

State Antitakeover Provisions Don't Actually Do Much

Andrew C. Baker

University of California, Berkeley

Draft: April 17, 2025

Abstract

Corporate governance scholars have engaged in a longstanding debate over the impact of state antitakeover provisions. Corporate law practitioners and researchers argue that the affirmation of the “poison pill” made the second generation of antitakeover statutes redundant, while empirical scholars in corporate finance continue to find wide-ranging impacts from their adoption. This paper subjects the standard approach used in the empirical literature to a series of straightforward extensions using current best practice in panel data analysis. Contrary to the majority of published research, there is scant evidence for a consistent and reliable impact of antitakeover statute adoption on firm activity. These findings follow logically from the legal argument that takeover statutes provide little additional takeover deterrence in the presence of a “shadow pill.”

I thank Bernie Black and the participants in the Northwestern University Law and Economics Colloquium and the 2022 Conference on Empirical Legal Studies for helpful comments. A prior version of this paper was circulated as “Do State Antitakeover Provisions Matter?”

Address: 2763-2719 Bancroft Way, Berkeley CA 94704

Email: andrew.baker@berkeley.edu

Conflict-of-interest disclosure statement

Andrew Baker: I have nothing to disclose

1 Introduction

Over the past two decades a robust literature in corporate finance has studied the impact of state antitakeover legislation—most notably business combination, fair price provisions, and control share acquisition statutes—on firm-level outcomes. These provisions, designed largely to encumber hostile takeover attempts, are thought to further entrench a management class that often prioritizes its own interest over those of its shareholders when facing a change of control decision ([Macey, 1998](#)). Because coverage by an antitakeover statute ostensibly shifts the balance of power within a firm towards executives and away from shareholders, the staggered adoption of such statutes in the 1980s and '90s have been used extensively to test how emboldened managers change their actions when faced with a decreased likelihood of a successful takeover attempt.

This work is part of a broader literature across subfields in economics, finance, and law, devoted to the study of the relationship between managers, shareholders, and stakeholders. Management scholars have long been interested in how the level of authority delegated to corporate executives impacts entrepreneurship and strategy ([Davis, Greg Bell, Tyge Payne, and Kreiser, 2010](#); [Medcof, 2001](#)). Most importantly for this paper, the fundamental driving question in corporate legal studies since the 1980s has been the cause and consequence of separated management and control. After [Jensen and Meckling \(1976\)](#) developed their influential model of agency frictions within the firm, corporate governance has devoted itself to studying the pitfalls of delegating power to managers whose preferences often diverge from those of their shareholder constituents.

Any research on corporate outcomes must grapple with the equilibrium nature of the measurements used. Perhaps more than any other field in economics, corporate finance and corporate law research is “plagued by endogeneity” ([Karpoff and Wittry, 2018](#)). Managers of firms face a dynamic competitive environment, and select their combination of policies and structure subject to these market constraints. As a result, firm attributes and performance are endogenous to their specific market conditions, and inferring causal connections between firm actions and outcomes is often difficult, if not often impossible. State antitakeover statutes are thought to provide a plausibly exogenous shock to the market environment, by wholesale

shifting the structure of managerial power at a level higher than where corporate actions are taken. As a result, researchers have used the passage of antitakeover statutes to study a diverse set of firm outcome measures, from compliance with workplace safety regulations to information asymmetry and investment.

A number of legal scholars raised a conceptual institutional concern with this line of research. A rights plan, colloquially known as a “poison pill”, is the strongest deterrent to a hostile takeover attempt, arguably rendering other forms of takeover deterrence redundant. As a result, once Delaware confirmed the legality of the poison pill in the mid-1980s, the presence of other state-level antitakeover provisions became moot. Moreover, the legal critique notes that many of the published papers use data with clear measurement error and design flaws. One article in particular, [Catan and Kahan \(2016\)](#), replicated three influential papers in this area and showed how each was driven by flaws in the data structure or research design process. These concerns were arguably idiosyncratic to the papers being reviewed, and the critique in [Catan and Kahan \(2016\)](#) cannot explain why such a large number of significant effects have been found in prior studies, or whether it is reflective of a more pervasive problem with the approach taken across areas of empirical legal research.

In more recent work, [Karpoff and Wittry \(2018\)](#) partially confirms and partially rebuts the legal critique. Many results in the finance literature are indeed driven by the failure to consider firms’ institutional and legal context, and the effect of an antitakeover provision on takeover protection depends critically on the interaction between multiple firm level defenses. However, they strongly disagree that antitakeover laws provide no incremental takeover protection for firms, citing consequences for managers and directors that invoke a poison pill, and the continued significance of such statutes in many of their regression estimates.

In this paper I undertake a systematic review of the prior results on antitakeover statutes to determine the magnitude of the disagreement between institutionally- and empirically-oriented scholarship. While [Catan and Kahan \(2016\)](#) document flaws in a limited number of studies, their paper does not explain how dozens of prior studies consistently found positive impacts from the law. Moreover, they take the general empirical approach used in most prior work as implicitly valid, focusing instead on more specific and contestable arguments about institutional structure and data quality. I test whether the basic underlying

framework is generating biased results.

Tying the specific study design used in these papers to recent advances on the pitfalls of using fixed effects regression models with time-varying policy changes, I establish a series of results that further calls into question this line of research. First, even before correcting for problems generated by the staggered nature of antitakeover statute adoption over time, a standard “event study” model shows that the timing of differences between covered and uncovered firms is often inconsistent with the inferences drawn in prior work. This holds even using identical data, and the same underlying model of expected outcomes, as in prior work that finds consistent significant effects. When using modern empirical methods designed expressly to address the shortcomings of the standard approach, there is little evidence to support the proposition that antitakeover statutes had a material effect on corporate outcomes, consistent with the critique by corporate law scholars.

These findings carry significance outside of the debate over takeover protections and tender offers. [Baker, Larcker, and Wang \(2022\)](#) documents how this methodological concern impacts a diverse range of findings in law and finance, from the effect of bank deregulation on the income distribution to whether securities enforcement fosters equity ownership. Moreover, such fixed effects panel regressions are used extensively in the study of legal changes, from the law and economics of crime ([Ludwig, 1998](#)) to tort reform ([Avraham, 2007](#)) and affirmative action ([DuBois, 2016](#)). While nothing in this paper is meant to cast doubt on specific prior research, it is consistent with the argument that the rise in the empirical study of legal and regulatory changes needs to be matched with methodological rigour, especially when being used to influence policy debates ([Donohue, 2015](#)).

2 History of Antitakeover Provisions

Hostile takeovers are governed by a series of overlapping regulatory provisions at both the state and federal level that have changed substantially over time. Both the empirical and institutional approach to takeover research has emphasized the importance of the interaction of federal and state regulation with firm-level defenses. The following section details the laws that govern takeover defense, including the specific antitakeover provisions that have been

the subject of much empirical research.

2.1 Federal Oversight

Corporate takeovers are governed by federal law through the Williams Act and the Hart–Scott–Rodino Antitrust Improvements Act (HSR Act). The HSR Act does not address hostile takeovers specifically, but instead provides for general pre-merger notification to the Federal Trade Commission and the Department of Justice, and a mandatory waiting period before transactions can be completed (Baer, 1997). Prior to the Williams Act, there in fact existed minimal substantive regulation of tender offers,¹ outside of the broadly applicable civil liability provisions in the Securities Acts. In the absence of such regulation, bidders frequently provided little or no information about the purpose of their stock purchases, and, as a result, shareholders deciding whether to tender shares lacked the requisite information to guide their decisions. In addition, bidders commonly gave shareholders a short period of time to make tender decisions, prohibited withdrawals of tendered shares, and used two-tiered transactions,² which generated a prisoner’s dilemma for target shareholders.³

In response to complaints about the deficient information environment surrounding hostile takeovers, and a surge in tender offers in the 1960s, Congress passed the Williams Act in 1968, which governs the provision of information on share acquisitions by bidders in tender offer and go-private transactions. Crucially, it also requires that bidders accept tendered shares on a pro-rata basis, allows shareholders to withdraw their tendered shares while the offer is open, ensures all tendering is paid at an equivalent price, and forces the offer to remain open for twenty business days. The sole purpose of these provisions was to provide information to shareholders in a way that did not create an informational advantage

¹While the term “tender offer” is left undefined by the Williams Act, it generally refers to a situation where a bidder seeks to acquire control of a target company by offering to purchase some or all of the outstanding shares of the target firm directly from the target’s shareholders, often at a premium over the prevailing market price (Easterbrook and Fischel, 1981).

²A two-tiered transaction is one where the bidder initially presents a superior tender offer for a limited number of shares of the target to achieve majority control, followed by a inferior offer for the remaining shares once control is achieved. The secondary transaction to “squeeze out” the remaining shareholders usually comes with inferior terms—at either a lower value per share or substituting junk bonds for cash.

³Because the terms in the second tier are inferior to the first tier, each shareholder may find it beneficial to tender their shares quickly even if they would all be better off by collectively not tendering.

for either bidder or target management.⁴ The language of the Williams Act makes clear that it merely confers limited protections to shareholders of target companies, “while disclaiming any intent to strengthen or weaken the hands of bidders or opponents” (Johnson and Millon, 1989).

2.2 First-Generation Statutes

Meanwhile, the continued rise in hostile takeovers after passage of the Williams Act spurred state governments to pass legislation expressly designed to suppress takeover activity. Unlike Congress, which declined to speak to the normative implications of the market for corporate control, state legislatures acted on a “perception that hostile takeovers disrupt local economies and harm resident nonshareholders dependent on corporate activity—perceptions that increasingly are explicitly acknowledged in the language and legislative history of these recent statutes” (Johnson and Millon, 1989).

The state law provisions designed to slow takeover activity put in place shortly following the Williams Act are colloquially known as “first-generation statutes.” As noted in Romano (1987), they were enacted across states at a faster rate than any other modification to state corporate law codes at the time. While first-generation statutes contained certain provisions that mirrored those in the Williams Act, focused largely on increased disclosure provisions, they also mandated substantially more extensive disclosures, which were required to be filed with the target and the state securities commissions in advance of any takeover. In addition, some states also required tender offers to be held open for longer periods of time than required under the Williams Act, and others created administrative review of tender offers by state securities regulators. The practical effect of such provisions was to generate lengthy delays for any hostile takeover attempt, and provide target management with ample opportunity to use tactics to foreclose a takeover bid. Most available evidence suggests that first-generation statutes raised average cash bids and decreased the quantity of hostile takeovers (Jarrell and Bradley, 1980; Smiley, 1981).

Threats to the constitutionality of first-generation statutes were typically founded on the argument that they violated both the Commerce and the Supremacy Clauses of the

⁴S.Rep. No. 550, 90th Cong., 1st Sess., 2 (1967)

Constitution (Snipes, 1983). Court decisions held that the onerous requirements imposed in the statutes “destroyed the delicate balance reached by the Williams Act”, and as a result were preempted under federal law.⁵ In addition, because they usually applied to offers made outside of the state, as well as to companies incorporated elsewhere, first-generation laws were often ruled to be inappropriately regulating interstate commerce. Given that the purpose of first-generation statutes was often to explicitly limit plant closures and related effects on the state’s economy, courts found that they contravened *Hood & Sons v. Du Mond*, which held that such statutes could not be enacted “solely for protection of local economic interests”.⁶ Ultimately, of the 32 lower courts rulings on the constitutionality of first-generation laws, 17 ruled that at least one provision of a first-generation law was unconstitutional, while 15 upheld the law (Karpoff and Wittry, 2018). The constitutional question was resolved in a 1982 Supreme Court decision, *Edgar v. MITE Corp.*⁷, concerning Illinois’s antitakeover law. The statute’s provisions were found to unconstitutionally “frustrate the congressional purpose” of the Williams Act by imposing unnecessary delays in the tender process, and also that it was a “direct restraint on interstate commerce, [with] a sweeping extraterritorial effect.”⁸

2.3 Second-Generation Statutes

Although *MITE* struck down the Illinois statute, it plainly did not preempt all state regulation of tender offers due to the Williams Act. Given the Supreme Court’s acute unease with the broad jurisdictional reach taken by states and their securities regulators in first-generation statutes, states crafted new legislation that minimized the scope of regulated activity. The statutes passed after the decision, known in the literature as “second-generation statutes”, only covered tender offers of firms incorporated in the state of the law’s passage, and required confirmation only by a firm’s shareholders, and not state regulatory agencies. While second-generation statutes avoided the specific provisions held unconstitutional in the

⁵See *Great W. United Corp. v. Kidwell*, 439 F. Supp. 420 (N.D. Tex. 1977), aff’d, 577 F.2d 1256 (5th Cir. 1978), *rev’d on other grounds sub nom. Leroy v. Great W. United. Corp.* 443 U.S. 173 (1979).

