Tax Windfall or White Elephant? The Intensive-Margin Innovation Response of U.S. Pharmaceutical Firms to the 2017 Corporate Tax Reform

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Abstract

Did the 2017 Tax Cuts and Jobs Act (TCJA) stimulate pharmaceutical innovation, or did it primarily raise after-tax cash flows with limited effects on innovation outcomes? Using data on publicly traded pharmaceutical firms from 2012–2021, we study how the reform affected twelve innovation outcomes spanning the drug development pipeline, including patenting, trial initiation, trial completion, and development speed. Our empirical strategy combines descriptive analysis, nonparametric event studies, as well as event-study and difference-in-differences models that use pre-policy leverage as a proxy for differential sensitivity to the reform's liquidity effects. Comparing firms with high versus low pre-policy debt-to-asset ratios, we estimate that more leveraged firms experienced roughly a 12 percent increase in patenting and a 22 percent increase in patent value, along with a modest 3 percent increase in Phase I trial initiations after the reform. However, we find no significant effects on the nine other innovation levers, including later-stage trial initiations, project completions, or development speed. Robustness tests using alternative exposure measures—free cash flow, firm age, and firm size—yield similar patterns. Overall, our evidence suggests that the TCJA has been associated with modest increases in upstream intellectual-property activity among more leveraged firms, with little evidence of changes in downstream stages of development.

Keywords: Corporate taxation; Pharmaceutical innovation; Financing constraints; Drug development; R&D policy

1 Introduction

Pharmaceutical innovation generates enormous social value, yet the process of discovering and developing new medicines has become increasingly costly and uncertain (DiMasi et al. (2003); Alpert et al. (2023); Angelis et al. (2023)). Over the past several decades, the productivity of drug development has declined despite rising investments in research and development (R&D), a phenomenon widely described as Eroom's Law. At the same time, the returns to pharmaceutical innovation follow a highly skewed distribution in which a small number of breakthrough therapies account for a large share of both profits and health gains. These structural features make public policy central to the functioning of the medical innovation system.

To stimulate innovation, governments routinely deploy a combination of push policies—such as research funding, tax incentives, and grants—and pull incentives—including patent protection, market exclusivity, and reimbursement rules (Finkelstein (2004); Dubois et al. (2015); Williams (2017)). Much less is known, however, about the innovation consequences of broad fiscal policies that are not explicitly targeted toward research and development.

The pharmaceutical industry is an especially important setting in which to study this question. Compared with most sectors of the economy, pharmaceutical firms devote an unusually large share of revenues to R&D, often exceeding 15–25 percent of sales. Innovation occurs through long and staged investments that begin with basic scientific discovery and proceed through multiple phases of clinical trials before regulatory approval. Moreover, the returns to innovation are highly concentrated: a small share of successful drugs generate most industry profits and social benefits. These characteristics make pharmaceutical innovation particularly sensitive to changes in financial conditions and policy incentives. Financial shocks may not only influence how much firms invest in

research, but also how they allocate resources across different stages of the innovation pipeline.

At the same time, broad fiscal shocks may not necessarily translate into greater innovative activity. Increased liquidity can generate short term windfalls that stimulate exploration and scientific discovery, but it may also be directed toward other corporate uses of cash. Firms may use additional funds for share repurchases, debt reduction, acquisitions, marketing expansion, or organizational restructuring rather than for R&D investment. These alternative uses of cash are particularly relevant in industries characterized by large firms, significant financial markets, and complex corporate structures. As a result, the net effect of broad tax cuts on innovation is theoretically ambiguous: additional liquidity may either stimulate innovation at different stages of research; or be diverted toward other activities that do not directly increase scientific output—null effect.

The 2017 Tax Cuts and Jobs Act (TCJA) offers a natural setting to examine this question. By reducing the federal corporate tax rate from 35 percent to 21 percent and reforming the taxation of foreign earnings, the reform generated one of the largest corporate tax shocks in modern U.S. history. The Congressional Budget Office estimates that the legislation will reduce federal revenues by roughly $1.46 trillion over the 2018–2027 period, with about $654 billion attributable to corporate provisions alone. These changes substantially increased after-tax cash flows for U.S. corporations, raising the possibility that firms would expand investment—including innovative activity—as financing constraints eased. Yet whether such broad liquidity shocks translate into meaningful changes in innovation remains an open empirical question.

Corporate finance theory provides a useful framework for understanding how firms may respond to such liquidity shocks. Highly leveraged firms may underinvest in risky projects because part of the upside accrues to creditors rather than shareholders, a

distortion commonly referred to as debt overhang (Myers (1977)). When internal funds increase, this distortion may be partially alleviated, allowing financially constrained firms to undertake investments that were previously unattractive. Innovation investments are particularly sensitive to these financing frictions because R&D projects are risky, intangible, and difficult to collateralize (Hall and Lerner (2010)). Financing conditions can also shape the type of innovation firms pursue, shifting investment toward projects with different risk profiles (Thakor and Lo (2022)). Empirical evidence further suggests that financial shocks tend to influence upstream research activities—such as patenting and early-stage discovery—more than later stages of development (Mezzanotti (2021)).

This paper examines whether the TCJA stimulated pharmaceutical innovation and how firms adjusted their innovation strategies in response to the reform. Rather than focusing solely on aggregate R&D spending, we study the intensive margin of innovation—how firms allocate effort across the stages of the drug development process. To capture this structure, we measure twelve operational "innovation levers," which we group into four strategic bundles: strengthening the intellectual-property moat through patenting activity; expanding the research pipeline through the initiation of clinical trials; crossing the "valley of death" through the completion of trials; and accelerating time-to-knowledge through faster clinical development.

Our empirical strategy combines descriptive analysis, non-parametric event studies, and difference-in-differences event analysis. We assemble firm-level data on patenting, clinical trial initiation and completion, and development timelines using patent datasets, ClinicalTrials.gov, and Cortellis. To identify heterogeneous exposure to the tax reform, we exploit variation in firms' leverage prior to the policy change, comparing firms with high debt-to-asset ratios to otherwise similar firms with lower leverage.

Across all empirical approaches, we find little evidence that the TCJA broadly stimulated pharmaceutical innovation. Descriptive and non-parametric analyses reveal modest

improvements in the quality and value of patenting activity but no visible shifts in the initiation or completion of clinical trials or in the speed of development. The difference-in-differences analysis yields a similar pattern. Firms with higher leverage—those most exposed to the liquidity shock—generate more patents and patents of higher estimated value, and they modestly increase the initiation of Phase I clinical trials. However, we find no corresponding effects on later-stage development, project completion, or development speed.

These results point to a sharp asymmetry in how firms respond to broad fiscal shocks. The tax reform appears to stimulate upstream innovation activities that are relatively flexible and option-like—patenting and early-stage research—but it does not accelerate the downstream execution of drug development. This pattern suggests that while liquidity shocks may expand the set of scientific opportunities explored by firms, they do not necessarily overcome the organizational, scientific, and regulatory bottlenecks that shape the later stages of pharmaceutical innovation. Such bottlenecks and frictions are well-documented and frequently discussed as major hurdles to the development pipeline (for instance, recently in Teslo (2026)). Our findings have implications for the design of innovation policy. Broad corporate tax cuts may have limited effectiveness as tools for stimulating pharmaceutical innovation because they do not directly address the structural bottlenecks that slow the translation of scientific discoveries into new medicines. Policies that target specific stages of the innovation process—such as support for basic science, regulatory reforms that accelerate clinical trials (Rao (2016)), or incentives tied to the development of high-value therapies—may therefore be more effective in addressing the productivity challenges facing the pharmaceutical sector.

2 Policy Incentives and the TCJA Shock

2.1 Traditional Innovation Incentives and the Role of Demand

A large literature shows that innovation can be induce via policies that increase the expected returns from successful discoveries. In the pharmaceutical sector, these incentives typically operate by expanding or securing revenue streams for new therapies. Policies that increase the size or value of potential markets can induce firms to redirect research effort toward areas where demand becomes more attractive.

A seminal contribution is Acemoglu and Linn (2004), who show that pharmaceutical firms respond to changes in market size generated by demographic shifts. As the population of potential patients increases, firms increase innovation directed toward diseases affecting those groups. Their findings highlight the role of demand-driven innovation: when expected revenues rise, firms increase research activity in the corresponding therapeutic areas.

Policy-induced demand shifts can also arise through public insurance expansions and regulatory reforms. Finkelstein (2004) shows that the introduction of Medicare increased innovation in medical technologies by expanding the market for treatments used by elderly patients. Similarly, changes in reimbursement rules or insurance coverage can alter the expected profitability of new therapies, encouraging firms to redirect research toward areas where demand becomes more secure (Dubois et al. (2015); Williams (2017); Dranove et al. (2022)).

In addition to demand-side incentives, governments also stimulate innovation through policies that reduce the cost of research investment. One common instrument is the tax treatment of R&D expenditures. Allowing firms to deduct or accelerate the expensing of R&D costs lowers the effective user cost of innovation and increases the expected return on research investments. Several studies show that such tax incentives can stimulate pri-

vate R&D investment, particularly in industries characterized by high research intensity and long development cycles.

These traditional policy tools share an important feature: they are targeted toward specific components of the innovation process. Demand-side policies raise the expected revenues from successful discoveries, while tax incentives directly reduce the cost of R&D. In both cases, the policy instrument is closely tied to the innovation activity it seeks to stimulate.

Broad corporate tax cuts differ in important ways from these targeted policies. By reducing corporate tax rates, such reforms simultaneously increase after-tax profits and lower the cost of capital across all corporate activities. In this sense, they operate as a hybrid policy instrument combining elements of both push and pull incentives. On the one hand, higher retained earnings increase the expected returns to successful innovations. On the other hand, lower effective tax burdens reduce the cost of financing new investment, potentially encouraging firms to undertake riskier projects.

From a dynamic perspective, such policies could stimulate innovation by expanding the set of research opportunities firms are willing to explore. Higher expected returns increase the probability that firms will pursue projects with uncertain outcomes but potentially large payoffs. At the same time, increased internal funds may relax financing constraints that limit the ability of risk-averse firms to invest in exploratory research.

Yet the impact of broad fiscal shocks on innovation is theoretically ambiguous. Additional liquidity may stimulate research activity, but it may also be diverted toward other corporate uses of cash. Firms may increase share repurchases, reduce leverage, or pursue acquisitions rather than expand internal research programs. They may also invest in organizational improvements, marketing capabilities, or other forms of intangible capital that are not directly observable in standard innovation metrics.

These potential leakages are particularly relevant in industries dominated by large

firms with substantial financial flexibility. Cash windfalls may be used to improve earnings per share through financial engineering, strengthen balance sheets, or acquire smaller innovative firms rather than expand internal research. Organizational innovation—such as improvements in commercialization capabilities, supply chains, or marketing strategies—may also absorb additional liquidity without immediately affecting measurable R&D outputs.

As a result, broad fiscal policies such as corporate tax cuts may produce weaker innovation responses than targeted policy instruments that directly affect research incentives. Whether the net effect of such policies stimulates innovation or simply reallocates corporate resources across different uses of cash remains an empirical question.

2.2 The 2017 Tax Cuts and Jobs Act and Pharmaceutical Innovation

The Tax Cuts and Jobs Act (TCJA) of 2017 was the most consequential reform of the U.S. corporate tax system in more than three decades. The legislation reduced the federal statutory corporate tax rate from 35 percent to 21 percent and introduced major changes to the taxation of corporate income and multinational profits. These reforms included limits on the deductibility of interest payments, changes to the treatment of net operating losses, provisions affecting the taxation of foreign income, and a one-time transition tax on previously accumulated foreign earnings. Together, these measures significantly altered the tax environment facing U.S. corporations and generated a large fiscal shock to corporate cash flows.

The Congressional Budget Office projected that the TCJA would reduce federal revenues by roughly $1.46 trillion over the 2018–2027 period. Corporate provisions alone account for a large share of this fiscal impact, reflecting both the reduction in the statutory corporate rate and the restructuring of international taxation. Some elements

of the reform partially offset these revenue losses—such as limits on interest deductions and changes to investment and loss provisions—but the overall effect was a substantial decline in corporate tax liabilities. In aggregate, the reform therefore represented a large increase in after-tax cash flows for many U.S. corporations.

The macroeconomic rationale for the reform was that lower corporate tax rates would stimulate investment, productivity, and long-run economic growth. By reducing the cost of capital and increasing retained earnings, the TCJA was expected to encourage firms to expand both physical and intangible investment. In this view, the reform could also indirectly stimulate innovation by providing firms with greater internal resources to finance risky and long-horizon research activities.

