi\_PAT_{i,t+1}$	14,768	16.445	151.724	0.000	0.000	0.000	2.000	47.000
$Size_{i,t}$	14,768	4.805	2.128	1.435	3.190	4.746	6.309	8.466
$ROA_{i,t}$	14,768	-0.075	0.417	-0.682	-0.067	0.032	0.085	0.206
$MTB_{i,t}$	14,768	1.841	2.665	0.140	0.657	1.192	2.089	5.947
$LEV_{i,t}$	14,768	0.159	0.214	0.000	0.000	0.084	0.246	0.528
$PPE_{i,t}$	14,768	0.197	0.166	0.023	0.075	0.151	0.268	0.557
$RDC_{i,t}$	14,768	0.215	0.378	0.000	0.000	0.072	0.276	0.874
$HHI_{f,t}$	14,768	0.031	0.027	0.011	0.015	0.021	0.042	0.069
$Numest_{i,t}$	14,768	0.954	0.969	0.000	0.000	0.693	1.729	2.691
$Age_{i,t}$	14,768	2.759	0.711	1.609	2.303	2.773	3.332	3.871
$OCF_{i,t}$	14,768	0.006	0.275	-0.458	-0.025	0.065	0.130	0.259

Panel B: Pre-treatment comparison

Table 3, Panel B reports mean differences prior to the implementation of the first wave of bonus depreciation. Detailed definitions of all variables are provided in Appendix 1. To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Control	Treatment	Difference
$Size_{i,t}$	5.162	4.454	0.708***
$ROA_{i,t}$	-0.013	-0.076	0.063***
$MTB_{i,t}$	1.363	2.227	-0.863***
$LEV_{i,t}$	0.210	0.142	0.068***
$PPE_{i,t}$	0.253	0.195	0.058***
$RDC_{i,t}$	0.047	0.246	-0.199***
$HHI_{f,t}$	0.042	0.031	0.011***
$Numest_{i,t}$	0.960	0.975	-0.015
$Age_{i,t}$	2.639	2.560	0.079***
$OCF_{i,t}$	0.041	-0.004	0.045***

Table 4

Effect of Bonus Depreciation on Innovation Efforts

Table 4 reports the results from regressions of total patented innovation efforts ($ihs(PAT_{i,t+1})$), incremental innovation efforts ($ihs(Incr\_PAT_{i,t+1})$), and radical innovation efforts ($ihs(Radi\_PAT_{i,t+1})$) for the first wave of bonus depreciation sample period. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Pred. Sign	(1) $ihs(PAT_{i,t+1})$	(2) $ihs(Incr\_PAT_{i,t+1})$	(3) $ihs(Radi\_PAT_{i,t+1})$
$TREAT_i \times POST_t$	- /+/-	-0.059**	0.088***	-0.069**
		(-1.992)	(3.617)	(-2.341)
$Size_{i,t}$		0.121***	0.057***	0.112***
		(6.617)	(5.093)	(6.208)
$ROA_{i,t}$		0.000	-0.000	0.003
		(0.002)	(-0.019)	(0.121)
$MTB_{i,t}$		0.009***	-0.002	0.008***
		(3.261)	(-1.163)	(3.177)
$LEV_{i,t}$		-0.014	-0.014	-0.012
		(-0.352)	(-0.611)	(-0.322)
$PPE_{i,t}$		0.280***	0.043	0.274***
		(2.947)	(0.774)	(2.932)
$RDC_{i,t}$		0.023	0.000	0.022
		(0.784)	(0.017)	(0.748)
$HHI_{f,t}$		-0.019	0.314	-0.107
		(-0.049)	(1.069)	(-0.278)
$Numest_{i,t}$		0.069***	0.024*	0.064***
		(2.980)	(1.906)	(2.823)
$Age_{i,t}$		-0.043	-0.259***	-0.038
		(-0.810)	(-5.549)	(-0.720)
$OCF_{i,t}$		-0.034	0.002	-0.037
		(-1.118)	(0.096)	(-1.198)
Observations		14,768	14,768	14,768
Fixed Effects		Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.874	0.431	0.873