⁶*Id.* at 438 (citing *Hood & Sons v. Du Mond*, 336 U.S. 525 (1949)).

⁷457 U.S. 624 (1982).

⁸*Edgar v. MITE Corp.*, 457 U.S. 624, 642 (1982).

MITE decision, they exhibited substantially more variation in their specific provisions, in what has been called “a striking example of extensive experimentation by states in legal innovation” (Romano, 1987).

Second-generation laws are the subject of the overwhelming majority of empirical papers on the effect of state antitakeover provisions, and thus will be explained more fully here. The first state to pass a second-generation statute was Ohio, which implemented what is now known as a “control share acquisition statute”. Control share acquisition statutes allow a target firm to avert changes in corporate control by restricting voting rights when a person or firm acquires the ownership of an amount of stock over a specified percentage of the company’s total voting power, referred to as “control shares”. Once an entity crosses the percentage threshold stipulated in the statute, they are no longer able to vote their shares unless the firm’s stockholders affirmatively approve the restoration of voting rights by a specific proportion (usually a two-thirds majority excluding interested parties) (SEC, 2020). Control share acquisition statutes align tender offers with the historical requirements for asset purchases and mergers, thus treating different forms of acquisitions similarly (Romano, 1987).

The second form of antitakeover provision to be implemented after *MITE* was Maryland’s “fair price law”. Fair price laws govern two-tiered acquisitions, and are the statutory equivalent to one of the more common antitakeover defenses implemented in company bylaws and charter amendments. The law prevents business combinations between a target firm and significant stockholder unless certain conditions are met. The offer must either i) receive prior approval from a supermajority (typically 80%) of all outstanding voting shares and a supermajority (e.g., two-thirds) of the stock held by disinterested parties, ii) be approved by a majority of the disinterested board of directors, or iii) stockholders must receive a “fair price”, which is typically the higher of the price the bidder paid for its shares or the market price at the time of the combination. (Romano, 1987; Karpoff and Wittry, 2018) This essentially prevents a bidder from receiving any of the benefit of the post-announcement stock price increase.

Other second generation statutes include business combination laws, which impose a waiting period, typically three to five years, for significant asset sales or mergers between large

shareholder and targeted firms once a shareholder crosses an ownership threshold. Business combination statutes frequently stipulate that the merger can only be consummated after the waiting period if it also satisfies the fair price provisions, and are often considered the most stringent of the second-generation laws. Directors’ duties laws explicitly allow board members to consider the interests of non-shareholder (i.e. stakeholder) interests when making corporate decisions, and poison pill endorsement laws codify in statute the right of a corporation to adopt a rights plan, also known as a poison pill. Poison pills allow a firm to effectively prevent takeovers by issuing “rights”, usually in the form of a stock dividend for non-bidding shareholders, diluting the position of the bidder and making the cost of a takeover prohibitive. In the time since Ohio passed its control share acquisition statute in 1982, 43 states have adopted at least 157 second generation antitakeover laws. The dates of adoption for each statute are presented in Table A.1 of the Appendix.

Second-generation statutes avoid the specific provisions found by the *MITE* Court to violate the Supremacy and Commerce Clauses, but also faced robust constitutional challenges. For example, Romano (1987) notes that control share acquisition laws had universally been held constitutional upon judicial review. This was eventually resolved by the Supreme Court in a surprise 1987 ruling, *CTS Corp. v. Dynamics Corp. of America*.⁹ The case overturned a series of district and circuit court holdings, declaring that Indiana’s control share acquisition did not burden interstate commerce, and in fact furthered the intent of the Williams Act by allowing for more collective decisionmaking in tender offers. The constitutionality of business combination statutes was similarly upheld by the Seventh Circuit in *Amanda Acquisition Corp. v. Universal Foods Corp.*¹⁰, and the legality of poison pills was established for Delaware corporations¹¹ in 1985 in *Moran v. Household International, Inc.*¹² and confirmed in 1990 in *Paramount Communications, Inc. v. Time, Inc.*¹³

⁹481 U.S. 69 (1987)

¹⁰877 F.2d 496 (1989).

¹¹Delaware is far and away the most important jurisdiction for corporate law purposes. The majority of large corporations are incorporated in the state, and there is a commonly held belief that their common law court sets the standard followed by other jurisdictions.

¹²500 A.2d 1346 (Del. 1985).

¹³571 A.2d 1140 (Del. 1990). While *Moran* upheld the right of a Delaware corporation to implement a poison pill in advance to discourage a takeover bid, *Paramount* confirmed the ability to “just say no” to hostile bids without a preconceived plan or alternative transaction.

3 Prior Research

The field of corporate governance has historically revolved around a narrow set of questions concerning power relations within the firm, and is typically defined by most economists and legal scholars in terms of a defense of shareholder interest (Tirole, 2001). Building upon Jensen and Meckling (1976), a seminal article in finance laying out the theoretic argument for the prevalence of agency costs within the modern corporate structure, governance scholars have been occupied by the question of whether managerial self-interest harms shareholders. Given the separation of ownership and control within the firm, managers are believed to take actions that harm shareholders, including engaging in external activities that distract from internal duties, building corporate “empires” that sacrifice profitability for visibility, or by entrenching themselves within the firm. Most trends in governance practice over the past three decades—from the renewed market for corporate control with private equity buyouts and hedge fund activism, to the increased prevalence of equity based compensation—have been implemented with an eye towards minimizing the divergence between managerial and shareholder interests.

Yet, while the agency-theoretic arguments are often clear in their conclusions, evidence supporting their propositions has been decidedly mixed (Klausner, 2013; Kershaw and Schuster, 2021). From removal rights and staggered board provisions in corporate bylaws,¹⁴ to hedge fund activism¹⁵ and board independence,¹⁶ advocates can almost always find empirical support suggesting that the measures are either value destructive or enhancing. While inconclusive findings are part and parcel to observational econometric work, the consistent inconsistency in corporate governance research stands apart from other areas of research. Almost 50 years after Jensen and Meckling (1976), we still have little empirical evidence for

¹⁴Compare Cremers and Ferrell (2014) (finding that firms with staggered boards have lower firm values) with Johnson, Karpoff, and Yi (2015) (finding that management insulation measures are instead associated with higher value at the time of initial public offering (IPO)) and Cremers, Litov, and Sepe (2017) (finding “no evidence that staggered board changes are negatively related to firm value”).

¹⁵Compare Brav, Jiang, Partnoy, and Thomas (2008) (hedge fund activism is associated with increased firm value and operating performance) with deHaan, Larcker, and McClure (2019) (finding no relation between activism and firm value).

¹⁶Compare Pi and Timme (1993) (finding that cost efficiency and return on assets is lower for firms where the CEO is also the chairman of the board) with Baliga, Moyer, and Rao (2016) (finding only minor evidence that leadership structure and CEO duality matter) and Brickley, Coles, and Jarrell (1997) (arguing that CEO duality is efficient and generally consistent with shareholders’ interests for the typical large firm).

the optimal allocation of rights and control within the firm, even taking shareholder value maximization as the correct normative framework.

One reason why solid empirical evidence is so difficult to achieve in corporate governance research is because of the equilibrium nature of market outcomes, as firms respond to their economic environment when making decisions of payout policy, board structure, and governance (Alchian and Demsetz, 1972; Karpoff and Wittry, 2018). The endogenous relationship between firm characteristics and past and future performance makes attributing causality to specific corporate actions challenging, at least without putting substantially more structure on the research problem. As an example, in an influential paper in governance research, Gompers, Ishii, and Metrick (2003) developed a now commonly-used index (called the G-Index) to test the relationship between firm governance quality and equity prices. This index is meant to serve as a “proxy for the balance of power between shareholders and managers”, and is constructed by counting, at the firm level, the number of 24 specific governance-related provisions implemented by a firm. Even setting aside measurement issues (Daines, Gow, and Larcker, 2010; Larcker, Reiss, and Xiao, 2015), because firms expressly adopt the provisions in the index, studies risk confusing correlation with causality if, as one would expect, the firms that adopt provisions most heavily are those with high takeover likelihoods (Karpoff, Schonlau, and Wehrly, 2017).

Recognizing this difficulty in assigning causality to firm-selected governance measures, researchers have looked for “exogenous shocks” to the governance environment. Rather than testing the change in firm performance in response to a firm’s *choice* in governance provision, one should instead focus on changes instituted at a higher level (either through statutory enactment or judicial decree). Unlike with firm-level defenses, laws passed by a state legislature, or, even better, changes initiated through district court decisions, are plausibly disconnected from firm-specific market conditions. While second-generation laws were often passed at the behest of lobbying by individual local firms (Karpoff and Malatesta, 1995), these firms have been at least partially identified, and there is little evidence of simultaneous lobbying by broader coalitions including organized labor and community groups (Romano, 1987).

3.1 Empirical Research on Antitakeover Statutes

A large body of work has now used the connection between antitakeover statutes and a range of valuation and productivity measures to study the effect of managerial power. Because each second-generation statute ostensibly functions to insulate managers from takeover pressure, they are used as plausibly exogenous increases in the relative power of management in relation to shareholders and other outsiders. Under standard agency theory, managers who face lower prospects of a credible takeover threat are, all else equal, less likely to engage in efficient management to the benefit of shareholder wealth ([Manne, 1965](#)).

One of the first papers to explore this relationship empirically was [Garvey and Hanka \(1999\)](#), which tested the relationship between corporate debt and antitakeover statutes. Based on a series of theoretical results,¹⁷ firm leverage is thought to constrain managers who would otherwise prefer to issue less than the value-maximizing amount. Comparing firms incorporated in states that passed antitakeover statutes between 1987 and 1990 to those incorporated in states that did not, the authors find that covered firms substantially reduced their use of debt, and that uncovered firms did the reverse. In a contemporaneous paper, [Bertrand and Mullainathan \(1999\)](#) focus exclusively on business combination statutes and, using firm-level data, find that managers covered by the statute raised annual wages for workers by 1-2%.

In an influential follow-up article, [Bertrand and Mullainathan \(2003\)](#) use more granular plant-level data to control for both plant location and firm state-of-incorporation effects. Again using the adoption of a business combination statute as a shock to managerial entrenchment, the authors find that insulated managers increase worker wages, dismantle fewer old plants, and are associated with lower productivity and profitability. This is argued to be evidence consistent with a “quiet life hypothesis”, wherein insulated managers care more about worker outcomes than shareholders do, but are also more likely to avoid the difficult decisions that drive profitability growth.