Empirical evidence on the macroeconomic effects of the TCJA, however, has produced mixed conclusions. While some studies document modest increases in business investment following the reform, the magnitude of these effects appears smaller than the policy's fiscal cost would suggest (Chodorow-Reich et al. (2024); Gale et al. (2024)). Similarly, the evidence on employment and wage growth following the reform indicates relatively limited effects compared with early policy projections. In addition, a number of analyses show that a substantial portion of the liquidity generated by the tax cut was returned to shareholders through increased dividends and share repurchases rather than through new investment.

The implications of the TCJA for innovation are even less clear. Broad corporate tax reductions differ from focus policies in that they are not directly tied to research activities. Instead, they simultaneously increase after-tax profits and lower the cost of capital across a wide range of corporate decisions. As a result, firms may use the additional liquidity generated by tax reductions for multiple purposes, including shareholder payouts, debt reduction, acquisitions, or organizational investment.

This ambiguity is particularly relevant in the pharmaceutical industry. Pharmaceu-

tical firms are among the most research-intensive corporations in the economy, but their innovation process is also long, sequential, and highly uncertain. Drug development unfolds through multiple stages—from early scientific discovery to clinical trials and regulatory approval—and financial shocks may influence different stages of this process in distinct ways. For example, firms may expand exploratory research and patenting activity while leaving later-stage clinical development largely unchanged.

Despite the importance of these dynamics, little empirical evidence exists on how broad corporate tax reforms affect the structure of pharmaceutical innovation. Most studies focus either on aggregate R&D spending or on targeted tax incentives designed specifically to stimulate research investment. As a result, we know relatively little about how large fiscal shocks—such as the TCJA—affect the allocation of innovation activities within firms.

This paper addresses that gap by examining how the TCJA influenced the internal structure of pharmaceutical innovation. Rather than focusing solely on aggregate R&D spending, we study twelve operational levers of innovation that capture different stages of the drug development process, including patenting activity, the initiation and completion of clinical trials, and the speed of clinical development. By analyzing how these innovation levers respond to a large fiscal shock, we provide new evidence on whether broad corporate tax cuts stimulate productive innovation or primarily generate financial windfalls that are absorbed elsewhere within firms.

3 Innovation at the Intensive Margin: Conceptual Framework and Hypotheses

Pharmaceutical innovation is often measured through aggregate R&D expenditures or counts of new drug approvals (Danzon et al. (2005b); Danzon et al. (2005a); Buxbaum et al.

(2020)). While useful, these measures obscure how firms allocate resources across the stages of the innovation process. Drug development is inherently sequential: scientific discovery leads to intellectual property, which may translate into early clinical trials, which in turn must survive multiple phases of testing before regulatory approval. Changes in financial conditions may therefore affect not only the level of research spending but also the allocation of effort across different stages of the innovation pipeline. To capture these dynamics, we focus on the intensive margin of innovation.

We conceptualize pharmaceutical innovation through twelve operational levers that represent distinct stages of the drug development process. These levers fall into four strategic bundles that capture the main ways firms can adjust their innovation strategies.

The first bundle reflects the intellectual-property moat of the firm. Patents protect scientific discoveries and secure future revenue streams. We measure three related dimensions of patent activity: patent count, patent value, and patent citations. Patent counts capture the scale of inventive activity, while patent value and citation measures capture the economic and scientific importance of these discoveries.

The second bundle captures pipeline expansion, which reflects the initiation of new research programs. Firms may start clinical trials at different stages of development. We therefore examine the initiation of Phase I, Phase II, and Phase III trials. These outcomes measure the extent to which firms expand their research portfolio and explore new therapeutic opportunities.

The third bundle reflects firms' ability to cross the "valley of death". Many drug candidates fail during clinical development, and the transition between phases represents a critical bottleneck in the innovation process. We therefore measure completion of Phase I, Phase II, and Phase III trials. These outcomes capture firms' ability to move projects from early research into later stages of development.

The fourth bundle measures time-to-knowledge, which reflects the speed at which

firms advance drug candidates through the development process. Faster clinical development increases the net present value of innovation by bringing therapies to market sooner and by reducing the uncertainty surrounding research outcomes. We therefore measure the time required to complete each clinical phase.

Taken together, these twelve innovation levers provide a granular view of how firms allocate effort across the pharmaceutical innovation pipeline. Rather than focusing solely on aggregate R&D spending, this framework allows us to observe whether firms respond to policy changes by strengthening their intellectual property position, expanding their research portfolio, improving the execution of clinical trials, or accelerating the speed of development.

Corporate finance theory provides a framework for understanding how firms may adjust these innovation levers when financial conditions change. A central insight of this literature is that capital structure can distort investment incentives, particularly for risky projects with uncertain payoffs. Myers (1977) shows that firms with high levels of debt may underinvest in risky growth opportunities because some of the benefits accrue to creditors rather than shareholders. This debt overhang problem is particularly relevant for innovation investments, which often involve substantial uncertainty and longtime horizons.

Innovation activities are also especially sensitive to financing frictions. R&D investments rely heavily on intangible assets that are difficult to collateralize, making external financing more costly and increasing firms' reliance on internal funds (Myers (1977)). As a result, changes in internal liquidity can significantly affect firms' ability to pursue research opportunities.

Financial structure can also shape the type of innovation projects firms undertake. When financing constraints are relaxed, firms may shift toward projects with higher risk and higher potential returns (Thakor and Lo (2022)). This perspective suggests that

liquidity shocks may alter the composition of innovative activity rather than simply increasing the level of R&D spending.

Empirical evidence further suggests that financing shocks primarily influence upstream stages of innovation. Mezzanotti (2021) shows that increases in financing costs reduce research investment and patenting activity, while later stages of product development are less sensitive to financial conditions. This evidence implies that financial shocks may affect early discovery and patenting activity more strongly than downstream clinical development.

Together, these insights provide the theoretical bridge connecting the corporate finance literature to our empirical setting. The mechanism linking financial shocks to innovation can be summarized as follows. Capital structure distortions may limit firms' ability to pursue risky research opportunities. When liquidity constraints are relaxed, firms may respond by expanding exploratory research and strengthening their intellectual property position. However, later stages of innovation—such as clinical development and regulatory approval—may depend more heavily on scientific and organizational constraints than on financing conditions.

This framework yields several testable implications. If broad tax cuts increase internal liquidity, firms with greater financial constraints should respond more strongly to the policy shock. Firms with higher leverage prior to the reform may experience a larger relaxation of financing constraints. These firms may therefore increase upstream innovation activities—such as patenting and early-stage research—relative to firms with lower leverage.

At the same time, the framework suggests that downstream innovation activities may be less responsive to liquidity shocks. Advancing drug candidates through clinical trials requires substantial organizational capabilities, regulatory interactions, and scientific progress. These factors may limit firms' ability to accelerate development even when

internal funds increase.

Guided by these insights, our analysis focuses on three research questions. First, did firms adjust the allocation of innovation activities across the four strategic bundles following the 2017 tax reform? We examine whether the policy affected upstream activities such as patenting and trial initiation differently from downstream activities such as clinical completion and development speed. Second, did the TCJA causally change any of the twelve innovation levers that characterize the pharmaceutical innovation pipeline? Third, did firms with greater financial constraints respond more strongly to the tax-induced liquidity shock? We focus primarily on differences between firms with high and low debt-to-asset ratios prior to the reform.

These questions lead to our central hypothesis: if corporate tax cuts relax financing constraints, firms that were more financially constrained before the reform should increase upstream innovation activities—such as patenting and early-stage trial initiation—while showing weaker responses in downstream stages of development.

4 Empirical Strategy and Data

This section describes the empirical strategy and data used to evaluate the causal effect of the 2017 Tax Cuts and Jobs Act (TCJA) on pharmaceutical innovation. Our objective is to determine whether the tax-induced liquidity shock causally altered how firms allocate effort across the innovation pipeline. Rather than focusing exclusively on aggregate R&D spending, we examine the intensive margin of innovation, captured through the twelve operational innovation levers described in Section 3.

Our empirical approach combines three complementary strategies. First, we present descriptive evidence comparing innovation outcomes before and after the policy reform. Second, we estimate non-parametric event-time models that trace the evolution of innovation outcomes around the introduction of the TCJA. Third, we implement an event-

study difference-in-differences (DiD) framework that exploits variation in firms' exposure to the tax shock. This strategy allows us to evaluate whether firms that benefited more from the policy (larger exposure to the tax cut) changed their innovation trajectories relative to comparable firms with lower exposure.

All analyses are conducted using quarterly firm-level data, which allows us to track the timing of innovation responses with greater precision.

4.1 Data and Sources

Our dataset combines several sources of information on pharmaceutical firms and their innovation activities. Patent data are obtained from patent databases that provide information on patent filings, citations, and related bibliometric indicators. These data allow us to construct measures of patent quantity, patent influence, and estimated patent value. Patent-based measures are widely used in the economics of innovation literature to capture inventive activity and the economic importance of discoveries (Henderson et al. (2005); Akcigit et al. (2022)).

Information on clinical trials is obtained from ClinicalTrials.gov and the Cortellis drug development database, which provide detailed information on the initiation, progression, and completion of clinical trials. These sources allow us to track the initiation and completion of Phase I, Phase II, and Phase III trials as well as the duration of each stage of clinical development. These data are widely used to study the pharmaceutical innovation process because they provide a comprehensive record of drug development activity.

Firm-level financial information is drawn from Compustat, which provides data on balance sheets, income statements, and firm characteristics. These data are used to construct measures of firm leverage, free cash flow, firm size, age, and other financial variables used in the empirical analysis. Combining these sources yields a panel dataset

of publicly traded pharmaceutical firms covering the period before and after the TCJA reform. The use of multiple data sources allows us to track innovation outcomes from the earliest stages of discovery (patenting) to later stages of clinical development.

4.2 Innovation Outcomes

The dependent variables correspond to the twelve innovation levers introduced in Section 3. These outcomes capture different stages of the pharmaceutical innovation process. The first group of outcomes measures the strength of the firm's intellectual-property position. These variables include the number of patents filed by the firm, the estimated economic value of those patents, and the number of citations received by those patents. Patent citations capture the scientific importance and influence of a discovery, while patent value provides an estimate of the economic significance of the innovation. We follow the approach propose by (Kogan et al. (2017)) which provides a method to measure patent value from an event study style extraction of the stock market reaction to patent grants.

The second group of outcomes captures pipeline expansion, measured through the initiation of Phase I, Phase II, and Phase III clinical trials. These measures reflect firms' willingness to begin new research programs and explore new therapeutic opportunities. The third group of outcomes measures firms' ability to cross the valley of death in drug development. These variables capture the completion of Phase I, Phase II, and Phase III clinical trials, which represent critical bottlenecks in the innovation process. The final group measures time-to-knowledge, which captures the speed of the innovation process. These outcomes measure the time required to complete each stage of clinical development.

Together, these twelve measures provide a detailed view of how firms allocate resources across the different stages of the pharmaceutical innovation pipeline.

4.3 Econometric strategy

As a first step, we examine how innovation outcomes evolve before and after the TCJA. The descriptive analysis compares the mean values of the twelve innovation levers in the pre-policy period and the post-policy period. This exercise provides an initial indication of whether innovation activity changed following the reform. While these descriptive comparisons cannot establish causal effects, they provide useful information about broad patterns in the data and help motivate the econometric analysis that follows.

Second, the non-parametric event analysis was conducted to examine how innovation outcomes evolve around the policy change. In this approach, we exploit the exogenous timing of the policy and track the average trajectory of each innovation outcome relative to the year of the tax reform. Like other use cases of non-parametric event analysis (such as in Dobkin et al. (2018)), this analysis allows event-time coefficients to capture how outcomes change before and after the policy relative to a baseline period. Major advantages include flexible and visual assessments of the evolution of innovation activity around the policy change without imposing strong parametric assumptions. In particular, event-time plots allow us to examine whether innovation outcomes follow similar trajectories before the reform and whether they diverge afterward. Yet, given the lack of counterfactual, these estimates may not be interpreted as a causal effect. Our econometric specification is of the following form:

$$Y_{it} = \gamma_t + X_{it}\alpha + \sum_{r=-5}^{-1} \mu_r + \sum_{r=1}^{4} \mu_r + \varepsilon_{it}.$$

In this equation, Y_it denotes (log of) each of the outcomes in the 12 levers we are interested in for firm i in quarter t; r represents yearly event-time indicators relative to the TCJA enactment, omitting $r = 0$ as the reference year. μ captures calendar time fixed effects, and X_it is a vector of firm-level and macroeconomic control variables. Specif-

ically, the controls include firm assets, market capitalization, cash reserves, leverage, and operating income. We also control for macroeconomic conditions using quarterly GDP, inflation, unemployment, the 10-year Treasury yield, as well as exchange rates. To assess robustness and the role of omitted variable bias, we estimate sequential models, progressively adding control sets from a baseline to a fully specified version.