Table 5
Heterogenous Effect of Bonus Depreciation on the Innovation Efforts

Table 5, Panel A presents the results of examining whether the effects of bonus depreciation on innovation efforts vary with the exposure to bonus depreciation induced demand surge measured as proximity to final demand for the first wave of bonus depreciation sample period. Table 5, Panel B presents the results of examining whether the effects of bonus depreciation on innovation efforts vary with product market power for the first wave of bonus depreciation sample period. Detailed definitions of all variables are provided in Appendix 1. The proximity to final demand is measured as inverse industry upstreamness from Antràs et al. (2012). B2B (Treated) firms falling in above-median inverse industry upstreamness measure are identified as high proximity to final demand treated firms, otherwise low proximity to final demand treated firms. The product market power is measured as the industry-adjusted price-cost margin. B2B (Treated) firms falling in above-median industry-adjusted price-cost margin are identified as high product market power treated firms, otherwise low product market power treated firms. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. All regressions include firm and year fixed effects. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance (two-tailed) at 1%, 5%, and 10%, respectively.

Panel A: Proximity to End Users

			(1)	(2)	(3)
Dependent Variable	Pred. Sign		$ihs(PAT_{i,t+1})$	$ihs(Incr\_PAT_{i,t+1})$	$ihs(Radi\_PAT_{i,t+1})$
Partition Variable				Proximity to Final Demand	
$HighTREAT_i \times POST_t$	- /+/-	[1]	-0.088**	0.114***	-0.102***
			(-2.446)	(3.857)	(-2.896)
$LowTREAT_i \times POST_t$	0/+/0	[2]	-0.039	0.057**	-0.042
			(-1.107)	(1.985)	(-1.201)
Test of [1]-[2]			-0.0533	0.0626*	-0.0659*
p-value for [1]=[2]			0.1858	0.0652	0.0964
Controls			Yes	Yes	Yes
Observations			14,768	14,768	14,768
Fixed Effects			Firm, Year	Firm, Year	Firm, Year
Adj R-squared			0.873	0.432	0.873

Panel B: Product Market Power

			(1)	(2)	(3)
Dependent Variable	Pred. Sign		$ihs(PAT_{i,t+1})$	$ihs(Incr\_PAT_{i,t+1})$	$ihs(Radi\_PAT_{i,t+1})$
Partition Variable				Product Market Power	
$HighTREAT_i \times POST_t$	0/+/0	[1]	-0.030	0.144***	-0.046
			(-0.892)	(5.191)	(-1.390)
$LowTREAT_i \times POST_t$	- /+/-	[2]	-0.148***	0.080***	-0.156***
			(-3.670)	(2.684)	(-3.866)
Test of [1]-[2]			0.1182***	0.0643*	0.1100***
p-value for [1]=[2]			0.0091	0.0759	0.0143
Controls			Yes	Yes	Yes
Observations			14,768	14,768	14,768
Fixed Effects			Firm, Year	Firm, Year	Firm, Year
Adj R-squared			0.874	0.435	0.874

Table 6

Additional Innovation Outcomes Analyses

Table 6, Panel A reports the results from regressions of alternative trademark-based innovation efforts measured as the number of newly filed service trademarks ($ihs(TM\_Service_{i,t+1})$) and the number of newly filed product trademark families ($ihs(TM\_Family_{i,t+1})$) for the first wave of bonus depreciation sample period. Table 6, Panel B reports the results from regressions of alternative incremental innovation efforts, product differentiation ($ProdDiff_{i,t+1}$) and number of patents that receive zero forward citations within 5 years following the patent application date ($ihs(NoFC\_PAT_{i,t+1})$) for the first wave of bonus depreciation sample period. Table 6, Panel C reports the results from regressions of alternative radical innovation efforts, incidence of breakthrough patents ($Bkr\_PAT_{i,t+1}$) and the number of patents that fall in the top decile of non-self forward citations within ten years of application ($ihs(TOP10NSFC\_PAT_{i,t+1})$) for the first wave of bonus depreciation sample period. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Alternative Non-patented Innovation Efforts Measures