Following [Bertrand and Mullainathan \(2003\)](#) a burgeoning interest for studies on the impact of state antitakeover statutes developed. [Karpoff and Wittry \(2018\)](#) identify 81 papers that use the passage of second-generation laws as a feature in their identification

¹⁷[Grossman and Hart \(1982\)](#), [Stulz \(1990\)](#), and [Hart and Moore \(1995\)](#).

strategy. These studies either follow [Bertrand and Mullainathan \(2003\)](#) and use the passage of a business combination statute as the shock to governance,¹⁸ use a combination of different second-generation laws,¹⁹ or create an index that counts the number of discrete provisions covering a firm.²⁰ They have in turn applied the strategy of testing changes across second-generation statute adoption to a wide range of firm-level outcomes, from director and officer ownership levels ([Cheng, Nagar, and Rajan, 2005](#)) to credit spreads ([Qiu and Yu, 2009](#)) and innovation ([Becker-Blease, 2011](#)). While the setting and time periods differ, the studies by and large find that second-generation antitakeover statutes have a significant impact on corporate outcomes.²¹

3.2 The Academic Legal Critique

In contrast to the growing empirical literature on the impacts of antitakeover laws, legal academics have expressed skepticism about the practical importance of second-generation statutes. [Coates IV \(2000\)](#) argues that poison pills are the most effective takeover deterrent, making a hostile tender offer effectively impossible once implemented. Moreover, pill adoption can usually occur within a single business day, requiring only a board meeting and approval, and lawyers can keep necessary documents held in abeyance. Thus, even firms that have yet to adopt a rights plan are effectively covered by its takeover deterrence, given that a poison pill can almost surely be implemented in the delay induced by the Williams and HSR Act requirements. This latent ability to adopt a poison pill, now frequently called a “shadow pill”, has effectively covered every firm in Delaware since the 1985 *Moran* decision, making tests of the effect of antitakeover measures something of a fool’s errand. While most of his critique dealt with the impact of the shadow pill on firm-specific antitakeover measures, [Coates IV \(2000\)](#) also notes that pill validation “rendered vestigial” state antitakeover laws, because a

¹⁸[Amore and Bennedsen \(2016\)](#), [Atanassov \(2013\)](#), and [Kim and Ouimet \(2014\)](#).

¹⁹[Barnhart, Spivey, and Alexander \(2000\)](#), [Armstrong, Balakrishnan, and Cohen \(2012\)](#), and [John, Knyazeva, and Knyazeva \(2015\)](#)

²⁰[Wald and Long \(2007\)](#) and [John and Litov \(2010\)](#)

²¹However, two concurrent working papers also show empirical issues with this strand of literature. [Spamann \(2019\)](#) notes that cluster sizes in research using corporate law changes are extremely unbalanced, largely because more than half of all public corporations are incorporated in Delaware, creating issues for cluster-robust inference. [Heath, Ringgenberg, Samadi, and Werner \(2019\)](#) caution against the repeated use of a natural experiments in empirical research, using business combination statutes as an example where repeated studies without the use of multiple testing significantly increases the likelihood of false discoveries.

pill already prevents bids not coupled with proxy fights.

The irrelevance of antitakeover provisions in the presence of a shadow pill was reiterated by [Klausner \(2013\)](#). which argued that “at the margin, alternative measures can have no causal impact on takeover exposure or firm value” once the Delaware Supreme Court upheld the use of the poison pill. Even without a staggered board, which makes a proxy contest to remove the board (and the pill) substantially more costly, the poison pill has rendered essentially all other defenses moot, including business combination, fair price, and control share acquisition provisions. It may be possible to study firms incorporated outside of Delaware after *Moran*, but most states are thought to follow Delaware case law, and it would regardless be an “exercise of short-lived utility” given that all states shortly thereafter accepted the legality of the pill.

The most thorough critique of the empirical literature on second-generation statutes was delivered by [Catan and Kahan \(2016\)](#). They argue that the existing empirical work fails to take into account how various provisions interact with each other in practice. The article again stresses how standard antitakeover provisions do not materially alter the legal ability of management to prevent a takeover in the presence of a shadow pill, and also directly explores why some studies found evidence for an empirical effect in light of the statutes’ redundancy. [Catan and Kahan \(2016\)](#) document a series of design flaws—from using static measure of firm state of incorporation to ignoring the interaction and overlap among takeover defenses—that seemingly plague the literature. In addition they identify specific design and measurement issues in three studies, which when corrected render the results insignificant. The authors attribute these flaws to the incentives of empirical economists to use readily available policy measures to churn out empirical studies even when conflicting with existing theory. Ultimately, the authors conclude that “decades of empirical studies have yielded little empirical knowledge.”

3.3 A Partial Response

In a contemporaneous paper, [Karpoff and Wittry \(2018\)](#) respond to the substantive critiques of the empirical literature made in [Catan and Kahan \(2016\)](#), [Klausner \(2013\)](#) and [Coates IV \(2000\)](#). Building on the legal arguments, they confirm that statistical evidence

for the law’s impact on a firm’s takeover protection and outcomes depends on “(i) other state antitakeover laws, (ii) preexisting firm-level takeover defenses, and (iii) the legal regime as reflected by important court decisions. In addition, (iv) state antitakeover laws are not exogenous for many easily identifiable firms.” Using a common research design and multiple different outcome measures, they find that inferences from many studies change substantially once accounting for firm’s institutional and legal context.

However, while conceding that some prior results were biased by not adjusting for preexisting defenses and concurrent changes to the legal regime, [Karpoff and Wittry \(2018\)](#) strongly reject the strong form critique that antitakeover statutes are de-facto redundant. They argue that poison pills are costly for managers to implement, and thus even if a shadow pill could effectively prevent all unwanted takeover attempts, in equilibrium they would be less than fully preemptive. Moreover, even correcting for the presence of other statutory enactments and defenses, [Karpoff and Wittry \(2018\)](#) continue to find that the business combination and poison pill statutes have a causal effect on a number of firm-level outcomes. The authors claim that economics is a naturally inductive science, and in light of “the current lack of evidence about which laws and court decisions best identify exogenous shocks to firms’ takeover protections, research in this area may best proceed, at least in the short run, by embracing an inductive approach to empirical inference.” They conclude by “reject[ing] the notion that all empirical relations between state antitakeover laws and firm outcomes must be spurious.”

4 Antitakeover Statutes and Difference-in-Differences

We are left with a residual disagreement between scholars who address the issue of antitakeover statutes from a doctrinal or institutional perspective, and those who instead use an inductive-empirical approach. [Karpoff and Wittry \(2018\)](#) concede that many of the results from the prior literature are likely confounded by unaddressed features of the legal environment, but continue to find a significant effect for antitakeover statutes across a number of measures. [Catan and Kahan \(2016\)](#) find it implausible that any of the results are truly causal, but directly explain away the results from only a handful of studies. At the same time,

a new literature in econometrics has documented that the standard method used in empirical studies of second-generation statutes—“difference-in-differences” (DiD) analysis—suffers from limitations when the policy adoption is staggered across time, as is the case here. In the following sections I will explore whether more general flaws in the empirical approach taken in the literature can explain this disagreement, above and beyond the already documented conceptual concerns.

4.1 Difference-in-Differences

Most studies of the impact of second-generation statutes use a DiD design, which is one of the more commonly used methods for identifying causal effects in applied research.²² The intuition behind DiD is best understood through the simplest example, which uses a single policy adoption or treatment, two discrete time periods—pre- and post-treatment—and two treatment groups, one receiving treatment (“treated”) and one not (“control”). In this simple 2x2 design, the effect of the treatment on the outcome of interest can be estimated by simply comparing the change in the average outcome in the treated units to the change in the average outcome in the control units.

As a clarifying example, imagine that a researcher wants to test the impact of the resolution of a circuit split over corporate subsidies on firm creation. In this stylized example, assume that there are only two circuits in the country—the 7th and 9th Circuits—and that previously the 7th Circuit allowed states to give subsidies with preferential treatment for firms established in states in their circuit, while the 9th Circuit did not. The Supreme Court subsequently rules in favor of the 7th Circuit position, holding that states can provide such targeted subsidies. Under certain assumptions the researcher can estimate the causal effect of the decision on the frequency of firm incorporation decisions in the 9th Circuit (where the standard changed) using difference-in-differences estimation.

²²For a longer treatment on the DiD design, see [Angrist and Pischke \(2009\)](#); [Goodman-Bacon \(2021\)](#); [Callaway and Sant’Anna \(2021\)](#)

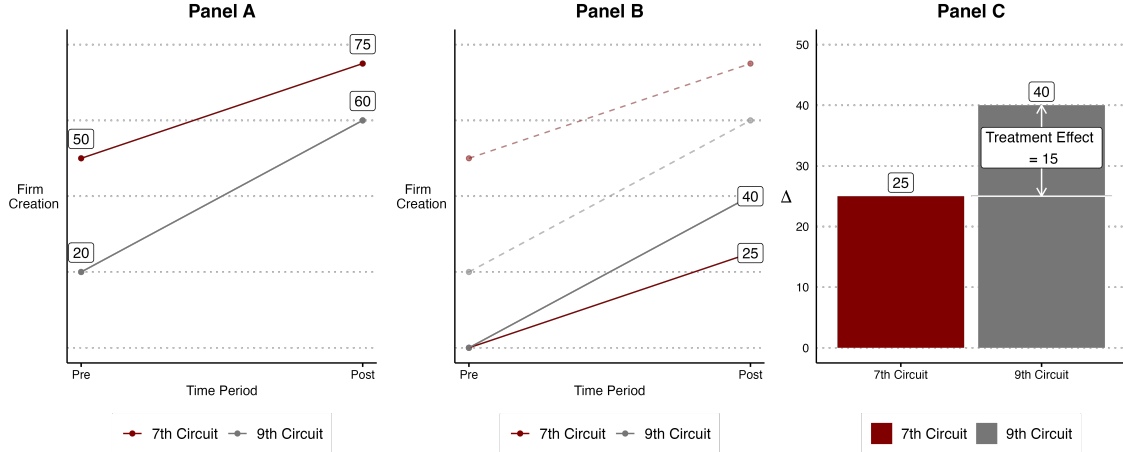


Fig. 1 Basic DiD Example Figure 1 graphically represents the DiD analysis for this stylized example. Panel A shows the trends in firm creation between circuits in both the pre- and post-decision periods. Panel B shows how the first difference works—for both the treated (9th Circuit) and untreated (7th Circuit) units, we subtract the pre-decision firm count to get a measure of differences over time. In Panel C we calculate the differences-in-differences—under the assumption that the 7th and 9th Circuits would have had similar trends in firm creation without the Supreme Court decision, this can be thought of as the causal impact of the holding.

Figure 1 presents the schematics of how a DiD analysis would calculate the effect of the decision in this case. Panel A shows a hypothetical set of trends in firm creation by circuit for the periods before and after the Supreme Court issues its decision. Initially, there is a higher level of new firm incorporation in the 7th Circuit (50) than the 9th Circuit (20), consistent with the prevailing firm-friendly subsidy rules. In the post-decision period both circuits see an increase in firms incorporated in their states, but there is a larger change in the 9th Circuit, which increases from 20 to 60, while the 7th Circuit only increases from 50 to 75.

Under the assumption that both circuits would have experienced a similar change in firm starts over time in the absence of the Supreme Court ruling,²³ a researcher can generate an estimate of the causal effect of the decision using a simple double-differencing technique. First, they would find the change in firm starts between the post- and pre-decision period for each circuit, which is visualized in Panel B of Figure 1. The residual difference between the treated (9th) and untreated (7th) circuits, shown in Panel C, is thus an unbiased estimate of

²³This is known as the “parallel trends assumption.” In addition to this assumption, to generate a causal interpretation from the DiD one must also assume that there is no anticipation of the ruling by plaintiffs, and that there are no spillovers from the 9th Circuit to the 7th Circuit as a result of the change in the standard.

the effect of the ruling under general assumptions. In this example we see that the Supreme Court decision led to fifteen more firms choosing to incorporate in the 9th Circuit than would have occurred without the holding.

This “treatment effect” can also be estimated through the use of a linear regression model. If we define a treatment indicator variable, $TREAT_i$, to be set equal to one for the 9th Circuit and zero for the 7th Circuit, and another, $POST_t$, to be one in the post-decision period and zero before, then we can recover the same treatment effect from the coefficient on δ in:

$$y_{it} = \alpha + \beta_1 TREAT_i + \beta_2 POST_t + \delta (TREAT_i \times POST_t) + \epsilon_{it} \quad (1)$$

Here y_{it} , our outcome variable, is the number of firms incorporating in period t for circuit i . The advantage of the regression-based DiD model is that it provides an estimate for the treatment effect δ , as well as a measure of its statistical uncertainty when there are multiple units per group and/or multiple time periods. In settings where there are more than two units and two time periods, the regression DiD model is most often modified as:

$$y_{it} = \alpha_i + \gamma_t + \delta^{DD} D_{it} + \epsilon_{it} \quad (2)$$

Here, α_i and γ_t are circuit and time “fixed effects” that identify the unit or the time period,²⁴ and D_{it} is an indicator variable that is set to one only in the periods after the treatment (here the decision) and only for units that receive the treatment (here the 9th Circuit). The variables for $TREAT_i$ and $POST_t$ are subsumed by the unit and time fixed effects. This model is called the two-way fixed effects estimator and is pervasive in the applied economics literature, where it frequently includes the use of additional covariates.