Lastly, to estimate causal effects, we implement an event-study difference-in-differences design with treatment and comparison groups. The key idea is to compare firms that were more exposed to the tax reform with firms that were less exposed. Our main measure of exposure is based on pre-policy leverage, defined as the ratio of debt to assets. Firms with higher leverage prior to the reform are more likely to experience a relaxation of financing constraints when after-tax cash flows increase. We therefore classify firms into two groups: a treatment group consisting of firms with high debt-to-asset ratios (above 10%) and a control group consisting of firms with lower leverage (below 10%). The econometric specification is as follows:

$$Y_{it} = \gamma_t + \beta_1 \text{TreatPost}_{it} + \beta_2 \text{Treat}_i + \beta_3 \text{Post}_t + X_{it}\alpha + \varepsilon_{it}.$$

Treat_i is the treatment group dummy variable; it is equal to 1 for firms with high debt-to-asset ratios in pre-policy periods. Post_t is the time dummy variable that takes the value of 1 after the TCJA in 2017. TreatPost_{it} is the interaction term between the treatment group and the time period dummy variable, and the coefficient β_1 captures the causal effects of the policy change. Outcome variables, firm controls covariates, time fixed effects, and macroeconomic controls are as in the non-parametric event analysis. The identifying assumption is that treatment and control firms follow parallel trends in innovation outcomes prior to the policy change. We test this assumption by examining pre-policy trajectories in the event-study framework. To test the robustness of our findings, we also examine alternative measures of financial constraints and liquidity

exposure. We repeat the analysis using three additional dimensions of heterogeneity.

First, we examine differences between firms with low versus high free cash flow (FCF cutoff non-positive prior to policy vs positive). Firms with low internal cash flow are more likely to face financing constraints and may therefore respond more strongly to a tax-induced increase in internal liquidity. Second, we compare young (founded after 2000) versus mature (founded before 2000) firms. Younger firms often face greater financing frictions and rely more heavily on internal funding to support research investment. Third, we examine small (market cap below 2 billion) versus large (market cap above 2 billion) firms. Smaller firms may have more limited access to external financing and may therefore be more sensitive to changes in internal funds.

For each of these dimensions, firms are classified into high- and low-exposure groups based on sample cutoff points frequently mentioned in the literature. These additional specifications allow us to examine whether the innovation response varies across firms with different financial characteristics. Taken together, these analyses generate 48 empirical tests across the twelve innovation levers and four measures of exposure to the tax reform. All regressions used semi-log specification so that coefficient can be interpreted as percentage changes with respect to the control group.

Table 0 (in the Appendix) reports descriptive statistics for all variables used in the analysis. The table includes summary statistics for the twelve innovation outcomes as well as the key financial variables used to construct treatment and control groups.

On average, firms in the sample generate around 14 patents each year before the tax cut policy, reflecting the high research intensity of the pharmaceutical industry. Clinical trial activity also varies widely across firms, consistent with the sequential nature of drug development and the concentration of research activity among large pharmaceutical companies. These descriptive statistics highlight the substantial heterogeneity in innovation activity across 175 pharmaceutical firms and provide a baseline for interpreting

the econometric results presented in the next section.

5 Results

5.1 Descriptive Evidence

We begin by examining how innovation outcomes evolve before and after the implementation of the 2017 Tax Cuts and Jobs Act. This descriptive exercise compares average values of the 12 innovation levers in the pre-policy period (2012–2016) and the post-policy period (2017–2021). While these comparisons do not establish causality, they provide an initial view of whether broad shifts occurred across the innovation pipeline.

First, the first bundle captures the strength of the intellectual-property moat, measured through patent counts, patent value, and patent citations. The descriptive evidence suggests that the scale of patent production remains broadly stable while the quality of patents improves modestly. Average patent counts change little, declining slightly from 14.5 patents per firm in the pre-policy period to 14.2 in the post-policy period. In contrast, indicators of patent influence increase. Average patent value rises from $832.4 million to $854 million, and patent citations increase from 37 to 43.7 on average. The last two results are statistically significant.

These patterns indicate that firms did not necessarily produce more patents after the reform, but the patents they generated appear to be more influential and potentially more valuable. This pattern is consistent with our proposed mechanism—debt-overhang relief and upstream innovation—where additional liquidity strengthens early-stage discovery and intellectual property. At the same time, the increase in patent quality may also reflect strategic patenting behavior, including secondary patents that reinforce intellectual-property protection.

The outcome of need patents and completion are not discussed as they do not change

(See Table 0 with descriptive statistics). Now, moving to the time-to-knowledge bundle measures how quickly firms move drug candidates through clinical development. If tax-driven liquidity were used to accelerate development, we would expect shorter completion times for clinical trials.

Interestingly, the descriptive evidence shows the opposite pattern. Average completion times increase across all three phases of development. Phase I completion times rise from 5.3 to 9.2 months, Phase II from 7.1 to 19.4 months, and Phase III from 5.3 to 9.6 months. All these results are statistically significant. These results suggest that the additional liquidity generated by the tax reform was not used to accelerate clinical development or to shorten the path to market. The increase in development timelines may partly reflect broader industry trends—such as greater trial complexity and stricter regulatory requirements—rather than firm-level responses to the tax policy.

Taken together, the descriptive evidence points to three broad patterns. First, the IP moat strengthens, with improvements in patent value and citations. Second, pipeline expansion and project execution remain broadly unchanged, suggesting little movement in trial initiation or completion. Third, time-to-knowledge does not accelerate, as development timelines lengthen rather than shorten. These patterns suggest that if the TCJA affected innovation, its effects are likely concentrated in upstream research activities rather than downstream clinical development. However, descriptive comparisons cannot establish whether these changes reflect causal effects of the policy or broader industry trends. We therefore turn next to non-parametric event analysis, which allows us to examine whether innovation trajectories exhibit structural changes around the introduction of the tax reform.

5.2 Non-parametric analysis

To move beyond simple before–after comparisons, we next examine whether innovation trajectories exhibit structural changes around the introduction of the TCJA. We estimate non-parametric event-time models that trace the evolution of each innovation lever relative to the year of the tax reform. This approach allows us to visualize how outcomes evolve before and after the policy while imposing minimal functional form assumptions. Event-time plots provide a transparent way to assess whether innovation outcomes follow similar trajectories prior to the policy and whether they diverge afterward. The figures plot estimated coefficients relative to a pre-policy baseline with confidence intervals that indicate statistical significance.

Figure 1 presents the non-parametric event trajectories for the three levers that define the intellectual-property moat: patent counts, patent value, and patent citations. The trajectories show modest but visible upward shifts in patent value and citations following the tax reform. These patterns indicate that the economic and scientific influence of patents increases slightly after 2017. Yet, most estimated coefficient are not statistically significant after the tax cuts. In contrast, the trajectory of patent counts remains largely flat, suggesting that the reform did not substantially increase the number of patents produced. Taken together, these results indicate that any response in patenting activity appears to occur primarily through quality rather than quantity. This pattern is consistent with the hypothesis that additional liquidity may strengthen upstream discovery activities or intellectual-property positions without necessarily expanding the overall scale of patent production.

As pipeline expansion, Figure 2 examines the pipeline expansion bundle, which includes the initiation of Phase I, Phase II, and Phase III clinical trials. Across all three stages, the event-time trajectories show no visible break around the policy change. The initiation of new clinical trials follows similar trends before and after the reform, sug-

gesting that firms did not broadly expand their research pipelines in response to the tax-induced liquidity shock. These results imply that the TCJA did not generate a noticeable increase in exploratory research activity measured through new trial initiation. In other words, the policy does not appear to have significantly broadened the set of new drug development projects entering the pipeline.

Figure 3 presents results for the valley-of-death bundle, which captures the completion of Phase I, Phase II, and Phase III clinical trials. Completion of early clinical stages—Phases I and II—shows no structural change in trajectory following the tax reform. The event-time coefficients remain close to zero, indicating that firms did not move drug candidates through these stages at higher rates after the policy change. There is some evidence of an uptick in Phase III completion, though the pattern is modest and does not appear to represent a broad disruption in the trajectory of late-stage development. Overall, the results suggest that the TCJA did not materially improve firms' ability to convert early-stage research into clinically validated therapies.

Figure 4 reports the non-parametric event-time trajectories for the time-to-knowledge bundle, which measures the speed of clinical development across Phases I, II, and III. If additional liquidity were used to accelerate the innovation process, we would expect to observe shorter development timelines following the policy change. Instead, the results show slightly longer development timelines, with coefficients moving upward rather than downward. This pattern suggests that clinical development did not accelerate following the reform. If anything, development times lengthen modestly after the policy change.

Taken together, the non-parametric analysis reveals a consistent pattern across the four innovation bundles. First, the intellectual-property moat improves modestly, with upward shifts in patent value and citation measures. Second, pipeline expansion remains largely unchanged, with no visible increase in the initiation of clinical trials. Third, throughput across the valley of death remains broadly flat, as completion rates in early

clinical phases show little movement. Finally, time-to-knowledge does not accelerate, as development timelines increase slightly rather than decrease.

These results reinforce the descriptive evidence presented earlier. The main observable response to the tax reform appears concentrated in upstream innovation activities, while downstream stages of the pharmaceutical development process remain largely unaffected. However, non-parametric patterns alone cannot establish causal effects because they do not account for a counterfactual of the policy. In our next step, our identification (still work in progress) tries to assess differences in firms' exposure to the tax reform. We therefore turn next to our event-study difference-in-differences analysis with treatment and controls, which exploits variation in firms' financial exposure to the tax cut to estimate causal effects across the twelve innovation levers. We will focus on our main results: comparing firm with high and low debt ratio to asset firm. Our robustness test will follow the event analysis with diff-in-diff results.

5.3 Event-Study Difference-in-Differences Results

Tables 1–4 report the main causal estimates of the paper. Each table corresponds to one of the four innovation bundles introduced earlier. Table 1 reports results for the intellectual-property moat (patent count, patent value, and citations), Table 2 for pipeline expansion (trial starts), Table 3 for valley-of-death completion, and Table 4 for time-to-knowledge (trial speed). Within each table, Panel A presents the baseline specification comparing firms with high versus low debt-to-asset ratios prior to the reform. Additional panels report robustness analyses using alternative measures of financial exposure (free cash flow, firm age, and firm size). The coefficient of interest throughout is the interaction Treatment $\times$ Post, which captures the differential change in innovation outcomes for treated firms after the tax reform relative to control firms.

Before discussing the results, the full results to show parallel trends are shown in

(Appendix Tables A1-A4). Full results of the event analysis with difference-in-differences are shown in (Appendix Tables A5-A8). We now proceed to discuss the main results.

Table 1 shows that firms with higher pre-policy leverage exhibit a significant improvement in intellectual-property outcomes following the tax reform. The Treatment $\times$ Post coefficient indicates that highly leveraged firms generate approximately 12 percent ($p<0.05$) more patents relative to lower-leverage firms after the reform. The effect is even larger for the value of patents, which increases by roughly 22 percent ($p<0.10$) for treated firms. In contrast, the coefficient for patent citations is positive (3%) but not statistically significant. Taken together, these results indicate that firms with tighter financial constraints strengthened their intellectual-property positions after the tax reform. The increase in patent counts and patent value suggests that additional liquidity translated into greater upstream research output or stronger intellectual-property protection. These patterns are consistent with the mechanism discussed earlier: relaxing financing constraints allows firms to expand exploratory innovation activities and strengthen their intellectual-property moat.

Table 2 examines whether the tax-induced liquidity shock affected firms' decisions to initiate new drug development projects. The results show a statistically significant increase in Phase I trial starts among high-debt firms. The Treatment $\times$ Post coefficient implies roughly a 3 percent ($p<0.5$) increase in Phase I trial initiation relative to low-debt firms. However, the coefficients for Phase II and Phase III trial starts are small and statistically not significant. This pattern suggests that while financially constrained firms initiated more early-stage projects after the tax reform, they did not significantly expand later-stage clinical development. The response therefore appears concentrated in the earliest stage of pipeline formation, which is consistent with the idea that liquidity shocks primarily affect exploratory research decisions rather than the entire development pipeline.