		(1)	(2)
Dependent Variable	Pred. Sign	$ihs(TM\_Service_{i,t+1})$	$ihs(TM\_Family_{i,t+1})$
$TREAT_i \times POST_t$	+/-	0.029*	-0.045**
		(1.645)	(-2.010)
Controls		Yes	Yes
Observations		14,768	14,768
Fixed Effects		Firm, Year	Firm, Year
Adj R-squared		0.457	0.652

Panel B: Alternative Incremental Innovation Efforts Measures

		(1)	(2)
Dependent Variable	Pred. Sign	$ProdDiff_{i,t+1}$	$ihs(NoFC\_PAT_{i,t+1})$
$TREAT_i \times POST_t$	+/+	0.238***	0.068**
		(3.972)	(2.331)
Controls		Yes	Yes
Observations		13,908	14,768
Fixed Effects		Firm, Year	Firm, Year
Adj R-squared		0.803	0.792

Panel C: Alternative Radical Innovation Efforts Measures

		(1)	(2)
Dependent Variable	Pred. Sign	$Bkr\_PAT_{i,t+1}$	$ihs(TOP10NSFC\_PAT_{i,t+1})$
$TREAT_i \times POST_t$	-/-	-0.055***	-0.061***
		(-5.642)	(-3.132)
Controls		Yes	Yes
Observations		14,768	14,768
Fixed Effects		Firm, Year	Firm, Year
Adj R-squared		0.532	0.814

Table 7

Robustness Checks

Table 7, Panel A presents the results for the effect bonus depreciation on capital-goods producing firms' innovation efforts on matched sample for the first wave of bonus depreciation sample period. Table 7, Panel B presents the results for the effect of bonus depreciation on capital-goods producing firm's innovation efforts on the global sample for the first wave of bonus depreciation sample period. The global sample encompass both capital-goods producing firms incorporate in the U.S. and those incorporate outside U.S. with at least 30% U.S. sales exposure. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. Standard errors are clustered by firm, and t-statistics are in parentheses. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. ***, **, * indicate statistical significance (two-tailed) at 1%, 5%, and 10%, respectively.

Panel A: Matched Sample Analysis

(a) Propensity Score Matched Sample: Pre-treatment Comparison

	Control	Treat	Difference
$Size_{i,t}$	5.126	4.513	0.613
$ROA_{i,t}$	-0.227	-0.215	-0.011
$MTB_{i,t}$	0.908	2.122	-1.213
$LEV_{i,t}$	0.235	0.166	0.069
$PPE_{i,t}$	0.194	0.188	0.006
$RDC_{i,t}$	0.514	0.287	0.227
$HHI_{f,t}$	0.051	0.025	0.026***
$Numest_{i,t}$	0.867	0.908	-0.040
$Age_{i,t}$	2.948	2.674	0.274**
$OCF_{i,t}$	0.006	-0.013	0.018

(b) Propensity Score Matched Sample: Regression

		(1)	(2)	(3)
Dependent Variable	Pred. Sign	$ihs(PAT_{i,t+1})$	$ihs(Incr\_PAT_{i,t+1})$	$ihs(Radi\_PAT_{i,t+1})$
Matching procedure		Propensity Matching within 4-digit NAICS industry		
$TREAT_i \times POST_t$	-/+/-	-0.118**	0.086***	-0.125***
		(-2.459)	(3.488)	(-2.614)
Controls		Yes	Yes	Yes
Observations		10,189	10,189	10,189
Fixed Effects		Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.878	0.466	0.879