4.2 The Karpoff & Wittry Results

In the following sections I test the sensitivity of the empirical results in [Karpoff and Wittry \(2018\)](#) to recently proposed design considerations with the use of panel data. I focus

²⁴Including time and unit fixed effects controls for the fact that different units (circuits) and different time periods may have unobserved differences that are reflected in the level of the outcome variable.

on the primary results of the paper, which are located in their Table IV. The authors examine the impact of second-generation laws (with a focus on business combination statutes) for seven different outcome variables that have been explored in prior published papers: return on assets (ROA), capital expenditures (Capex), growth in plant, property, and equipment (PPE growth), growth in firm assets (Asset Growth), selling, general and administrative expense (SG&A expense), and debt (Leverage). In order to match the sample period in [Bertrand and Mullainathan \(2003\)](#) and [Giroud and Mueller \(2010\)](#) they use annual firm data from 1976 to 1995, excluding financial firms and utilities that face separate takeover regulations.

The model used to test the impact of antitakeover provisions on firm outcomes is just a minor variant of Equation 2:²⁵

$$y_{it} = \alpha_i + \gamma_{lt} + \eta_{jt} + \delta BC_{it} + \Omega X_{it} + \epsilon_{it} \quad (3)$$

Here y_{it} is one of the seven outcome measures listed above, measured for firm i in year t . Instead of having only two levels of fixed effects (e.g. just firm and year), the authors use a higher dimensional model, which along with firm fixed effects (α_i), includes headquarter state-year (γ_{lt}) and industry-year (η_{jt}) fixed effects.²⁶ The main analysis in their paper follows the bulk of the literature and focuses on business combination statutes in particular—thus BC_{it} is an indicator variable set to one when a firm is incorporated in a state with a business combination statute, and zero otherwise. The regression coefficient on δ is now assumed to be the average effect of the adoption of a business combination statute on the outcome variable.

The authors also control for a set of variables measured at the firm-year level, X_{it} , which vary with the regression specification. In what they label their “short regression model”, [Karpoff and Wittry \(2018\)](#) follow [Giroud and Mueller \(2010\)](#) in controlling for firm

²⁵Note that [Karpoff and Wittry \(2018\)](#) do not refer to their model as a difference-in-differences, although they motivate their tests based on other papers which do (e.g. [Bertrand and Mullainathan \(2003\)](#) and [Giroud and Mueller \(2010\)](#)).

²⁶It is more common in the literature to use two levels of fixed effects. [Karpoff and Wittry \(2018\)](#) claim that their high dimensional model “decrease[s] the likelihood of finding a significant coefficient” on second-generation laws, which is actually only true under certain assumptions. Because I am looking to modify their approach as little as possible I stick with their choice of fixed effects structure.

size and age.²⁷ Their “full model” corrects for some of flaws noted in [Catan and Kahan \(2016\)](#) by including, in addition to the short regression model controls, other variables that reflect the regulatory and legal environment of the firm. These include whether the firm is covered by the other common second-generation statutes (poison pill laws, control share acquisition statutes, directors duties laws, and fair price statutes) and whether the firm is covered by a first-generation statute (only applicable to the pre-*MITE* period). The full model also controls for whether there is a business combination statute after the *Amanda* decision or a control share acquisition law after *CTS*, when the legality of the statutes were affirmed. Finally, it includes a control for corporations that were active in lobbying for a business combination statute’s passage, to adjust for the clearly endogenous impact for those firms.²⁸ The standard errors are clustered at the level of the state of incorporation to adjust for correlation in the errors.

Before reporting the results for the short and full regression models, it is useful to visualize the distribution of policy adoption across states. DiD models exploit the difference in outcomes across treated and untreated units, as well as the differences across treatment timing groups—for example the comparison of firms that begin coverage by a business combination statute in 1990 rather than 1992. [Figure 2](#) below reports the coverage of firms incorporated in different states by each of the five second-generation statutes. It is evident that most of the adoptions occur in the mid 1980s and that there is reasonable dispersion in the timing across states. In addition, because states often adopt multiple statutes simultaneously, there is correlation across laws *within* a state.

²⁷This includes the natural logarithm (log) of firm age, the square of the log of firm age, the log of firm size, as measured in assets, and the square of the log of firm assets.

²⁸[Karpoff and Wittry \(2018\)](#) note that most other papers drop these firms from the sample.

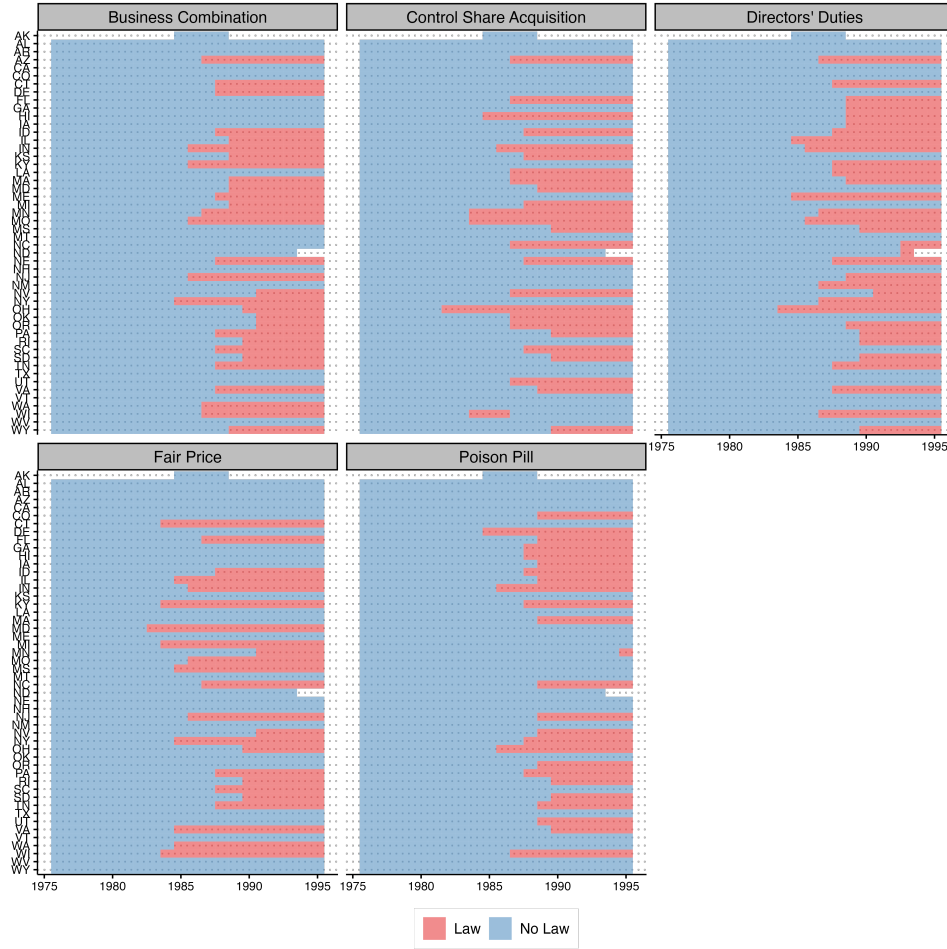


Fig. 2 Statutory Adoption Timing Figure 2 presents the timing of adoption for each second-generation law across states in the data from [Karpoff and Wittry \(2018\)](#). Blue tiles signify state of incorporation years with no law in place and red tiles reflect when the laws are in place.

The empirical results from [Karpoff and Wittry \(2018\)](#) Table IV are replicated in Table 1 below.²⁹ The table confirms findings from prior studies that business combination statutes are associated with statistically significant changes in a range of outcome variables when the legal and institutional environment is omitted from the model. For each outcome variable, the coefficient on the presence of a business combination is statistically significant at at least the 10% confidence level in the short regression model. However, once controls for multiple second-generation statutes and court decisions are included (the “full model”), the results only hold for leverage, SG&A expenses, and asset growth. There is some evidence that the passage of a business combination statute was important after the *Amanda* decision for firm ROA

²⁹I thank Professors Karpoff and Wittry for generously sharing their data and code used in their study.

and SG&A expenses, and that poison pill laws are associated with statistically significant decreases in ROA, and increases in SG&A expenses and leverage. Overall, these results are presented as confirmation that, “a firm’s institutional and legal context has first-order effects in tests that use state antitakeover laws for identification”, but that “one would have to maintain unrealistically strong priors to therefore infer that all previous results are spurious” ([Karpoff and Wittry, 2018](#)).

Table 1
Replication of Table IV from Karpoff-Wittry (2018)

	Dependent Variable													
	(1) ROA		(2) Capex		(3) PPE Growth		(4) Asset Growth		(5) Cash		(6) SGA Expense		(7) Leverage	
	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model
Business combination law (BC)	-0.017* (0.010)	-0.008 (0.007)	0.003** (0.002)	0.002 (0.002)	-0.016** (0.008)	-0.008 (0.013)	-0.044* (0.024)	-0.041** (0.020)	-0.008*** (0.003)	-0.005 (0.003)	0.018** (0.008)	0.011** (0.005)	0.023** (0.010)	0.020** (0.008)
First-generation law		-0.030** (0.015)		0.004 (0.003)		-0.001 (0.012)		-0.026 (0.022)		0.004 (0.007)		0.017 (0.012)		-0.019 (0.021)
Poison Pill law (PP)		-0.011** (0.005)		0.002 (0.002)		-0.005 (0.012)		-0.027 (0.019)		-0.002 (0.003)		0.012** (0.005)		0.027*** (0.009)
Control share acquisition law (CS)		-0.021** (0.010)		0.002 (0.003)		-0.003 (0.017)		0.018 (0.029)		0.008* (0.004)		0.011 (0.008)		0.020 (0.014)
Directors' duties law (DD)		0.002 (0.009)		-0.001 (0.001)		0.010 (0.011)		0.022 (0.023)		0.005 (0.004)		-0.004 (0.009)		-0.007 (0.012)
Fair price law (FP)		-0.009 (0.010)		0.003 (0.002)		-0.017 (0.013)		0.014 (0.025)		-0.003 (0.003)		-0.001 (0.008)		0.000 (0.013)
CS x CTS		0.000 (0.011)		0.000 (0.002)		-0.012 (0.016)		-0.029 (0.029)		0.000 (0.006)		0.021** (0.010)		0.004 (0.020)
BC x Amanda		-0.026* (0.015)		0.002 (0.002)		-0.016 (0.031)		-0.024 (0.027)		-0.003 (0.007)		0.026** (0.011)		0.015 (0.015)
BC x MF (motivating firms)		0.201*** (0.048)		0.012 (0.010)		0.060* (0.036)		0.142** (0.056)		-0.041*** (0.013)		-0.114*** (0.040)		-0.057 (0.039)
Observations	88,307	88,307	87,248	87,248	79,603	79,603	80,646	80,646	88,493	88,493	81,428	81,428	88,280	88,280
R2	0.603	0.604	0.438	0.438	0.053	0.053	0.247	0.247	0.575	0.575	0.706	0.706	0.485	0.485

Table 1 replicates the estimates from Table IV of [Karpoff and Wittry \(2018\)](#). The table reports results of the impact of business combination laws on seven different outcome variables, and tests for the effects of including controls for other types of states, court decisions, and motivating firms. The outcome variables are ROA, Capex, PPE growth, asset growth, cash, SGA expenses, and leverage. ROA is EBITDA divided by total assets, Capex, PPE, cash, and SGA expenses are scaled by total assets; PPE and asset growth are the percentage change in PPE and total assets, respectively; and leverage is debt divided by total assets. All outcome variables and continuous control variables are winsorized at the 0.5% and 99.5% levels. Control variables include size, size squared, age, and age squared. All regressions include firm, state-year, and industry-year fixed effects. Robust standard errors are clustered at the state of incorporation level. *, **, and *** denote two-tailed significance tests at the 10%, 5%, and 1% levels, respectively.