Table 3 evaluates whether the tax reform improved firms' ability to move drug candidates through the clinical development process. Across all three measures—completion of Phase I, Phase II, and Phase III trials—the Treatment × Post coefficients are small and statistically insignificant. These results indicate no measurable improvement in the rate at which firms convert early research into successful clinical progression. In other words, the liquidity shock generated by the tax reform did not help firms cross the critical attrition points that characterize pharmaceutical development. Advancing drug candidates through clinical testing requires substantial scientific progress, regulatory interaction, and organizational capabilities. These factors appear to limit firms' ability to translate additional financial resources into higher completion rates.

Table 4 examines whether the tax reform affected the speed of clinical development, measured through the time required to complete Phases I–III trials. Across all three phases, the Treatment × Post coefficients are statistically insignificant but high in size. Interestingly, they indicate longer time after the reform rather than shorter times. In one outcome the estimates are slightly negative but small, suggesting marginally smaller development times. These results indicate that additional liquidity did not shorten development timelines or accelerate the arrival of new therapies to market. The absence of a speed response reinforces the idea that downstream stages of pharmaceutical innovation are constrained by factors other than financing, including scientific uncertainty, regulatory requirements, and trial complexity.

In sum, the difference-in-differences estimates reveal a clear pattern across the innovation pipeline. The tax reform appears to affect upstream innovation activities but has little impact on downstream stages of development. Firms with higher pre-policy leverage increase patent production and patent value and modestly expand early-stage research through additional Phase I trial starts. However, we find no evidence that the reform improved project completion or accelerated development timelines.

These results are consistent with the corporate-finance mechanism discussed earlier. If the tax reform relaxed financing constraints, its effects should appear first in option-like upstream innovation activities, where projects are relatively flexible and inexpensive to initiate. In contrast, later stages of drug development involve larger commitments of capital and depend more heavily on scientific and regulatory factors, making them less responsive to changes in internal liquidity.

The remaining panels of Tables 1–4 examine whether similar patterns emerge when exposure to the tax reform is measured using alternative indicators of financial constraints. We turn to these sensitivity analyses in the next section.

5.4 Robustness Across Alternative Exposure Measures

We next examine whether the baseline results are robust to alternative definitions of firms' exposure to the tax-induced liquidity shock. Tables 1–4 (Panels B–D) repeat the event-study difference-in-differences analysis using three additional dimensions of financial exposure: free cash flow, firm age, and firm size. Table 5 summarizes these results by reporting the brackets containing the ranges [min, max] of statistically significant treatment effects across all specifications. Importantly, too highlight that parallel trend hold in all cases between treatment and control except we compare small vs large firm.

We now discuss the main results related to the coefficient of interest. Across the 48 estimated coefficients, the results display a consistent pattern. Significant effects are concentrated in the intellectual-property moat bundle, particularly for patent counts and patent value. Depending on the exposure measure, patent counts increase by roughly 3.6%–16.2%, while patent value rises between 3.7%–47.2%. Patent citations also show modest positive effects in some specifications, though the estimates are less consistently significant.

In contrast, the remaining innovation bundles show little evidence of systematic

responses. Pipeline expansion outcomes (Phase I–III starts) display small and occasionally significant estimates. For instance, Start Phase I improves showing a range from [1.6%, 3.2%]. The rest of pipeline expansion results are not statistically significant and these effects are not consistent across exposure definitions. Similarly, the valley-of-death completion measures (Phase I–III completions) show very limited responses, with most coefficients statistically insignificant and economically small.

Finally, time-to-knowledge outcomes exhibit no evidence of acceleration. The estimated effects for trial speed are imprecise and span both positive and negative ranges, indicating that the tax reform did not systematically shorten development timelines.

Overall, the sensitivity analysis confirms the main pattern identified in the baseline specification. Across alternative measures of financial exposure—including low versus high free cash flow, young versus mature firms, and small versus large firms—the results broadly mirror the debt-based analysis. Innovation responses remain concentrated in upstream intellectual-property outcomes, while downstream stages of the pharmaceutical development process remain largely unaffected. These patterns are consistent with the debt-overhang relief mechanism discussed earlier, whereby improvements in internal liquidity primarily influence early-stage research activities rather than later phases of clinical development.

6 Limits of Our Lens on Innovation and future venues for research

Before concluding, it is important to recognize several limitations that shape the interpretation of our findings. First, our analysis focuses on publicly traded pharmaceutical firms, which represent a large share of industry R&D but do not capture the entire discovery ecosystem. Early-stage scientific exploration is increasingly conducted

by venture-backed biotechnology startups, which play a critical role in the upstream innovation pipeline. Because our dataset centers on publicly listed firms, part of the innovation response to the tax reform—particularly in early discovery—may occur outside the segment we observe.

Second, our identification strategy relies on proxies for financial constraints, most notably firms' pre-policy debt-to-asset ratios. While leverage captures an important dimension of financing frictions, the corporate finance literature suggests that financial constraints may be better understood through a broader set of indicators that combine firm size, age, and market capitalization. Several widely used measures—including the Kaplan–Zingales index, the Whited–Wu index, the Hadlock–Pierce index, and the Hoberg–Maksimovic approach—attempt to capture these multidimensional constraints using firm characteristics observable in datasets such as Compustat. Our sensitivity analyses using firm size, free cash flow, and firm age partially address these issues, but future work could further explore these richer measures of financial constraints.

Relatedly, the net effect of corporate tax cuts on investment incentives may vary across firms depending on their tax positions. While firms facing large tax liabilities may benefit from the reduction in statutory tax rates through higher after-tax cash flows, firms carrying large stocks of unused tax credits or accumulated deductions may experience different incentives. In such cases, lower tax rates may reduce the value of tax write-offs or investment deductions that were previously embedded in firms' balance sheets. These heterogeneous effects could potentially be identified through detailed tax information rather than accounting disclosures in Compustat. This important research remains beyond the scope of our current analysis.

Third, corporate finance theory suggests that the primary mechanical effect of a corporate tax cut is to increase the present value of after-tax cash flows for both existing assets and future projects. In principle, this change can make previously unprofitable

or marginal projects profitable. However, the transmission of this financial shock to innovation decisions depends on firms' ability to convert financial capital into productive research activities. In pharmaceutical development, this conversion requires complementary forms of capital—including human capital, organizational capabilities, and scientific knowledge—that may constrain firms' ability to scale research even when financial resources increase. We do not observe this time variant factors within a firm.

Fourth, firms may face complementarities between financial capital and non-financial inputs, such as organizational capital or accumulated technological knowledge. Even if tax cuts increase internal funds, deploying those funds productively may require investments in scientific teams, clinical infrastructure, and regulatory expertise. These forms of organizational capital, discussed in the corporate finance literature following work by Eisfeldt and coauthors, are difficult to observe directly in standard datasets. As a result, our empirical approach—based on patents and clinical trials—captures observable innovation outcomes but cannot fully measure investments in organizational capabilities that may shape the long-run productivity of R&D.

Fifth, tax policy interacts with investment incentives through complex dynamic channels. In particular, changes in statutory tax rates may alter the value of tax credits and accelerated write-offs for R&D investment. In extreme cases, if tax rates fall sufficiently, the tax benefits associated with expensing or crediting investment expenditures may decline. Firms that previously relied heavily on such provisions could therefore face altered incentives for R&D investment. These dynamic interactions between tax rates and investment deductions are difficult to isolate within our event-study framework.

One needs to consider that corporate tax cuts may also influence capital structure decisions. Classical corporate finance theory suggests that when tax rates fall, the tax advantage of debt financing declines, potentially leading firms to reduce leverage. In such cases, firms may choose to repay existing debt rather than expand investment.

Although our empirical design focuses on differences between high- and low-leverage firms prior to the reform, the broader adjustments in capital structure following the tax cut may partially offset the mechanisms we seek to identify.

In addition, tax reforms can also affect firms' payout policies, particularly the choice between dividends and share repurchases. Lower corporate taxes may increase the attractiveness of share repurchases, which offer flexibility relative to dividends. While our prior work (Trujillo et al. (2026)) finds no structural increase in buybacks following the reform in this sector, payout policies remain a potential channel through which tax-induced liquidity could be redistributed rather than invested.

Tax cuts may influence the relative attractiveness of acquisitions versus organic investment. Firms receiving large liquidity shocks may find it more profitable to acquire external innovation rather than develop it internally. Indeed, we observe evidence of increased mergers and acquisitions activity following the reform. In such cases, innovation may still occur but becomes reallocated across organizational boundaries, particularly as large pharmaceutical firms acquire smaller biotechnology companies with promising assets.

Some studies suggest that tax reforms can affect firms' decisions to repatriate overseas profits, potentially increasing domestic investment. Although repatriation provisions were part of the TCJA, identifying their impact specifically within the pharmaceutical sector remains challenging given the complex multinational structures of many firms in this industry.

Finally, part of our post-policy period overlaps with the COVID-19 pandemic, which disrupted global research activity and clinical trial operations. Although our empirical design includes macroeconomic controls and fixed effects, broader industry shocks associated with the pandemic may still influence the trajectory of pharmaceutical innovation during the later years of the sample. Taken together, these limitations highlight that

our empirical design captures an important but partial view of the innovation system, centered on observable outputs within publicly traded firms.

7 Concluding remarks

This paper, to the best of our knowledge, is the first attempt to measure whether the 2017 Tax Cuts and Jobs Act (TCJA) acted as a windfall that stimulated productive pharmaceutical innovation or instead functioned as a costly policy with limited effects on research activity. Using a framework that decomposes innovation into twelve operational levers grouped into four strategic bundles, we examine how firms reallocated effort across the pharmaceutical innovation pipeline following the reform.

Across three layers of empirical analysis—descriptive evidence, non-parametric event trajectories, and event-study difference-in-differences estimates—we find a consistent pattern. The tax reform appears to have shifted innovation activity primarily in upstream research domains, particularly among firms with high pre-policy leverage.

Consistent with corporate finance theory, the reduction in financing frictions associated with the tax reform appears to have relieved debt-overhang distortions, allowing highly leveraged firms to expand certain exploratory innovation activities. These firms increased patent production and patent value, and they initiated slightly more Phase I clinical trials, suggesting a modest expansion of early-stage research options.

However, the broader pharmaceutical innovation pipeline shows little evidence of structural change. Across the remaining nine innovation levers—including pipeline expansion beyond Phase I, project completion across clinical phases, and the speed of clinical development—we find no systematic improvements following the tax reform. Even when examining alternative measures of financial constraints, including low free cash flow, firm age, and firm size, the results remain largely unchanged.

These findings suggest that liquidity expansions alone are insufficient to transform

the downstream stages of pharmaceutical innovation. The key bottlenecks associated with Eroom's Law—rising development costs, longer clinical trials, and increasing scientific complexity—appear to lie in factors beyond firms' immediate financial capacity. Regulatory constraints, scientific uncertainty, and organizational capabilities may play a larger role in shaping the pace at which new therapies move through the development pipeline.

From a corporate finance perspective, the results are consistent with the idea that tax cuts primarily operate through changes in the present value of projects. By increasing the after-tax value of both assets in place and future investment opportunities, tax reductions may make some marginal projects profitable. Yet converting these financial incentives into productive innovation requires complementary resources—scientific expertise, organizational capabilities, and regulatory knowledge—that cannot be expanded as quickly as financial capital.

From a policy perspective, our findings align with a growing body of research showing that innovation responds most strongly to targeted incentives rather than broad fiscal shocks. Policies that directly address specific frictions in the innovation process—such as support for early-stage science, mechanisms to accelerate clinical trials, or incentives tied to specific therapeutic needs—may be more effective at improving research productivity.

Recent policy developments also point in this direction. For example, the Inflation Reduction Act (IRA) of 2022 introduced provisions allowing eligible startups to offset payroll taxes with R&D tax credits. Such targeted mechanisms may help stimulate innovation where financing constraints are most binding, particularly among smaller or younger firms engaged in early-stage scientific discovery.

In closing, our evidence suggests that the TCJA functioned less as a broad engine of pharmaceutical innovation and more as a modest liquidity shock whose effects were concentrated in upstream intellectual-property activity. Breaking the productivity slow-

down captured by Eroom's Law will likely require policy tools aimed directly at the scientific and regulatory bottlenecks of the innovation process, rather than relying on broad tax reductions to indirectly stimulate research investment.

Conflict of Interest and Funding

None of the authors has any conflicts of interest or additional funding sources to disclose.

Data Availability Statement

The data that support the findings of this study are available from S&P Compustat and Cortellis, but restrictions apply to the availability of these data based on institutional licenses, so they are not publicly available. Macro-economic data from FRED are publicly available at `https://fred.stlouisfed.org/`.