Panel B: Global Sample Analysis

		(1)	(2)	(3)
Dependent Variable	Pred. Sign	$ihs(PAT_{i,t+1})$	$ihs(Incr\_PAT_{i,t+1})$	$ihs(Radi\_PAT_{i,t+1})$
$TREAT_i \times POST_t$	-/+/-	-0.052**	0.073***	-0.060**
		(-1.983)	(3.149)	(-2.351)
Controls		Yes	Yes	Yes
Observations		17,997	17,997	17,997
Fixed Effects		Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.889	0.437	0.888

Table 8

Patent-Level Analyses

Table 7, Panel A reports the results from regressions of patent values measured by private economic value ($MKTVal_{i,t+1}$) and scientific value ($ihs(FNSCitation\_10Y_{i,t+1})$) for patens filed in the first wave of bonus depreciation sample period. Table 7, Panel B reports the results from regressions of patent scope measured by number of claims ($ihs(Claim_{i,t+1})$) and the average word counts of claims ($ihs(Claim\_WC_{i,t+1})$) for patens filed in the first wave of bonus depreciation sample period. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and industry(2-digit NAICS)-year fixed effects. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Patent Values

Dependent Variable	Pred. Sign	(1) $MKTVal_{i,t+1}$	(2) $ihs(FNSCitation\_10Y_{i,t+1})$
$TREAT_i \times POST_t$	+or0/-	0.158	-0.239***
		(0.597)	(-2.619)
$Size_{i,t}$		0.022	-0.086*
		(0.269)	(-1.930)
$ROA_{i,t}$		0.204	-0.000
		(1.520)	(-0.008)
$LEV_{i,t}$		-0.000	0.000**
		(-0.955)	(1.977)
$MTB_{i,t}$		0.012*	-0.001
		(1.732)	(-0.241)
$RDC_{i,t}$		-0.000	-0.000
		(-1.087)	(-0.604)
$Age_{i,t}$		-0.379	-0.116
		(-1.587)	(-0.931)
Observations		237,782	252,880
Fixed Effects		Firm, Ind-Year	Firm, Ind-Year
Adj R-squared		0.568	0.227

Panel B: Patent Scope

Dependent Variable	Pred. Sign	(1) $ihs(Claim_{i,t+1})$	(2) $ihs(Claim\_WC_{i,t+1})$
$TREAT_i \times POST_t$	-/+	-0.111**	0.052*
		(-2.131)	(1.745)
$Size_{i,t}$		0.008	-0.009
		(0.301)	(-0.644)
$ROA_{i,t}$		0.020	-0.002
		(0.597)	(-0.167)
$LEV_{i,t}$		-0.000**	0.000
		(-2.009)	(0.136)
$MTB_{i,t}$		0.001	-0.001
		(1.131)	(-1.266)
$RDC_{i,t}$		-0.000	0.000*
		(-1.585)	(1.846)
$Age_{i,t}$		-0.024	0.022
		(-0.300)	(0.389)
Observations		252,880	252,880
Fixed Effects		Firm, Ind-Year	Firm, Ind-Year
Adj R-squared		0.105	0.103

Table 9
Effect of the Second Wave of the Bonus Depreciation on Innovation Efforts

Panel A: Cumulative Abnormal return (CAR) Around the Critical Events during the Second Wave of Bonus Depreciation Legislative Process

Table 9, Panel A reports the CAR for B2B capital-goods producing firms (treated group) and B2C capital-goods producing firms (control group), and the difference between the treated group and control group. CAR = cumulative abnormal value weighted return for all 3 days around each legislative event day. See Appendix 3 for details of the legislative progress. Detailed definitions of all variables are provided in Appendix 1. ***, **, * indicate statistical significance (two-tailed) at 1%, 5%, and 10%, respectively.