Karpoff and Wittry (2018) argue that these results reinforce the importance of taking into consideration “institutional and legal context concerns” when conducting empirical tests of state antitakeover provisions. They stress that “inferences from nine prior studies ... change substantially when we include controls from these considerations.” However, it is not immediately clear from the table whether the differences documented in the table represent material changes in the underlying estimates after including additional explanatory variables. The difference in statistical significance could instead reflect marginal differences that are amplified by arbitrary significance thresholds in academic publishing.

Figure 3 reports the point estimates and confidence intervals for the coefficient on the business combination statute indicator variable for each of the seven outcome variables, and for both the short and long specifications. The outcome variables are standardized for presentation purposes, so that each measure is centered at zero with a standard deviation equal to one.³⁰ A cursory inspection of the estimated coefficient values between the short and long panels suggests that the differences are less dramatic than indicated by the changes in the level of statistical significance. In the third panel, I plot the median and center 95% range of the difference in the coefficients between the short and long specifications over 1,000 bootstrap samples of the data. Using a conventional level of statistical significance, one would reject that there is actually any difference in the coefficient values between the two specifications. The omitted variable bias from ignoring institutional and legal context may be less severe than alleged, given that the difference between statistically significant and not, is not itself statistically significant in this instance (Gelman and Stern, 2006).

³⁰This refactoring of the variables changes the interpretation of the coefficient estimates, but leads to identical inferences regarding potential effects of antitakeover statutes on firm outcomes. This is a cosmetic modification to make the regression estimates on a comparable scale, and does not represent an affirmative check of model sensitivity.

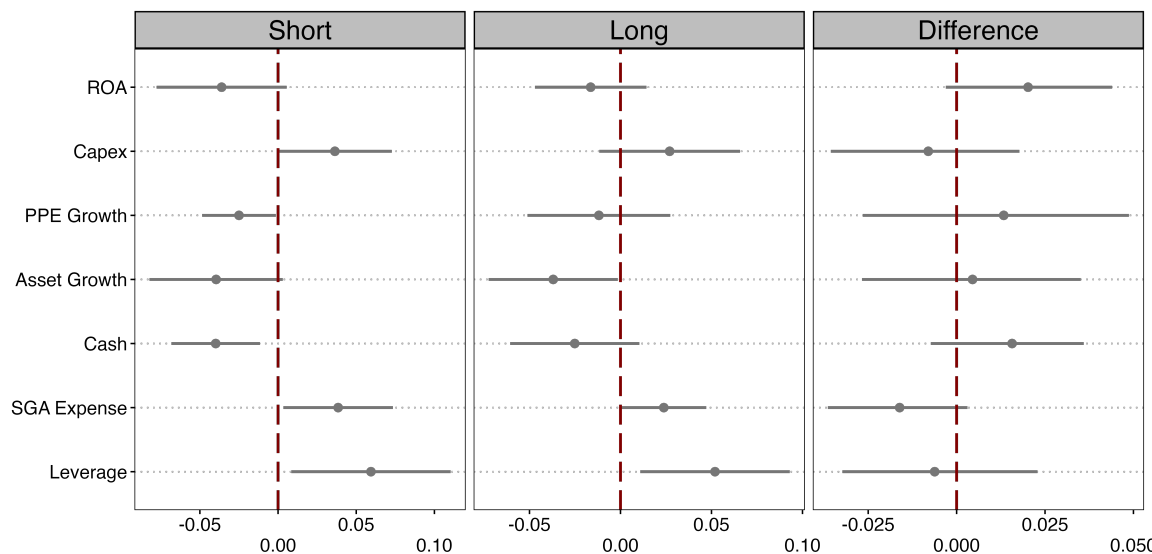


Fig. 3 Comparison of Short and Long Regression Models Figure 3 compares the coefficients on the indicator variable for the presence of a business combination statute across the short and long model results from [Karpoff and Wittry \(2018\)](#). The figure reports the coefficient value and 95% confidence interval for the business combination statute indicator for each of seven different indicator variables for both models. The third panel reports the median and center 95% mass on the difference in the coefficients using 1,000 bootstrap resamples of the data.

5 Testing Model Robustness

In light of the continued disagreement between legal³¹ and finance scholars regarding the materiality of state antitakeover provisions, this section explores whether the differences can be explained by data quality concerns and methodological challenges induced by using standard DiD designs with staggered policy adoption. It may be more than just a philosophical disagreement about feature-based attributes of the pre-existing studies; rather the now-ubiquitous use of standard fixed-effects DiD designs in corporate governance and other areas of legal studies simply may not provide credible estimates of the impacts of the laws.

Section 5.1 tests whether data concerns with the commonly-used financial database Compustat affect the DiD estimates. While the analysis in [Karpoff and Wittry \(2018\)](#) fix

³¹To be clear, I do not allege that corporate legal scholars universally agree that state antitakeover provisions are clearly redundant. For example, Professor Steven Davidoff Solomon uses a slightly different research design to find that fair price provisions *have* reduced hostile takeovers ([Cain, McKeon, and Solomon, 2017](#)). Their analysis relies on a different data sample and set of identifying assumptions to those analyzed here.

many of the design flaws from the literature described in [Catan and Kahan \(2016\)](#), they do not address certain important critiques about the use of stale identifying information. Section 5.2 extends the static DiD estimates from Table 1 to an “event study” design, which tests whether the timing of the differences between covered and un-covered firms is consistent with a causal story for the results being driven by the adoption of antitakeover statutes. Finally, Sections 5.3 and 5.4 incorporate recent work in the econometric literature about the use of fixed effects models to test for causality with staggered treatment adoption. I use stacked regression and semi-parametric methods, designed explicitly to avoid some of the more problematic attributes of fixed effects DiD methods, to re-test the analyses.

5.1 Data Quality

In this section I explore whether data quality issues drive the results found in the prior literature. [Karpoff and Wittry \(2018\)](#) address a number of concerns raised in the legal critique—most importantly by including additional variables to control for the legal environment, and by using unit and time-level fixed effects, the exclusion of which [Catan and Kahan \(2016\)](#) found to bias other prior studies. However, other criticisms of the methods used in the empirical literature are left unaddressed.

First, and most importantly, [Catan and Kahan \(2016\)](#) raise an issue with the financial database Compustat that compiles and reports annual and quarterly firm financial information, and is used in the majority of papers in empirical finance that test the impact of antitakeover statutes. For certain identifying attributes—including the state of headquarters and incorporation—Compustat reports “header information”, which contains the *most recently available* value for a given firm identifier. Compustat typically then backfills this information to all prior observations for a given firm, meaning that the information will be inaccurate for some firms in prior years. This is particularly problematic for the state of incorporation, which can change and would impact the variables that identify coverage by an second-generation statute.³²

To test the importance of data quality on this area of study, I re-estimate the models

³²This is a known issue that impacts numerous areas of research using commonly available financial datasets ([Spamann and Wilkinson, 2020](#); [Jennings, Kim, Lee, and Taylor, 2020](#)).

from Table 1 on four different but related datasets. The first dataset—Data (1)—is that used in Karpoff and Wittry (2018) and which produces the published results. I construct Data (2) in an identical manner, but use the most recent publicly available download from Compustat. The only difference between Data (1) and Data (2) are changes induced by firms changing their headquarter location, state of incorporation, or industry designation, between the time that Karpoff and Wittry (2018) downloaded the data for their study and today.³³

Data (3) partly corrects for the measurement error in Compustat. Since the advent of the SEC’s EDGAR system in 1994, this identifying information has been stored electronically on the internet. Using publicly available “scrapes” of the filings, I allow for changes in the state of incorporation, headquarter location, security identifier, and industry classification, in addition to coding law coverage using fiscal year filing date rather than calendar year.³⁴ The data construction process, including notes of all differences from the data construction process used in Karpoff and Wittry (2018), are explained in detail in Appendix C.

Finally, in Data (4) I make two additional research design changes that I believe are warranted. First, rather than including industry-year fixed effects based on a firm’s 3-digit SIC industry classification as done in Karpoff and Wittry (2018), I reduce the dimensionality by instead assigning each firm to one of 48 industries identified by Eugene Fama and Ken French (Fama and French, 1997). There is substantial measurement error in the industry classification—indeed identifying the SIC code from EDGAR filings, Compustat, and CRSP (a repository of firm stock prices) consistently leads to different values. Assigning each firm to a broader industry definition allows us to still control for industry-level trends without imposing as much structure on the data by fitting thousands of additional nuisance parameters. Finally, I also follow the standard in the literature and do not recode the law indicator variables for firms that opt out of coverage. This is an endogenous choice made by a narrow set of companies, and isn’t called for under the standard assumptions of a DiD design.

³³Note that Compustat also occasionally fixes other data quality issues or changes in firm reporting that may occur. The data used in this paper was downloaded from Compustat on April 11, 2025.

³⁴Compustat reports financial information based on firm fiscal year, and different firms have different fiscal year end dates. It is more appropriate to match second-generation law changes to the time period in which the data is measured—which calls for using fiscal rather than calendar year dates in the merging process.

Table 2

Comparison of DiD Estimates on Leverage Across Data and Models

	Leverage							
	Short Regression Model				Long Regression Model			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Business combination law (BC)	0.023** (0.010)	0.045*** (0.017)	0.011* (0.006)	0.014* (0.007)	0.020** (0.008)	0.029** (0.014)	0.011 (0.008)	0.011 (0.008)
First-generation law					-0.019 (0.021)	-0.020 (0.033)	0.010 (0.009)	0.005 (0.009)
Poison Pill law (PP)					0.027*** (0.009)	0.035*** (0.011)	0.021*** (0.007)	0.019*** (0.006)
Control share acquisition law (CS)					0.020 (0.014)	0.033* (0.018)	0.017 (0.016)	-0.002 (0.015)
Directors' duties law (DD)					-0.007 (0.012)	-0.002 (0.018)	-0.005 (0.008)	-0.008 (0.007)
Fair price law (FP)					0.000 (0.013)	-0.011 (0.015)	0.007 (0.010)	0.008 (0.010)
CS x CTS					0.004 (0.020)	0.005 (0.026)	-0.010 (0.015)	0.010 (0.016)
BC x Amanda					0.015 (0.015)	0.053* (0.027)	0.002 (0.010)	0.007 (0.009)
BC x MF (motivating firms)					-0.057 (0.039)	-0.160*** (0.048)	-0.083** (0.038)	-0.086*** (0.030)
Observations	88,280	88,043	90,320	90,320	88,280	88,043	90,320	90,320
R2	0.485	0.439	0.520	0.516	0.485	0.439	0.520	0.516

Table 2 presents the DiD estimates with leverage as the outcome variable for both the short and full regression models in Table IV of [Karpoff and Wittry \(2018\)](#) using our modified datasets. Column (1) presents the results with the published data from [Karpoff and Wittry \(2018\)](#); Column (2) reports data constructed using the same code but with today's value of header information; Column (3) reports results that correct for the use of stale identifying header information; and Column (4) reports results with corrected data and which use the Fama-French 48 industry definitions and don't adjust for firms that opt out of coverage.

For illustrative purposes, Table 2 reports the differences in the DiD estimate for the short and full regression models for each dataset with firm leverage as the outcome variable. While the results do change on the margin across data constructions, the conclusions are broadly similar. The results for the full replication of Table 1 for Data (2), (3), and (4) are reported in appendix tables [A.2](#), [A.3](#), and [A.4](#).

In Figure 4 I report the estimate and 95% confidence interval for the coefficient on the presence of a business combination law statutes for each variable/specification/dataset combination. Across modeling and data choice, the DiD estimates are generally fairly close. The standard error of the estimate usually increases from Data (1) to Data (2), which is consistent with the identifying information becoming more stale and inaccurate as we look further back into the past. There is little evidence that the data quality concerns raised by [Catan and Kahan \(2016\)](#) are driving the effect from the empirical studies. In fact, using the

preferred full model from [Karpoff and Wittry \(2018\)](#), we see that after correcting for data and design issues (Data (4)), the coefficients on the business combination indicator variable in the preferred full model are typically more statistically significant, suggesting that the prior results may in fact be *more* robust than alleged in their paper.