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Figure 1

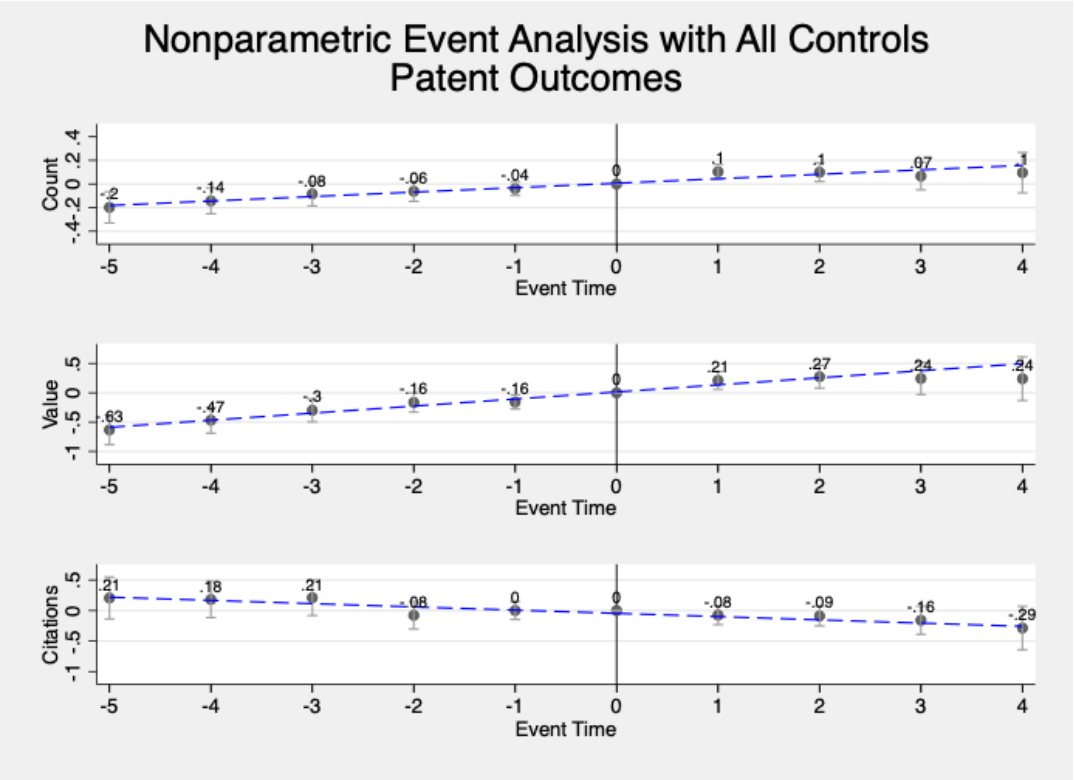


Figure 2

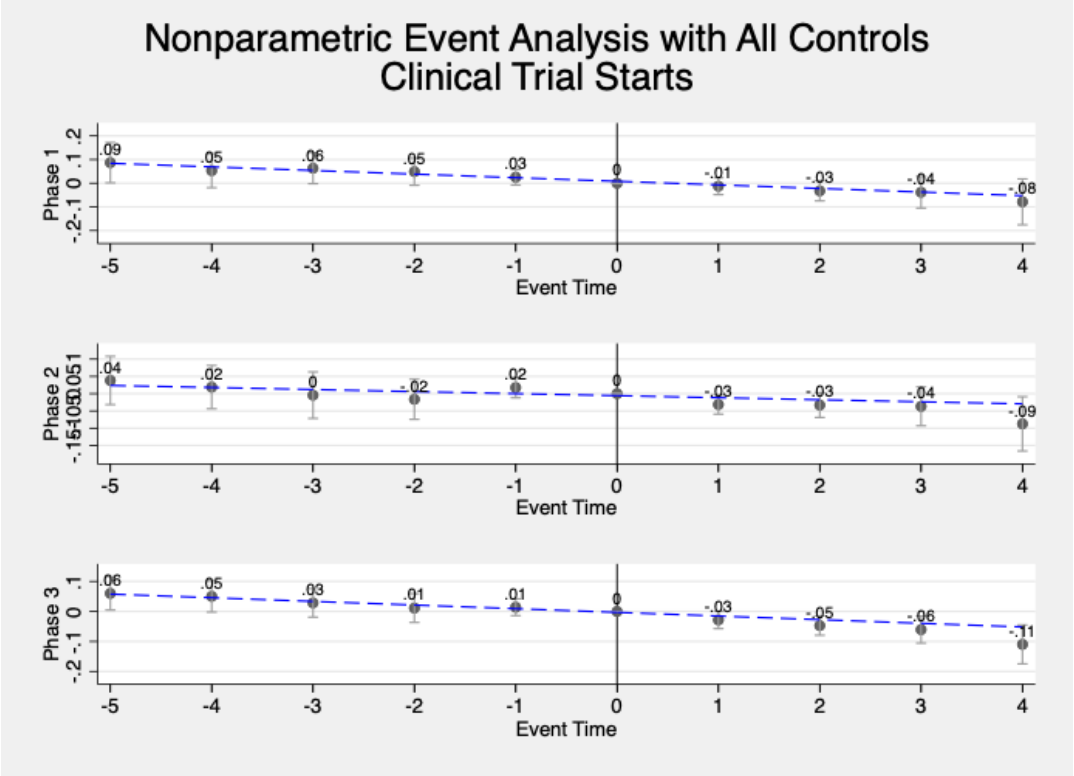


Figure 3

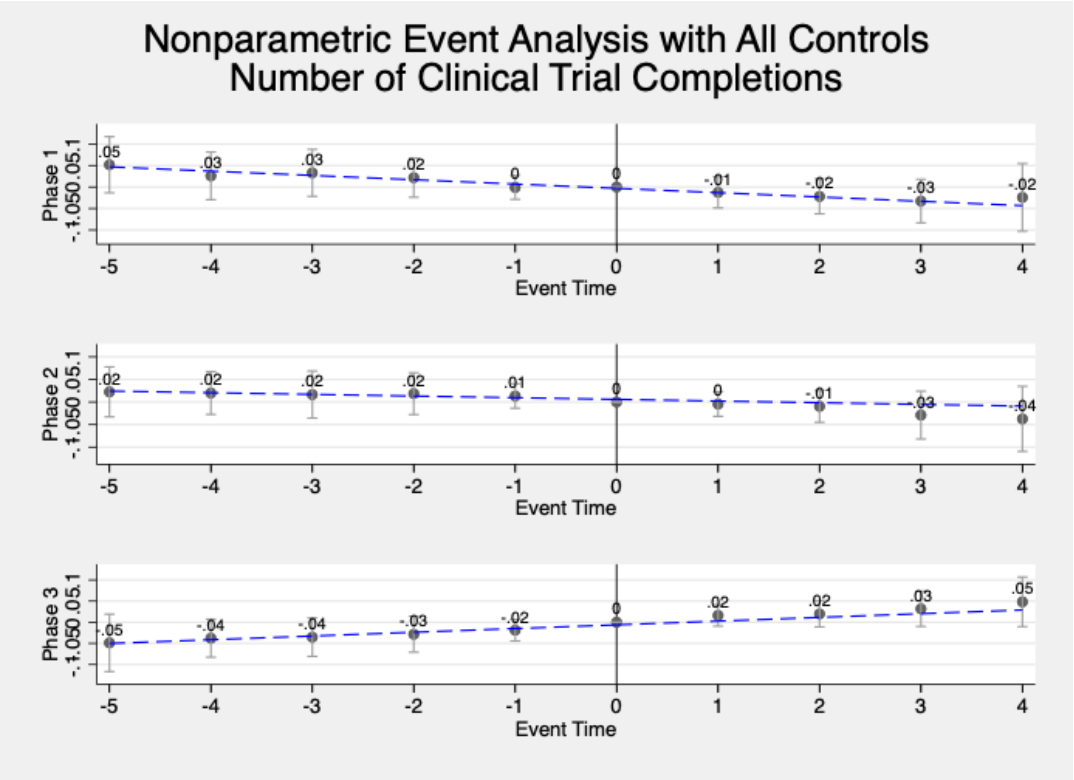


Figure 4

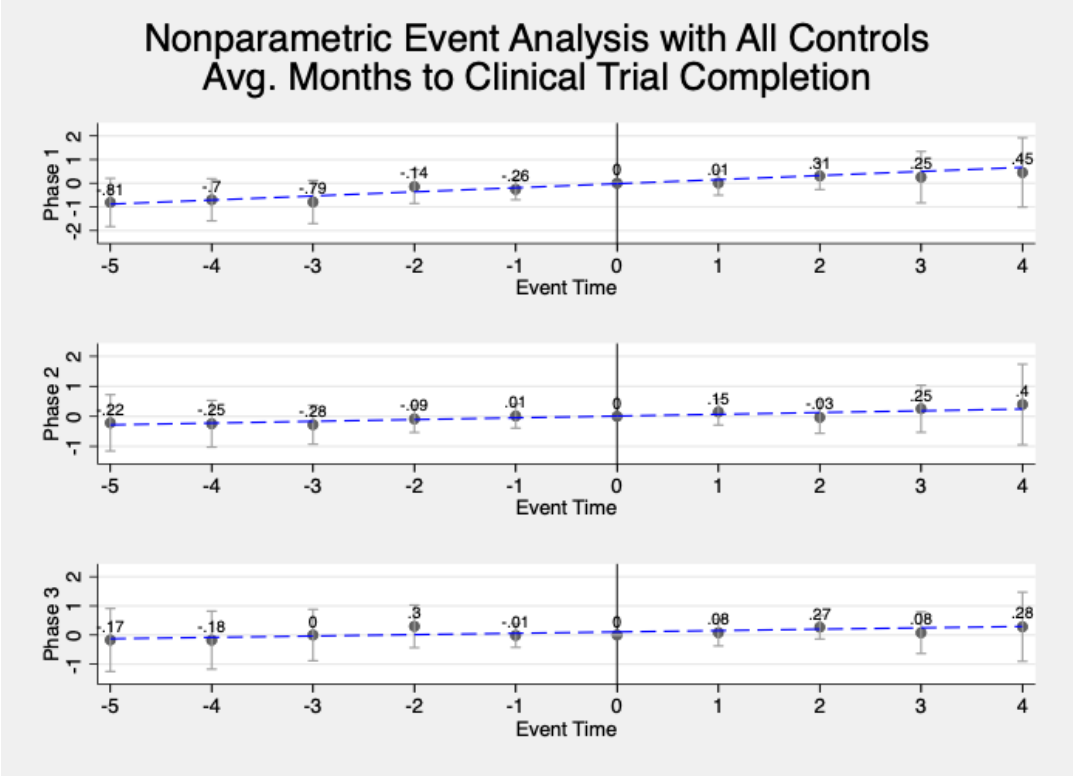


Table 1

Event analysis with difference-in-difference estimates on patents (Semi-log specification)

Panel A: High vs Low debt firms[1]

	Patent Count		Patent Value		Patent Citation	
Treatment x Post	0.1184	**	0.2192	*	0.0314	
	[0.047]		[0.118]		[0.079]	
Treatment	-0.2311	**	-0.5363	**	-0.3573	***
	[0.089]		[0.225]		[0.102]	
Post	0.2358	**	0.8132	***	-0.3765	
	[0.109]		[0.225]		[0.256]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel B: High vs Low cash firms[2]

	Patent Count		Patent Value		Patent Citation	
Treatment x Post	0.0403		0.0367		0.0666	
	[0.046]		[0.105]		[0.088]	
Treatment	-0.5311	***	-1.2263	***	-0.2366	
	[0.148]		[0.348]		[0.162]	
Post	0.1862		0.722	***	-0.4248	*
	[0.116]		[0.240]		[0.248]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel C: Young vs Old firms[3]

	Patent Count		Patent Value		Patent Citation	
Treatment x Post	0.0361		0.0685		0.0391	
	[0.041]		[0.099]		[0.098]	
Treatment	0.3213	**	0.6174	**	0.0365	
	[0.128]		[0.282]		[0.177]	
Post	0.2126	*	0.7614	***	-0.4083	
	[0.111]		[0.231]		[0.253]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel D: Small vs Large firms[4]

	Patent Count		Patent Value		Patent Citation	
Treatment x Post	0.1623	***	0.4762	***	0.0571	
	[0.048]		[0.115]		[0.091]	
Treatment	-0.6678	***	-1.904	***	-0.5015	***
	[0.114]		[0.281]		[0.145]	
Post	0.1220		0.4614		-0.4493	*
	[0.116]		[0.239]		[0.271]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