(a): CAR for B2B Capital-goods Producing Firms (Treated Group)			
Legislation	#Event Days	CAR	t-Statistics
ESA2008	4	0.008**	2.238
ARRA2009	5	0.021*	2.089
TRA2010	5	0.003	0.597
(b): CAR for B2C Capital-goods Producing Firms (Control Group)			
Legislation	#Event Days	CAR	t-Statistics
ESA2008	4	0.000	0.813
ARRA2009	5	0.003	0.104
TRA2010	5	0.005	0.321
(c): Sample Differences Between Treated and Control Groups			
Legislation	#Event Days	CAR	t-Statistics
ESA2008	4	0.008	1.238
ARRA2009	5	0.018	0.774
TRA2010	5	-0.001	-0.189

Panel B: Change in Production Activities During the Bonus Depreciation Period

Table 9, Panel B reports the results from regression of incremental sales ($SALES_{i,t}$), cost of goods sold ($COGS_{i,t}$), capital expenditures ($CAPX_{i,t}$), and R&D expenditure ($RD_{i,t}$) for the second wave of bonus depreciation (2005 – 2012). The second wave of bonus depreciation is implemented between 2009 and 2012 during Obama's administration. The year 2008 is excluded to mitigate confounding effects from the political uncertainty of the election year and the immediate reintroduction of the policy under the Economic Stimulus Act of 2008 due to Global Financial Crisis. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Pred. Sign	(1) $SALES_{i,t}$	(2) $COGS_{i,t}$	(3) $CAPX_{i,t}$	(4) $RD_{i,t}$
$TREAT_i \times BD\_0912_t$	+/+/0/0	0.030	0.037	0.000	0.028
		(0.866)	(0.911)	(0.160)	(0.815)
Controls		Yes	Yes	Yes	Yes
Observations		5,187	5,187	5,187	5,187
Fixed Effects		Firm, Year	Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.841	0.804	0.652	0.216

Table 9
Effect of the Second Wave of the Bonus Depreciation on Innovation Efforts

Panel C: Multivariate Analyses of Innovation Efforts

Table 9, Panel C reports the results from regressions of total patenting innovation efforts ($ihs(PAT_{i,t+1})$), incremental patenting innovation efforts ($ihs(Incr\_PAT_{i,t+1})$), and radical patenting innovation efforts ($ihs(Radi\_PAT_{i,t+1})$)for the second wave of bonus depreciation sample period. POST equal to 1 for fiscal years between 2009 and 2014, 0 for fiscal years between 2005-2007. Detailed definitions of all variables are provided in Appendix 1. All regressions include firm and year fixed effects. To reduce the influence of extreme values, all continuous independent variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm, and t-statistics are in parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Pred. Sign	(1) $ihs(PAT_{i,t+1})$	(2) $ihs(Incr\_PAT_{i,t+1})$	(3) $ihs(Radi\_PAT_{i,t+1})$
$TREAT_i \times POST_t$	-/+/-	-0.075*	0.173***	-0.227***
		(-1.823)	(3.004)	(-3.659)
$Size_{i,t}$		0.109***	0.113***	0.011
		(3.533)	(3.190)	(0.265)
$ROA_{i,t}$		0.000	0.003	-0.001
		(0.151)	(1.183)	(-0.761)
$MTB_{i,t}$		-0.006	0.008	-0.012*
		(-1.041)	(1.460)	(-1.895)
$LEV_{i,t}$		-0.078	0.036	-0.131
		(-1.134)	(0.485)	(-1.514)
$PPE_{i,t}$		0.260*	-0.124	0.460**
		(1.709)	(-0.614)	(2.016)
$RDC_{i,t}$		-0.000	0.005	-0.004*
		(-0.260)	(1.627)	(-1.710)
$HHI_{f,t}$		-0.046	0.145	-0.256
		(-0.225)	(0.938)	(-1.114)
$Numest_{i,t}$		0.103***	0.052	0.062
		(2.927)	(1.360)	(1.458)
$Age_{i,t}$		0.632***	-0.648**	1.319***
		(2.765)	(-2.417)	(4.036)
$OCF_{i,t}$		-0.007	-0.033	0.001
		(-0.117)	(-0.597)	(0.010)
Observations		6,409	6,409	6,409
Fixed Effects		Firm, Year	Firm, Year	Firm, Year
Adj R-squared		0.901	0.837	0.832