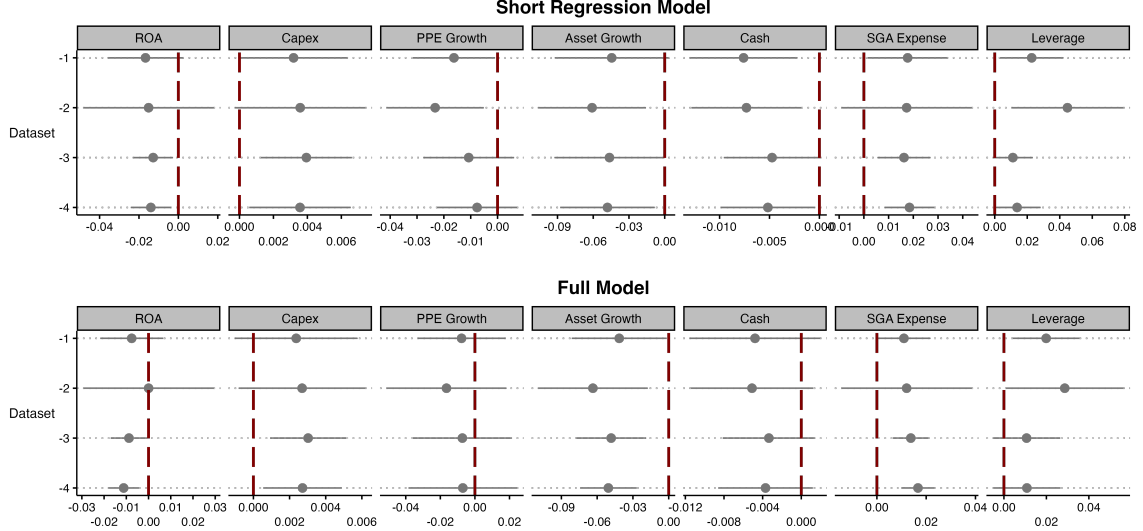


Fig. 4 Coefficient Estimate on Business Combination Law Across Datasets Figure 4 presents the coefficient estimate and the standard error from the basic DiD model in [Karpoff and Wittry \(2018\)](#) applied to the original and modified datasets. Row (1) presents the results with the published data from [Karpoff and Wittry \(2018\)](#); Row (2) reports data using the same code but with today’s value of header information; Row (3) reports results that correct for the use of stale identifying header information; and Row (4) reports results with corrected data and which use the Fama-French 48 industry definitions and don’t adjust for firms that opt out of coverage. The top panel reports the results from the short model that controls for measures of firm age age and size, while the bottom panel reports the full model with controls for the legal environment.

5.2 Event Study Designs

In this section I extend the analysis from the static fixed effects DiD design in Table 1 to what the applied empirical literature calls an “event study” approach ([Autor, 2003](#)). The results from the standard DiD only capture (at best) the difference between treated and untreated units before or after policy adoption. However, because analyses frequently use data with many time periods, the same average difference between post- and pre-adoption can occur in many different ways, only some of which are consistent with a causal explanation for the policy being studied. The advantage of an event study DiD is that it breaks down the average difference captured in $\widehat{\delta^{DD}}$ from Equation 2 into the differences between treated and

control units at each relative time period in relation to when treatment coverage begins.

To better understand this point, consider again the stylized example from Section 4.1, which tests the impact of a Supreme Court decision on the amount of firm incorporations in a state. Assume now that we have multiple periods of data, from three years prior to three years following the decision. The top panel of Column (1) in Figure 5 reports incorporation trends that are consistent with the causal story—the 7th and 9th Circuits had similar trends before the timing of the decision (the gray vertical line), while after the decision the 9th Circuit saw a larger increase in incorporations. The bottom panel of Column (1) shows the treatment effect path recovered from an event-study DiD, reflecting a positive treatment effect that begins after the ruling.

The top panel of Column (2) shows a different pattern in case trends. Here the higher rate of increase in incorporations for the 9th Circuit occurs *before* the Court issues its decision, and the treatment effect path in the bottom panel is now increasing in the periods before the ruling, but constant afterwards. Finally, Column (3) provides an example with no discontinuity, but where the two circuits simply have different trends in firm growth, irrespective of the Court’s ruling. Notably, each of these three examples would give *the exact same* treatment effect estimate using the standard, static DiD estimate from Equation 2, demonstrating the importance of reporting the treatment effect path when conducting the analysis.

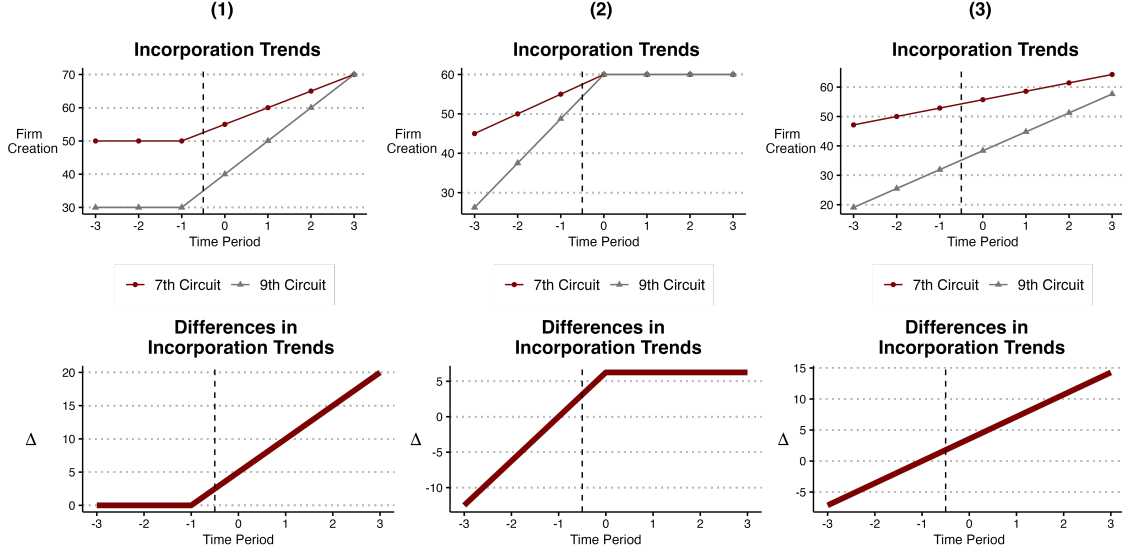


Fig. 5 Basic Event Study DiD Example Figure 5 presents three examples of data which generate the same estimate using fixed effects DiD, but which have very different interpretations. The top panels show the number of cases over time in the two circuits, while the bottom panel shows the difference after removing circuit and time period fixed effects. The vertical line represents the period when the decision is made. In Column (1), there is the standard process one would expect for a causal estimate—the two groups (circuits) have similar trends before the treatment (the decision), but diverge afterwards. In Column (2), the entirety of the change occurs *before* the decision, which would tend to make it less credible that the decision was indeed driving the DiD estimate. Finally, in Column (3) there are constant increasing trends of different slope between circuits, with no evidence of any change around the time of the decision.

To test the robustness of the empirical results to treatment effect dynamics, I conduct event study estimates for the impact of both business combination and poison pill laws (which [Karpoff and Wittry \(2018\)](#) found to be of comparable significance to business combination statutes). For each of the laws I now estimate the modified regression model:

$$y_{it} = \alpha_i + \gamma_{lt} + \eta_{jt} + \sum_l \delta_l \mathbb{1}\{t - E_i = l\} + \Omega X_{it} + \epsilon_{it} \quad (4)$$

Here again y_{it} represents one of our seven outcome variables measured at the firm-year level, the fixed effect terms α_i , γ_{lt} , and η_{jt} are firm, headquarter state-year, and industry-year effects respectively, and X_{it} is a vector of controls that vary by model. Now, instead of just one second-generation statute variable, each law is represented by a series of indicator variables that reflect whether a firm is l years away from beginning coverage by the statute. I omit the relative indicator variable for $l = -1$, as is standard in the literature ([Borusyak and Jaravel, 2017](#); [Sun and Abraham, 2020](#)). In addition, I drop all firms that enter Compustat

already covered by the statute at interest, as for these firms the relative time indicators are undefined.³⁵

The results of this analysis for business combination statutes are presented in Figure 6. Each plot represents the event study estimates for the relative time periods ranging from five years prior to five years post adoption for each dependent variable/model combination. Model 1 is the DiD analysis without the inclusion of any covariates; Model 2 includes the control variables from [Karpoff and Wittry \(2018\)](#)’s short regression model; and Model 3 includes the set of controls in their full model. The dependent variable used in each plot is identified by row. Because we omit the relative time indicator for the year prior to adoption ($l = -1$), the other coefficients are the deviations from the value in that year. The circle represents the point estimate for each coefficient, and the error bars represent the 95% point-wise confidence intervals.

³⁵Note that these observations are already inconsistent with a standard DiD design, which requires taking averages both before and after the treatment occurs. While studies frequently keep such observations in the data, inference in such designs is more akin to a selection on observable argument, which typically requires stricter assumptions ([Imbens, 2004](#)). However, this does lead to a different sample of observations than in the original analysis. In unreported results I confirm that the estimates using the standard fixed effects DiD are very close using the same methodology as in [Karpoff and Wittry \(2018\)](#) Table IV, but dropping firms that enter Compustat covered by a BC law. Thus, the differences between the event study and static DiD models are not driven by the change in sample composition.

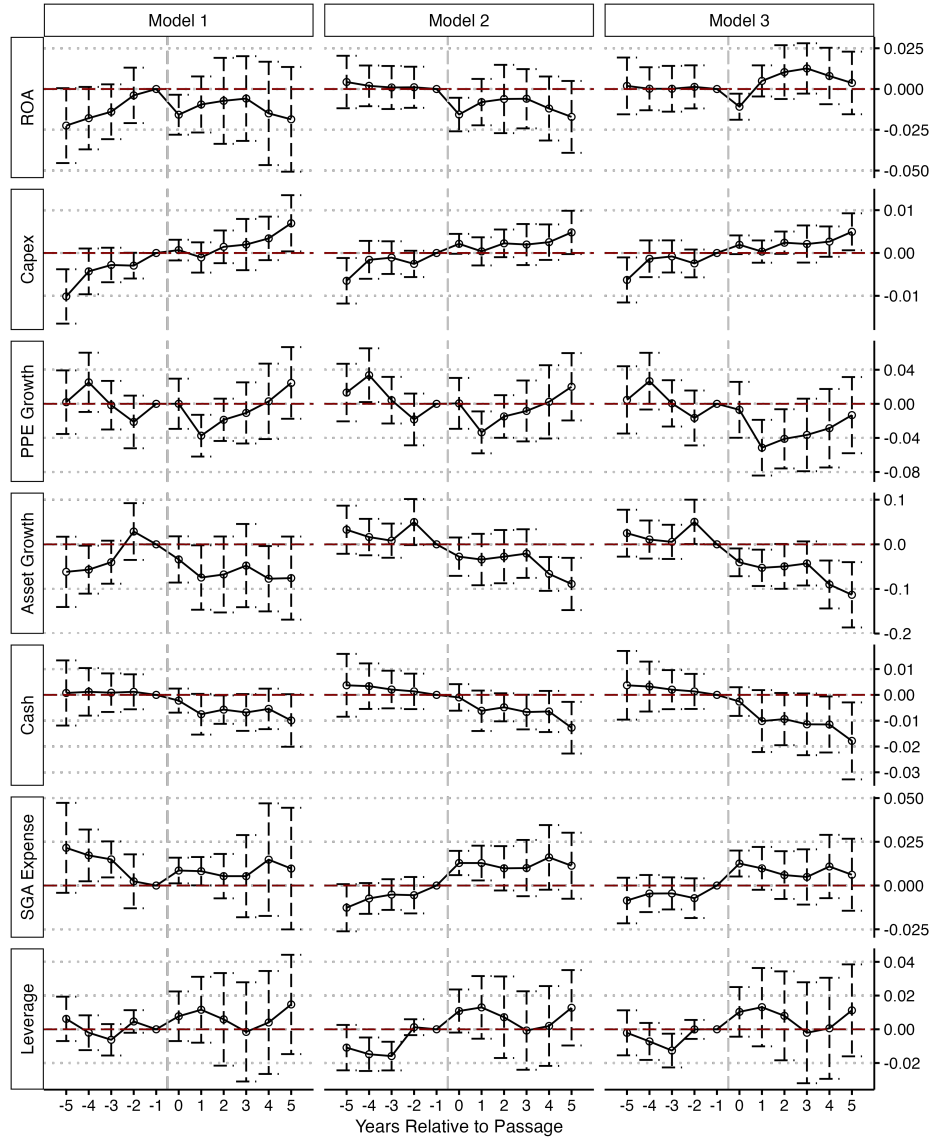


Fig. 6 Event Study Estimates - Business Combination Statutes Figure 6 reports the event study estimates and 95% confidence interval of the impact of business combination law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), and Model 3 includes their “full model”.