[1]High debt firms have debt-to-asset ratio higher than 10% in pre-policy periods; low debt firms have debt-to-asset ratio less than 10% in pre-policy periods

[2]High cash firms have positive free cash flows in pre-policy periods; low cash firms have non-positive free cash flows in pre-policy periods

[3]Young firms are those founded after year 2000; old firms are founded before 2000

[4]Small firms have market cap of less than $2 billion in pre-policy periods; large firms have market cap of more than $2 billion in pre-policy periods

Table 2

Event analysis with difference-in-difference estimates on trial starts (Semi-log specification)

Panel A: High vs Low debt firms[1]

	Phase I Start		Phase II Start		Phase III Start	
Treatment x Post	0.0323	**	0.0025		0.0036	
	[0.016]		[0.014]		[0.013]	
Treatment	-0.0561	**	-0.0448	**	-0.05	**
	[0.027]		[0.022]		[0.024]	
Post	-0.1287	*	-0.0755		-0.121	***
	[0.066]		[0.054]		[0.038]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel B: High vs Low cash firms[2]

	Phase I Start		Phase II Start		Phase III Start	
Treatment x Post	0.0168		0.0094		0.0168	
	[0.017]		[0.019]		[0.016]	
Treatment	-0.0897	*	-0.0637	*	-0.087	**
	[0.048]		[0.037]		[0.041]	
Post	-0.1405	*	-0.0864		-0.1353	***
	[0.072]		[0.060]		[0.042]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel C: Young vs Old firms[3]

	Phase I Start		Phase II Start		Phase III Start	
Treatment x Post	0.0156		0.0070		0.0078	
	[0.015]		[0.015]		[0.014]	
Treatment	0.0615		0.0331		0.0415	
	[0.071]		[0.051]		[0.054]	
Post	-0.1348	**	-0.0826		-0.129	***
	[0.068]		[0.056]		[0.039]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel D: Small vs Large firms[4]

	Phase I Start		Phase II Start		Phase III Start	
Treatment x Post	0.0300		0.0302		0.0187	
	[0.018]		[0.021]		[0.019]	
Treatment	-0.1407	***	-0.1138	***	-0.1139	***
	[0.041]		[0.034]		[0.039]	
Post	-0.149	**	-0.1007	*	-0.1397	***
	[0.069]		[0.060]		[0.040]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

[1]High debt firms have debt-to-asset ratio higher than 10% in pre-policy periods; low debt firms have debt-to-asset ratio less than 10% in pre-policy periods

[2]High cash firms have positive free cash flows in pre-policy periods; low cash firms have non-positive free cash flows in pre-policy periods

[3]Young firms are those founded after year 2000; old firms are founded before 2000

[4]Small firms have market cap of less than $2 billion in pre-policy periods; large firms have market cap of more than $2 billion in pre-policy periods

Table 3

Event analysis with difference-in-difference estimates on trial completion (Semi-log specification)

Panel A: High vs Low debt firms[1]

	Phase I Completion		Phase II Completion		Phase III Completion	
Treatment x Post	0.017		0.0028		0.0013	
	[0.014]		[0.011]		[0.012]	
Treatment	-0.0497	**	-0.0488	**	-0.0426	**
	[0.023]		[0.020]		[0.023]	
Post	-0.0892	*	-0.0534		0.0806	*
	[0.050]		[0.044]		[0.044]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel B: High vs Low cash firms[2]

	Phase I Completion		Phase II Completion		Phase III Completion	
Treatment x Post	0.0121		0.0222		-0.0035	
	[0.018]		[0.015]		[0.014]	
Treatment	-0.0819	*	-0.0716	*	-0.0765	**
	[0.046]		[0.039]		[0.036]	
Post	-0.102	*	-0.0726		0.0766	*
	[0.052]		[0.044]		[0.041]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel C: Young vs Old firms[3]

	Phase I Completion		Phase II Completion		Phase III Completion	
Treatment x Post	0.0226		0.0131		0.0083	
	[0.017]		[0.013]		[0.013]	
Treatment	0.0592		0.0281		0.0356	
	[0.067]		[0.049]		[0.048]	
Post	-0.1009	**	-0.0626		0.0727	*
	[0.049]		[0.044]		[0.042]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

Panel D: Small vs Large firms[4]

	Phase I Completion		Phase II Completion		Phase III Completion	
Treatment x Post	0.0235		0.0206		-0.0155	
	[0.018]		[0.017]		[0.014]	
Treatment	-0.1283	***	-0.1105	***	-0.081	***
	[0.036]		[0.033]		[0.030]	
Post	-0.1084	**	-0.0732	*	0.0831	**
	[0.052]		[0.044]		[0.041]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	6,632		6,632		6,632	

[1]High debt firms have debt-to-asset ratio higher than 10% in pre-policy periods; low debt firms have debt-to-asset ratio less than 10% in pre-policy periods

[2]High cash firms have positive free cash flows in pre-policy periods; low cash firms have non-positive free cash flows in pre-policy periods

[3]Young firms are those founded after year 2000; old firms are founded before 2000

[4]Small firms have market cap of less than $2 billion in pre-policy periods; large firms have market cap of more than $2 billion in pre-policy periods

Table 4

Event analysis with difference-in-difference estimates on speed of trials (Semi-log specification)

Panel A: High vs Low debt firms[1]

	Phase I Speed		Phase II Speed		Phase III Speed	
Treatment x Post	0.2216		0.403		-0.0995	
	[0.399]		[0.265]		[0.509]	
Treatment	-0.7787	**	-0.6223	***	-0.0352	***
	[0.301]		[0.196]		[0.452]	
Post	0.9432		0.5248		0.3171	
	[1.002]		[0.770]		[0.706]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	557		505		377	

Panel B: High vs Low cash firms[2]

	Phase I Speed	Phase II Speed	Phase III Speed
Treatment x Post	0.1986	0.1216	0.1784
	[0.248]	[0.148]	[0.182]
Treatment	-0.0123	-0.1064	-0.2697
	[0.266]	[0.178]	[0.222]
Post	0.9042	0.4619	0.1653
	[0.978]	[0.738]	[0.666]
Controls			
Firm	X	X	X
All	X	X	X
N	557	505	377

Panel C: Young vs Old firms[3]

	Phase I Speed		Phase II Speed		Phase III Speed	
Treatment x Post	0.4262		0.2752	*	0.0654	
	[0.267]		[0.158]		[0.217]	
Treatment	-0.5326	**	-0.2265		-0.3008	*
	[0.215]		[0.160]		[0.175]	
Post	0.7229		0.6035		0.4274	
	[1.003]		[0.767]		[0.700]	
Controls						
Firm	X		X		X	
All	X		X		X	
N	557		505		377	

Panel D: Small vs Large firms[4]

	Phase I Speed	Phase II Speed	Phase III Speed
Treatment x Post	-0.2375	-0.0136	-0.0577
	[0.233]	[0.177]	[0.281]
Treatment	0.0208	0.0012	-0.1903
	[0.292]	[0.180]	[0.227]
Post	1.0476	0.5979	0.2744
	[0.987]	[0.768]	[0.689]
Controls			
Firm	X	X	X
All	X	X	X
N	557	505	377

[1]High debt firms have debt-to-asset ratio higher than 10% in pre-policy periods; low debt firms have debt-to-asset ratio less than 10% in pre-policy periods

[2]High cash firms have positive free cash flows in pre-policy periods; low cash firms have non-positive free cash flows in pre-policy periods

[3]Young firms are those founded after year 2000; old firms are founded before 2000

[4]Small firms have market cap of less than $2 billion in pre-policy periods; large firms have market cap of more than $2 billion in pre-policy periods

Table 5

Bracketing of Outcomes Across All Panels of Analyses		
Coefficient Estimates on Treatment x Post		
Outcome	**Low**	**High**
Patent Count	**0.0361**	**0.1623**
Patent Value	**0.0367**	**0.4762**
Patent Citation	0.0314	0.0666
Phase I Start	**0.0156**	**0.0323**
Phase II Start	0.0025	0.0302
Phase III Start	0.0036	0.0187
Phase I Completion	0.0121	0.0235
Phase II Completion	0.0028	0.0222
Phase III Completion	-0.0155	0.0083
Phase I Speed	-0.2375	0.4262
Phase II Speed	-0.0136	0.403
Phase III Speed	-0.0995	0.1784

Note: Highlighted rows indicate statistically significant results in at least one panel of analyses

8 Appendix

Table 0

Summary Statistics of Annual Outcome and Firm Variables (N=175 firms)

	Pre-policy (2012-2016)				Post-policy (2017-2021)			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
Patent Count	14.5	76.7	0.0	921.4	14.2	84.6	0.0	1,085.0
Patent Value ($MM)	832.4	3,396.3	0.0	26,394.2	854.3	3,608.8	0.0	30,319.4
Patent Citations	37.0	147.8	0.0	1,529.6	43.7	135.4	0.0	1,070.8
Phase 1 Starts	0.9	4.5	0.0	53.6	0.9	3.7	0.0	43.0
Phase 2 Starts	0.6	2.3	0.0	20.4	0.6	1.9	0.0	18.8
Phase 3 Starts	0.6	2.7	0.0	21.2	0.6	2.2	0.0	20.6
Phase 1 Completions	0.8	4.7	0.0	58.4	0.8	3.4	0.0	40.8
Phase 2 Completions	0.6	2.6	0.0	28.0	0.5	1.8	0.0	16.6
Phase 3 Completions	0.4	2.2	0.0	22.4	0.6	2.2	0.0	17.0
Avg. Length of Phase 1, Months	5.3	13.5	0.0	98.1	9.2	21.1	0.0	134.3
Avg. Length of Phase 2, Months	7.1	19.4	0.0	161.5	9.2	22.6	0.0	144.6
Avg. Length of Phase 3, Months	5.3	20.4	0.0	153.8	9.6	27.1	0.0	174.5
Total Asset	3,835.1	19,277.3	0.2	173,990.7	5,088.3	21,937.1	2.7	167,729.0
Cash	373.2	1,710.6	0.1	16,348.7	548.2	2,035.2	0.7	15,741.8
Free Cash Flow	420.8	2,025.3	-9.6	15,032.6	599.9	2,576.6	0.0	19,234.6
Debt in Current Liabilities	134.3	778.9	0.0	8,111.6	198.3	970.5	0.0	9,362.3
Long-Term Debt	873.7	4,072.7	0.0	30,452.6	1,520.1	6,550.1	0.0	51,276.5
Market Cap	7,473.2	30,884.3	2.8	262,089.6	10,569.5	41,281.2	9.2	376,229.2
Total Revenue	1,701.2	8,017.5	0.0	70,966.2	2,227.1	9,526.7	0.0	83,289.8
Cost of Goods Sold	362.3	1,716.3	0.0	18,113.2	494.0	2,090.9	0.0	20,558.8
Pretax Income	401.1	2,079.1	-399.7	17,761.6	461.0	2,242.8	-768.9	18,454.6
Income Taxes	88.0	413.2	-36.4	3,238.2	98.5	539.3	-947.6	4,993.0