The inferences drawn from these estimates are decidedly different from those in the static DiD estimates reported in Table 1 and Figure 4.³⁶ There is little consistent evidence of an identified treatment effect in the 11-year window around business combination law

³⁶The event study results using the data as reported in [Karpoff and Wittry \(2018\)](#) are reported in appendix figures B1 and B2. Using their data there is in fact little consistent evidence across any of the variables, with the possible exception of cash holdings, for business combination statutes.

adoption for ROA or capital expenditures. There is perhaps some evidence for a decrease in PPE and Asset Growth following the adoption of business combination laws, although [Karpoff and Wittry \(2018\)](#) and our replication found no evidence using standard TWFE design for this outcome. For the remaining variables, some results are consistent with an effect, although in each model there is also either evidence of pre-trend differences between treatment and control firms, and/or the confidence intervals almost always include zero (the maroon line). Thus, even before addressing issues with staggered designs, assessing the dynamics of the treatment effects suggests that the prior results may not be robust. The same estimates using [Karpoff and Wittry \(2018\)](#)'s data³⁷ are reported in Figure B1 of the appendix, where there is effectively no evidence at all of a significant effect for business combination statutes on any variable once taking into consideration treatment effect dynamics.

³⁷As a reminder, the difference between the data used in Figure 6 and the data used to produce the published estimates in [Karpoff and Wittry \(2018\)](#) is that my data corrects for change in state of incorporation and other header information, and uses the Fama-French industry designations rather than 3-digit SIC codes.

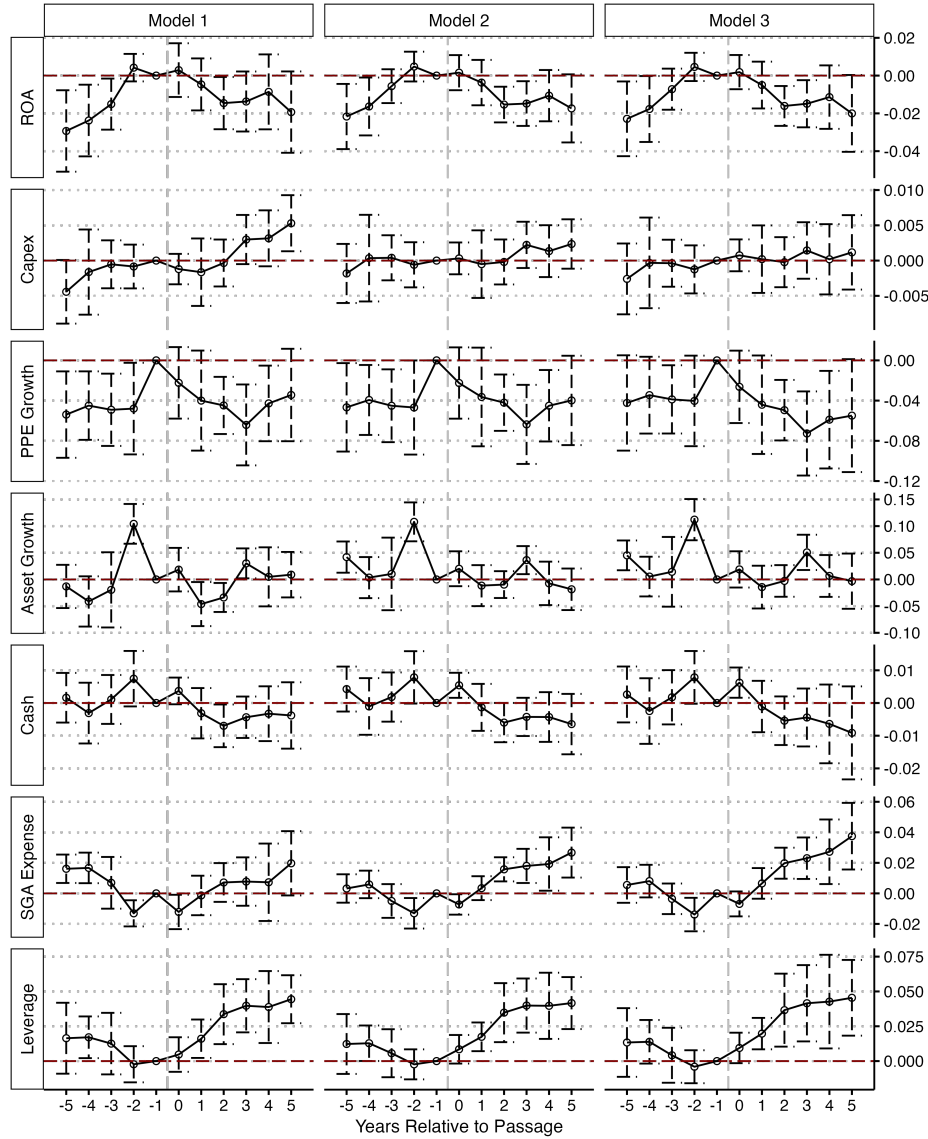


Fig. 7 Event Study Estimates - Poison Pill Laws Figure 7 reports the event study estimates of the impact of poison pill law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from Karpoff and Wittry (2018), and Model 3 includes their “full model”.

The corresponding results for poison pill laws are reported in Figure 7. The only change made to the estimation in 6 is that, with the full model, I include controls for the presence of a business combination law (rather than a poison pill law) and an indicator for firms that lobby for passage of the poison pill statute (rather than for the business combination laws). There is some evidence consistent with a standard causal story that poison pill laws may have increased leverage and SG&A expenses. It should be noted however

that this effect—an increase in firm leverage following the entrenchment of management—is actually the *opposite* of the prediction in most agency-theoretic models.

5.3 Stacked Regression Designs

To this point the robustness of the prior empirical results have only been tested against standard critiques of difference-in-differences analysis. Section 5.1 shows that data and design concerns with the empirical method used in [Karpoff and Wittry \(2018\)](#) impact the results but not the inference from their paper; indeed the evidence now more strongly suggests that antitakeover measures impact corporate outcomes than before these changes were made. When an event study design is used in place of static fixed effects DiD models, the trends in the differences in outcome variables complicates the causal story. Most prior results appear to be either 1) non-existent in the window surrounding the law’s adoption, when the impact would be expected to appear, 2) driven by pre-existing trend differences between firms receiving and not receiving coverage, and/or 3) substantially noisier in the relevant time window.

In the following two subsections I explore an additional concern about the use of DiD methods in the presence of staggered policy adoption. A large and growing literature has now established that the generalized version of DiD estimation with staggered rollout in treatment timing (e.g., the staggered adoption of an antitakeover statute across states of incorporation) is often invalid for the estimation of the usual treatment effect estimands of interest ([Athey and Imbens, 2018](#); [Strezhnev, 2018](#); [Callaway and Sant’Anna, 2021](#); [Goodman-Bacon, 2021](#); [Borusyak and Jaravel, 2017](#); [Imai and Kim, 2020](#)). [Baker et al. \(2022\)](#) provide an overview of this literature, and document how the specific econometric concerns at issue substantially changes a diverse set of prior results in law, finance, and accounting.

Of most relevance for our setting, firms that already received coverage by an antitakeover statute act as the comparison units for later-treated firms when using the standard fixed effects approach, and a portion of their treatment effect will be subtracted from the DiD estimate if there is time-variation in its impact ([Goodman-Bacon, 2021](#)). This in turn biases the estimates towards zero, and, depending on the weights and effect patterns for different treatment groups, may cause the estimated effect to even be of the wrong sign. In other words,

even if the adoption of antitakeover provisions was a valid exogenous shock to managerial entrenchment, and even if the true treatment effect was positive for *every* firm, the DiD estimate could be negative if the effect varies over time within a firm. A number of different methodological approaches have been advanced in the literature to address this concern, with “stacked regression” being the most similar in design and spirit to the fixed effects methods used in the literature on antitakeover provisions.³⁸

The stacked regression approach is a simple extension to the regular event study DiD design. In our setting it involves:

1. Identifying treatment cohort years where a state of incorporation adopts a statute.
2. Creating a smaller dataset that contains i) all firms incorporated in states that adopt in that cohort year, and ii) all firms that satisfy a set of conditions to be included as a valid control.
3. Restricting the years to a common window around the adoption year, here the five years prior to and the five year following adoption.
4. Stacking each of the cohort-specific datasets in relative time.
5. Estimating the event study DiD model on this stacked dataset, making sure to interact the fixed effects with an identifier for the cohort-specific data.

³⁸Stacked regression is used in [Cengiz, Dube, Lindner, and Zipperer \(2019\)](#) and [Deshpande and Li \(2019\)](#).

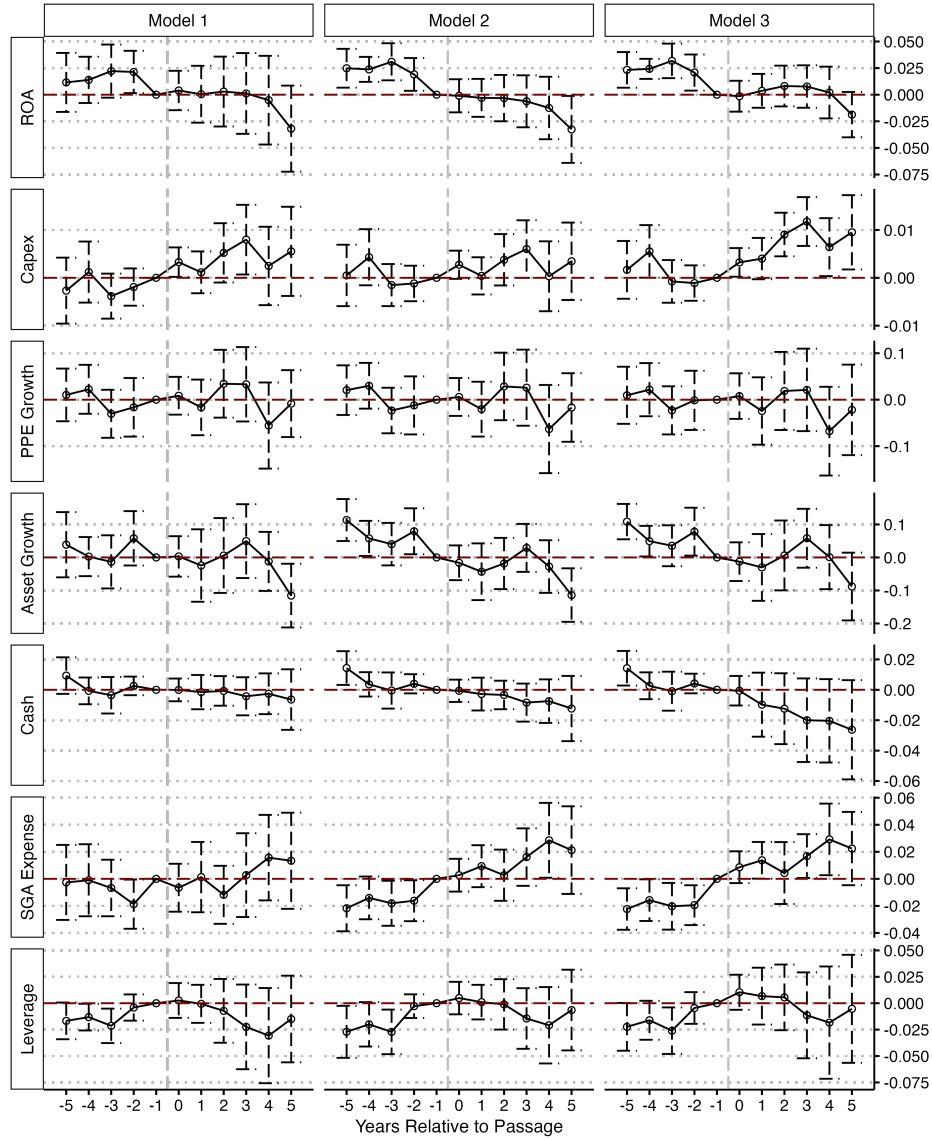


Fig. 8 Stacked Regression Event Study Estimates - Business Combination Statutes Figure 8 reports the stacked regression event study estimates and 95% confidence interval of the impact of business combination law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from Karpoff and Wittry (2018), and Model 3 includes their “full model”.