Note: Firm variables in millions of U.S. Dollars

Table A1

Testing for Parallel Trend prior to Policy, Debt as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Time	0.0520	0.0521	0.0973	0.0978	0.0866	0.0863	0.0284	0.0285	0.0176	0.0179	0.0117	0.0117
	[0.052]	[0.052]	[0.126]	[0.126]	[0.065]	[0.066]	[0.019]	[0.019]	[0.014]	[0.014]	[0.018]	[0.018]
Treatment	-0.2406**	-0.2406**	-0.5496**	-0.5499**	-0.3676***	-0.3673***	-0.0706***	-0.0706***	-0.0588**	-0.0590**	-0.0537**	-0.0537**
	[0.104]	[0.104]	[0.255]	[0.256]	[0.109]	[0.109]	[0.027]	[0.027]	[0.023]	[0.023]	[0.025]	[0.025]
Time	0.0569	0.1504	0.1985*	0.3895*	0.0913	-0.0224	-0.0044	-0.0574	0.0013	-0.0602	0.0156	-0.0301
	[0.048]	[0.108]	[0.110]	[0.227]	[0.069]	[0.268]	[0.017]	[0.053]	[0.014]	[0.067]	[0.016]	[0.042]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	38.8000***	37.8126***	83.6929***	83.6401***	1.0697	-7.2255	6.2329	6.6479	3.3685	5.1818	3.8337	5.2594
	[8.698]	[9.126]	[12.851]	[14.070]	[10.924]	[11.664]	[6.762]	[6.705]	[4.398]	[4.546]	[4.545]	[4.228]
N	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
r2	0.285	0.285	0.275	0.275	0.037	0.039	0.079	0.079	0.044	0.045	0.053	0.055
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Time	0.0209	0.0208	0.0016	0.0015	-0.0241*	-0.0240*	0.0959	0.0894	-0.0011	-0.0014	-1.0083	-1.1629
	[0.016]	[0.016]	[0.014]	[0.014]	[0.012]	[0.012]	[0.677]	[0.746]	[0.373]	[0.376]	[1.066]	[1.013]
Treatment	-0.0624***	-0.0624***	-0.0455**	-0.0454**	-0.0202	-0.0202	-0.6878	-0.6403	-0.5702*	-0.5584*	0.4852	0.5885
	[0.023]	[0.023]	[0.021]	[0.021]	[0.017]	[0.017]	[0.655]	[0.731]	[0.288]	[0.292]	[0.577]	[0.530]
Time	-0.0100	-0.0875*	0.0199	-0.0448	0.0360**	0.0343	0.1421	1.5344*	0.0416	0.3787	0.0164	0.6744
	[0.015]	[0.048]	[0.017]	[0.043]	[0.014]	[0.038]	[0.247]	[0.792]	[0.142]	[0.564]	[0.195]	[1.119]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	6.7375	6.9299	4.9551	5.9870	4.9173	4.5690	7.0953**	-24.4035	7.6672***	-2.3166	9.1027***	6.1609
	[6.797]	[6.732]	[5.118]	[5.044]	[4.611]	[4.385]	[3.309]	[19.651]	[2.329]	[16.501]	[2.363]	[18.907]
N	3,135	3,135	3,135	3,135	3,135	3,135	246	246	231	231	144	144
r2	0.085	0.085	0.068	0.069	0.073	0.073	0.117	0.143	0.241	0.247	0.212	0.228

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A2

Testing for Parallel Trend prior to Policy, Free Cash Flow as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Time	0.0334	0.0343	-0.0017	0.0018	-0.0286	-0.0225	0.0241	0.0249	-0.0033	-0.0026	0.0084	0.0089
	[0.046]	[0.046]	[0.106]	[0.106]	[0.076]	[0.076]	[0.017]	[0.017]	[0.014]	[0.014]	[0.017]	[0.017]
Treatment	-0.5471***	-0.5469***	-1.2055***	-1.2046***	-0.2110	-0.2106	-0.0979*	-0.0975*	-0.0631	-0.0629	-0.0937**	-0.0937**
	[0.155]	[0.155]	[0.362]	[0.362]	[0.161]	[0.160]	[0.051]	[0.051]	[0.040]	[0.040]	[0.043]	[0.043]
Time	-0.0446	0.0325	-0.0303	0.2043	0.0237	-0.2537*	-0.0169	-0.0323	-0.0017	-0.0232	0.0030	-0.0459*
	[0.038]	[0.068]	[0.085]	[0.141]	[0.063]	[0.135]	[0.013]	[0.028]	[0.012]	[0.029]	[0.016]	[0.025]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	1.2054***	-0.1794	2.8542***	1.4092	0.7547***	-4.8205	0.2466***	0.4851	0.1751***	1.8638*	0.1797***	1.2958
	[0.197]	[2.338]	[0.448]	[4.907]	[0.183]	[5.091]	[0.082]	[1.331]	[0.058]	[1.093]	[0.066]	[1.035]
N	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
r2	0.125	0.125	0.142	0.143	0.027	0.033	0.043	0.045	0.030	0.031	0.043	0.044
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Time	0.0046	0.0049	0.0061	0.0063	-0.0014	-0.0015	-0.0096	-0.0031	0.0050	0.0072	-0.3005	-0.3482
	[0.016]	[0.017]	[0.018]	[0.018]	[0.018]	[0.018]	[0.297]	[0.304]	[0.239]	[0.244]	[0.332]	[0.322]
Treatment	-0.0909*	-0.0909*	-0.0756*	-0.0757*	-0.0691**	-0.0691**	0.0017	-0.0126	-0.1520	-0.1441	0.0242	0.0143
	[0.048]	[0.048]	[0.039]	[0.039]	[0.034]	[0.034]	[0.335]	[0.341]	[0.195]	[0.198]	[0.305]	[0.309]
Time	-0.0092	-0.0307	0.0018	-0.0237	0.0181	0.0391*	0.1181	0.7634	0.0093	0.1141	-0.0760	-0.1007
	[0.015]	[0.032]	[0.016]	[0.025]	[0.017]	[0.021]	[0.172]	[0.574]	[0.106]	[0.358]	[0.152]	[0.585]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	0.2166***	-0.2167	0.1761***	0.8343	0.1248**	-0.3025	2.2967***	-24.8037	3.5327***	-4.5226	3.5149***	-7.4647
	[0.080]	[1.218]	[0.062]	[0.882]	[0.056]	[0.864]	[0.249]	[21.369]	[0.180]	[14.447]	[0.221]	[21.839]
N	3,135	3,135	3,135	3,135	3,135	3,135	246	246	231	231	144	144
r2	0.040	0.041	0.037	0.038	0.034	0.034	0.088	0.107	0.195	0.197	0.158	0.173

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A3

Testing for Parallel Trend prior to Policy, Age as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Time	0.0229	0.0225	-0.0408	-0.0417	-0.0954	-0.0938	0.0065	0.0067	0.0046	0.0050	0.0203	0.0202
	[0.052]	[0.052]	[0.117]	[0.117]	[0.073]	[0.073]	[0.019]	[0.019]	[0.016]	[0.016]	[0.015]	[0.015]
Treatment	0.3230**	0.3235**	0.6099**	0.6111**	0.0901	0.0888	0.0633	0.0631	0.0363	0.0361	0.0370	0.0370
	[0.135]	[0.135]	[0.297]	[0.297]	[0.188]	[0.188]	[0.071]	[0.071]	[0.051]	[0.051]	[0.053]	[0.053]
Time	0.0239	0.1321	0.1622	0.3804*	0.1227*	0.0095	-0.0084	-0.0589	-0.0018	-0.0621	0.0057	-0.0388
	[0.043]	[0.106]	[0.100]	[0.227]	[0.067]	[0.273]	[0.014]	[0.052]	[0.013]	[0.068]	[0.013]	[0.042]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	44.9864***	44.0278***	95.0402***	95.0341***	2.9243	-5.4277	7.5121	7.9247	4.1739	5.9815	4.7683	6.1910
	[9.288]	[9.635]	[12.160]	[13.279]	[12.114]	[12.862]	[7.666]	[7.587]	[4.964]	[5.104]	[5.092]	[4.817]
N	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
r2	0.297	0.298	0.278	0.279	0.025	0.028	0.081	0.081	0.042	0.043	0.054	0.055
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Time	-0.0221	-0.0220	0.0054	0.0055	0.0072	0.0073	0.5034	0.4889	-0.5041*	-0.5051*	-0.0782	-0.0870
	[0.020]	[0.020]	[0.019]	[0.019]	[0.019]	[0.019]	[0.338]	[0.349]	[0.258]	[0.259]	[0.322]	[0.296]
Treatment	0.0741	0.0739	0.0324	0.0323	0.0315	0.0316	-0.7754***	-0.7217**	0.0582	0.0676	-0.1300	-0.1110
	[0.069]	[0.069]	[0.053]	[0.053]	[0.047]	[0.047]	[0.276]	[0.294]	[0.246]	[0.250]	[0.315]	[0.300]
Time	-0.0060	-0.0801*	0.0137	-0.0499	0.0244*	0.0240	-0.1073	0.9714	0.1427	0.3945	0.0048	0.5185
	[0.013]	[0.048]	[0.016]	[0.044]	[0.013]	[0.040]	[0.236]	[0.802]	[0.144]	[0.557]	[0.197]	[1.079]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	7.9457	8.1393	5.6841	6.7149	5.6030	5.2634	5.0696*	-26.6983	5.8247**	-3.8931	8.5283***	2.5570
	[7.732]	[7.667]	[5.842]	[5.760]	[5.259]	[5.025]	[2.920]	[19.465]	[2.377]	[16.030]	[2.210]	[19.480]
N	3,135	3,135	3,135	3,135	3,135	3,135	246	246	231	231	144	144
r2	0.087	0.088	0.067	0.068	0.073	0.074	0.153	0.172	0.241	0.248	0.199	0.208

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A4

Testing for Parallel Trend prior to Policy, Firm Size as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Time	0.1784***	0.1805***	0.5422***	0.5474***	-0.0429	-0.0463	0.0198	0.0195	0.0481**	0.0476**	0.0207	0.0208
	[0.065]	[0.065]	[0.156]	[0.157]	[0.093]	[0.093]	[0.024]	[0.024]	[0.019]	[0.019]	[0.023]	[0.023]
Treatment	-0.7649***	-0.7671***	-2.2176***	-2.2234***	-0.4889***	-0.4853***	-0.1576***	-0.1573***	-0.1482***	-0.1475***	-0.1292***	-0.1292***
	[0.135]	[0.135]	[0.330]	[0.331]	[0.168]	[0.168]	[0.049]	[0.049]	[0.043]	[0.043]	[0.048]	[0.048]
Time	-0.1603**	0.0599	-0.4515**	0.1087	0.0448	0.0136	-0.0363	-0.0629	-0.0472**	-0.0839	-0.0156	-0.0398
	[0.077]	[0.116]	[0.190]	[0.245]	[0.101]	[0.273]	[0.030]	[0.057]	[0.023]	[0.067]	[0.028]	[0.043]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	36.9357***	36.0729***	77.8762***	78.2210***	0.4069	-7.8594	5.8766	6.3105	3.0500	4.8893	3.5520	4.9961
	[7.870]	[8.240]	[9.872]	[11.112]	[10.711]	[11.593]	[6.664]	[6.616]	[4.331]	[4.499]	[4.477]	[4.185]
N	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
r2	0.384	0.385	0.429	0.429	0.063	0.065	0.113	0.113	0.079	0.080	0.084	0.085
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Time	0.0182	0.0182	-0.0050	-0.0051	-0.0181	-0.0181	0.5299	0.5419	0.3981	0.4094	-0.1631	-0.1557
	[0.019]	[0.019]	[0.020]	[0.020]	[0.018]	[0.018]	[0.467]	[0.456]	[0.308]	[0.311]	[0.350]	[0.361]
Treatment	-0.1431***	-0.1431***	-0.1060***	-0.1060***	-0.0639**	-0.0639**	-0.2432	-0.2552	-0.0448	-0.0603	0.0447	0.0442
	[0.043]	[0.043]	[0.036]	[0.036]	[0.031]	[0.031]	[0.382]	[0.375]	[0.254]	[0.253]	[0.320]	[0.335]
Time	-0.0402*	-0.0938*	0.0049	-0.0420	0.0301	0.0392	-0.0547	1.5108*	-0.0836	0.2000	0.0061	0.5519
	[0.024]	[0.050]	[0.024]	[0.044]	[0.020]	[0.039]	[0.213]	[0.782]	[0.155]	[0.544]	[0.196]	[1.067]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	6.4171	6.6273	4.7236	5.7684	4.7838	4.4466	7.7893**	-24.2226	7.9524***	-3.8352	9.2877***	2.8982
	[6.696]	[6.640]	[5.040]	[4.971]	[4.545]	[4.324]	[3.316]	[20.232]	[2.302]	[15.289]	[2.286]	[20.177]
N	3,135	3,135	3,135	3,135	3,135	3,135	246	246	231	231	144	144
r2	0.115	0.116	0.095	0.095	0.088	0.088	0.114	0.142	0.222	0.230	0.194	0.203

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A5

Difference-in-difference Estimates with Debt as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Post	0.1183**	0.1184**	0.2190*	0.2192*	0.0315	0.0314	0.0323**	0.0323**	0.0025	0.0025	0.0036	0.0036
	[0.047]	[0.047]	[0.118]	[0.118]	[0.079]	[0.079]	[0.014]	[0.014]	[0.014]	[0.014]	[0.013]	[0.013]
Treatment	-0.2310**	-0.2311**	-0.5361**	-0.5363**	-0.3575***	-0.3573***	-0.0562**	-0.0561**	-0.0448**	-0.0448**	-0.0500**	-0.0500**
	[0.089]	[0.089]	[0.225]	[0.225]	[0.102]	[0.102]	[0.027]	[0.027]	[0.022]	[0.022]	[0.024]	[0.024]
Post	-0.0998*	0.2358**	-0.2556**	0.8132***	0.2105***	-0.3765	0.0056	-0.1287*	0.0140	-0.0755	0.0181	-0.1210***
	[0.051]	[0.109]	[0.118]	[0.225]	[0.076]	[0.256]	[0.018]	[0.066]	[0.016]	[0.054]	[0.018]	[0.038]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	36.4628***	37.5153***	82.8886***	85.9603***	-0.1579	-1.0167	5.6315	5.2195	3.3963	2.7881	3.2642	2.7475
	[8.589]	[8.623]	[12.972]	[13.099]	[10.139]	[10.065]	[6.402]	[6.336]	[4.296]	[4.265]	[4.267]	[4.201]
N	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632
r2	0.269	0.269	0.274	0.274	0.034	0.035	0.070	0.071	0.044	0.045	0.051	0.052
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Post	0.0170	0.0170	0.0028	0.0028	0.0013	0.0013	0.2319	0.2216	0.4247	0.4030	-0.0434	-0.0995
	[0.014]	[0.014]	[0.011]	[0.011]	[0.012]	[0.012]	[0.401]	[0.399]	[0.269]	[0.265]	[0.521]	[0.509]
Treatment	-0.0497**	-0.0497**	-0.0488**	-0.0488**	-0.0426**	-0.0426**	-0.7894***	-0.7787**	-0.6216***	-0.6223***	-0.0632	-0.0352
	[0.023]	[0.023]	[0.020]	[0.020]	[0.018]	[0.018]	[0.298]	[0.301]	[0.197]	[0.196]	[0.453]	[0.452]
Post	0.0225	-0.0892*	0.0141	-0.0534	0.0268*	0.0806*	0.4982*	0.9432	0.0293	0.5248	0.2425	0.3171
	[0.019]	[0.050]	[0.017]	[0.044]	[0.015]	[0.042]	[0.288]	[1.002]	[0.165]	[0.770]	[0.219]	[0.706]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	5.8344	5.6318	4.0283	3.9055	4.0003	4.3611	3.5343	2.8102	6.1047***	4.0762	8.1143***	8.6051**
	[6.300]	[6.303]	[4.487]	[4.452]	[4.330]	[4.279]	[2.594]	[4.417]	[1.315]	[3.517]	[1.323]	[3.328]
N	6,632	6,632	6,632	6,632	6,632	6,632	557	557	505	505	377	377
r2	0.074	0.075	0.058	0.058	0.059	0.059	0.117	0.120	0.096	0.107	0.108	0.113

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A6

Difference-in-difference Estimates with Free Cash Flow as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Post	0.0404	0.0403	0.0369	0.0367	0.0662	0.0666	0.0167	0.0168	0.0093	0.0094	0.0167	0.0168
	[0.046]	[0.046]	[0.105]	[0.105]	[0.087]	[0.088]	[0.017]	[0.017]	[0.019]	[0.019]	[0.016]	[0.016]
Treatment	-0.5314***	-0.5311***	-1.2268***	-1.2263***	-0.2366	-0.2366	-0.0897*	-0.0897*	-0.0638*	-0.0637*	-0.0870**	-0.0870**
	[0.147]	[0.148]	[0.347]	[0.348]	[0.161]	[0.162]	[0.048]	[0.048]	[0.037]	[0.037]	[0.041]	[0.041]
Post	-0.1372**	0.1862	-0.3199**	0.7220***	0.1690**	-0.4248*	-0.0037	-0.1405*	0.0048	-0.0864	0.0052	-0.1353***
	[0.060]	[0.116]	[0.133]	[0.240]	[0.078]	[0.248]	[0.022]	[0.072]	[0.020]	[0.060]	[0.021]	[0.042]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	1.1305***	2.1770***	2.6731***	5.7464***	0.6765***	-0.1585	0.2305***	-0.1828	0.1653***	-0.4402**	0.1645***	-0.3485**
	[0.193]	[0.493]	[0.440]	[1.122]	[0.178]	[0.878]	[0.077]	[0.224]	[0.055]	[0.212]	[0.060]	[0.159]
N	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632
r2	0.124	0.125	0.145	0.146	0.028	0.028	0.044	0.044	0.029	0.031	0.043	0.044
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Post	0.0121	0.0121	0.0222	0.0222	-0.0034	-0.0035	0.1958	0.1986	0.1404	0.1216	0.1817	0.1784
	[0.018]	[0.018]	[0.015]	[0.015]	[0.014]	[0.014]	[0.244]	[0.248]	[0.147]	[0.148]	[0.183]	[0.182]
Treatment	-0.0818*	-0.0819*	-0.0715*	-0.0716*	-0.0765**	-0.0765**	-0.0057	-0.0123	-0.1130	-0.1064	-0.2748	-0.2697
	[0.046]	[0.046]	[0.038]	[0.039]	[0.036]	[0.036]	[0.266]	[0.266]	[0.179]	[0.178]	[0.222]	[0.222]
Post	0.0123	-0.1020*	-0.0030	-0.0726	0.0242	0.0766*	0.2863	0.9042	-0.0140	0.4619	0.2061	0.1653
	[0.024]	[0.052]	[0.021]	[0.044]	[0.019]	[0.041]	[0.285]	[0.978]	[0.179]	[0.738]	[0.221]	[0.666]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	0.2152***	0.0075	0.1632***	0.0397	0.1307**	0.4947***	2.2964***	1.9921	3.2782***	1.4591	3.3908***	4.0579
	[0.075]	[0.227]	[0.059]	[0.210]	[0.054]	[0.180]	[0.246]	[3.712]	[0.174]	[3.254]	[0.221]	[2.989]
N	6,632	6,632	6,632	6,632	6,632	6,632	557	557	505	505	377	377
r2	0.040	0.041	0.034	0.035	0.040	0.040	0.090	0.093	0.064	0.073	0.097	0.102

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A7

Difference-in-difference Estimates with Age as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Post	0.0363	0.0361	0.0691	0.0685	0.0385	0.0391	0.0155	0.0156	0.0068	0.0070	0.0077	0.0078
	[0.041]	[0.041]	[0.099]	[0.099]	[0.098]	[0.098]	[0.015]	[0.015]	[0.015]	[0.015]	[0.014]	[0.014]
Treatment	0.3210**	0.3213**	0.6166**	0.6174**	0.0369	0.0365	0.0616	0.0615	0.0331	0.0331	0.0417	0.0415
	[0.128]	[0.128]	[0.282]	[0.282]	[0.177]	[0.177]	[0.071]	[0.071]	[0.051]	[0.051]	[0.054]	[0.054]
Post	-0.1184**	0.2126*	-0.2961**	0.7614***	0.1885**	-0.4083	0.0007	-0.1348**	0.0081	-0.0826	0.0113	-0.1290***
	[0.055]	[0.111]	[0.123]	[0.231]	[0.079]	[0.253]	[0.017]	[0.068]	[0.015]	[0.056]	[0.016]	[0.039]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	42.9633***	44.0252***	95.7745***	98.8690***	2.2022	1.3488	6.9738	6.5630	4.1981	3.5907	4.2380	3.7214
	[9.264]	[9.295]	[11.961]	[12.070]	[11.466]	[11.412]	[7.306]	[7.243]	[4.896]	[4.864]	[4.792]	[4.725]
N	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632
r2	0.284	0.285	0.281	0.282	0.023	0.023	0.075	0.075	0.043	0.044	0.051	0.051
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Post	0.0225	0.0226	0.0130	0.0131	0.0083	0.0083	0.4353	0.4262	0.2719*	0.2752*	0.0506	0.0654
	[0.017]	[0.017]	[0.013]	[0.013]	[0.013]	[0.013]	[0.269]	[0.267]	[0.158]	[0.158]	[0.210]	[0.217]
Treatment	0.0592	0.0592	0.0281	0.0281	0.0356	0.0356	-0.5404**	-0.5326**	-0.2303	-0.2265	-0.2993*	-0.3008*
	[0.067]	[0.067]	[0.049]	[0.049]	[0.048]	[0.048]	[0.216]	[0.215]	[0.161]	[0.160]	[0.171]	[0.175]
Post	0.0121	-0.1009**	0.0063	-0.0626	0.0200	0.0727*	0.2155	0.7229	-0.0212	0.6035	0.2740	0.4274
	[0.017]	[0.049]	[0.016]	[0.044]	[0.013]	[0.042]	[0.278]	[1.003]	[0.181]	[0.767]	[0.216]	[0.700]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	7.1930	6.9904	4.8075	4.6852	4.8492	5.2107	2.1273	1.6057	5.7513***	4.2848	6.2602***	7.0746**
	[7.205]	[7.205]	[5.154]	[5.113]	[4.942]	[4.890]	[2.389]	[4.420]	[1.638]	[3.786]	[1.186]	[3.515]
N	6,632	6,632	6,632	6,632	6,632	6,632	557	557	505	505	377	377
r2	0.079	0.080	0.055	0.056	0.058	0.059	0.112	0.115	0.078	0.088	0.131	0.134

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table A8

Difference-in-difference Estimates with Firm Size as Treatment Variation

	OUTCOMES (Log)											
	Patent Count		Patent Value		Patent Citation		Phase 1 Start		Phase 2 Start		Phase 3 Start	
Treatment x Post	0.1616***	0.1623***	0.4741***	0.4762***	0.0585	0.0571	0.0302	0.0300	0.0305	0.0302	0.0190	0.0187
	[0.048]	[0.048]	[0.115]	[0.115]	[0.092]	[0.091]	[0.018]	[0.018]	[0.021]	[0.021]	[0.019]	[0.019]
Treatment	-0.6670***	-0.6678***	-1.9017***	-1.9040***	-0.5031***	-0.5015***	-0.1409***	-0.1407***	-0.1141***	-0.1138***	-0.1142***	-0.1139***
	[0.114]	[0.114]	[0.281]	[0.281]	[0.145]	[0.145]	[0.041]	[0.041]	[0.034]	[0.034]	[0.039]	[0.039]
Post	-0.0985	0.1220	-0.2552	0.4614*	0.0606	-0.4493*	-0.0250	-0.1490**	-0.0338	-0.1007*	-0.0062	-0.1397***
	[0.061]	[0.116]	[0.155]	[0.239]	[0.085]	[0.271]	[0.029]	[0.069]	[0.023]	[0.060]	[0.027]	[0.040]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	35.8677***	37.1673***	80.9220***	84.6927***	0.2348	-0.4265	5.5197	5.1609	3.3536	2.7882	3.2337	2.7605
	[7.843]	[7.871]	[10.087]	[10.180]	[9.842]	[9.783]	[6.295]	[6.234]	[4.216]	[4.188]	[4.183]	[4.120]
N	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632	6,632
r2	0.353	0.353	0.395	0.396	0.054	0.055	0.099	0.099	0.069	0.070	0.077	0.078
	Phase 1 Complete		Phase 2 Complete		Phase 3 Complete		Phase 1 Length		Phase 2 Length		Phase 3 Length	
Treatment x Post	0.0236	0.0235	0.0206	0.0206	-0.0156	-0.0155	-0.2365	-0.2375	-0.0278	-0.0136	-0.0367	-0.0577
	[0.018]	[0.018]	[0.017]	[0.017]	[0.014]	[0.014]	[0.232]	[0.233]	[0.178]	[0.177]	[0.285]	[0.281]
Treatment	-0.1283***	-0.1283***	-0.1105***	-0.1105***	-0.0808***	-0.0810***	0.0172	0.0208	0.0238	0.0012	-0.1906	-0.1903
	[0.036]	[0.036]	[0.033]	[0.033]	[0.030]	[0.030]	[0.291]	[0.292]	[0.183]	[0.180]	[0.225]	[0.227]
Post	-0.0344	-0.1084**	-0.0241	-0.0732*	0.0228	0.0831**	0.4424	1.0476	0.0496	0.5979	0.2259	0.2744
	[0.026]	[0.052]	[0.023]	[0.044]	[0.017]	[0.041]	[0.299]	[0.987]	[0.179]	[0.768]	[0.203]	[0.689]
Firm Controls	X		X		X		X		X		X	
All Controls		X		X		X		X		X		X
Constant	5.7484	5.5942	4.0031	3.9219	3.9926	4.3858	4.6232	4.3825	6.4350***	4.5666	7.9643***	8.2359**
	[6.195]	[6.204]	[4.405]	[4.374]	[4.252]	[4.206]	[2.777]	[4.472]	[1.431]	[3.583]	[1.311]	[3.102]
N	6,632	6,632	6,632	6,632	6,632	6,632	557	557	505	505	377	377
r2	0.101	0.101	0.083	0.084	0.079	0.079	0.093	0.096	0.069	0.079	0.118	0.124

Clustered standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1