By explicitly controlling which firms are allowed to enter as effective comparison units in the analysis, stacked regression models prevent prior-treated firms from being used as controls, which generates most of the bias identified in the literature. The results for the stacked event study model for the adoption of business combination statutes are presented in Figure 8. After correcting for this particular form of potential bias there is now little

evidence consistent with a causal relationship between the passage of business combination statutes. Most of the estimates are centered around zero, signifying no impact of the law, and, when not, the results are generally driven more by trends in the pre-adoption period.

A similar set of results is reported for the stacked regression estimates of poison pill law adoption in Figure 9.³⁹ There is some evidence consistent with an increase in both leverage and SG&A expenses for firms incorporated in states with a poison pill law, as well perhaps a short-term decrease in ROA, above and beyond what can be explained by any set of control variables used in [Karpoff and Wittry \(2018\)](#). This is not necessarily inconsistent with the legal critique, as those papers stress the primacy of the poison pill defense, and [Catan and Kahan \(2016\)](#) call for the study of poison pill validation statutes. It should be noted again, however, that at least as pertains to firm leverage, these results cut against the majority of established corporate finance theory that has considered how managerial entrenchment and corporate debt interact.

³⁹The equivalent plots using the data in [Karpoff and Wittry \(2018\)](#) are reported in appendix figures [B3](#) and [B4](#) for business combination and poison pill laws respectively.

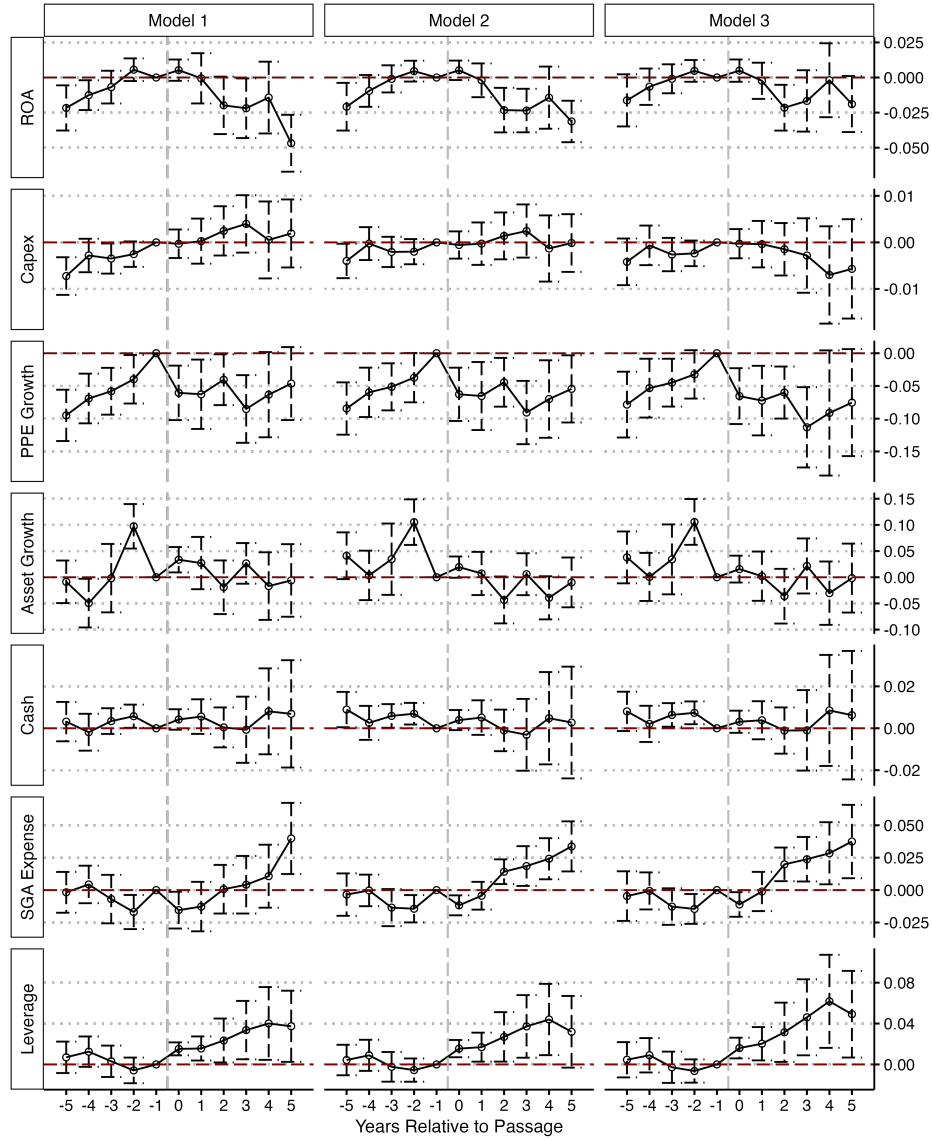


Fig. 9 Stacked Regression Event Study Estimates - Poison Pill Laws Figure 9 reports the stacked regression event study estimates of the impact of poison pill law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), and Model 3 includes their “full model”.

5.4 Callaway and Sant’Anna Estimator

Finally, I use the semi-parametric estimator from [Callaway and Sant’Anna \(2021\)](#) (CS estimator) as a final test of whether state antitakeover provisions are associated with changes in firm-level outcomes in a DiD framework. For brevity, I focus here only on the adoption of poison pill laws and three outcome variables—ROA, SG&A Expenses, and Leverage—where

there still exists some evidence for an effect using the stacked regression approach.

The CS estimator shares certain properties with the stacked regression approach, with a few minor but important differences. Similar to stacked regressions, it also allows for a tailored decision rule on selecting control firms to ensure that prior-treated firms are not used subsequently as control units. However, it uses a straightforward aggregation approach to weight the estimates by treatment cohort size, rather than relying on regression-based weighting with fixed effects. In addition, the CS estimator uses only pre-treatment observations of the covariates, which avoids the concern of including “bad controls” in the DiD analysis (Angrist and Pischke, 2009). Both the short and full regression models in Karpoff and Wittry (2018) use time-varying controls—for firm size, age, and legal environment—and to the extent that the levels of these covariates are impacted by the policy adoption, could lead to mechanically biased results. A fuller explanation of the CS estimator and its implementation here is presented in Appendix E.

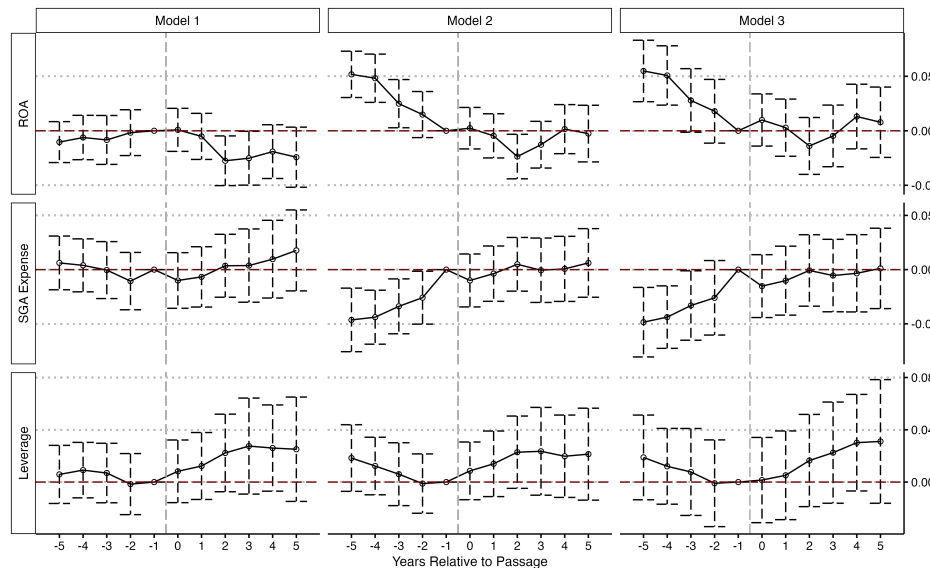


Fig. 10 Callaway & Sant’Anna Estimates - Poison Pill Laws Figure 10 reports the event study estimates of the impact of poison pill law changes using the estimator from Callaway and Sant’Anna (2021) and the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from Karpoff and Wittry (2018), and Model 3 includes their “full model”.

The event study estimates from the CS estimator are reported in Figure 10 above. Using straightforward weighting of different time effects, and restricting the use of confounded

control variables, changes the results. DiD estimates of the effect of poison pill statute adoption on ROA or SG&A expenses suggests either no effect (no controls), or substantial pre-trends followed by little detectable post-adoption differences in outcomes. The trend in leverage after passage appears to perhaps be consistent with a small subsequent increase, although there is again some evidence of pre-trends in the estimates.

In Table 3, I aggregate the post-passage event-time treatment effects for each outcome variable / specification combination. With each permutation, I report the average treatment effect on the treated firms, the aggregate standard error, and a 95% confidence range for the estimate.⁴⁰ In addition, I include estimated standard errors that bound the treatment effect by the relative magnitude of the pre-treatment violations of the parallel trends following [Rambachan and Roth \(2023\)](#). I bound the maximum pos-treatment violation of parallel trends between consecutive periods by \bar{M} times the maximum pre-treatment violation of parallel trends, and report the corresponding confidence intervals for values of \bar{M} equal to 0.5 and 1. None of the results are statistically significant at a 95% level (i.e. where 0 is not within the 95% confidence interval range). The only result that is close to conventional levels of statistical significance is the effect of poison pill laws on firm leverage. However, the confidence interval widens considerably once we account for pre-treatment violations of parallel trends, and the effect is in the opposite direction than predicted in the theoretical literature.

⁴⁰Following the recommendation in [Callaway and Sant’Anna \(2021\)](#), I use the critical value from a uniform confidence band on the event study coefficients if it is greater than 1.96, otherwise I use the standard t-statistic value of 1.96.

Table 3
Aggregated ATT (0, 5) for PP Laws—CS Method

		Model 1	Model 2	Model 3
ROA	ATT	-0.017	-0.007	0.003
	se	0.013	0.012	0.013
	Conf. Int.	[-0.044, 0.011]	[-0.030, 0.017]	[-0.023, 0.028]
	$\bar{M} = 0.5$	[-0.063, 0.024]	[-0.075, 0.059]	[-0.067, 0.087]
	$\bar{M} = 1$	[-0.099, 0.055]	[-0.136, 0.121]	[-0.132, 0.162]
SGA Expense	ATT	0.003	0.000	-0.006
	se	0.015	0.013	0.014
	Conf. Int.	[-0.028, 0.034]	[-0.028, 0.027]	[-0.035, 0.023]
	$\bar{M} = 0.5$	[-0.072, 0.049]	[-0.096, 0.065]	[-0.115, 0.072]
	$\bar{M} = 1$	[-0.130, 0.095]	[-0.174, 0.143]	[-0.209, 0.165]
Leverage	ATT	0.020	0.018	0.018
	se	0.013	0.013	0.014
	Conf. Int.	[-0.009, 0.049]	[-0.009, 0.046]	[-0.010, 0.046]
	$\bar{M} = 0.5$	[-0.032, 0.067]	[-0.035, 0.068]	[-0.053, 0.088]
	$\bar{M} = 1$	[-0.067, 0.095]	[-0.068, 0.095]	[-0.109, 0.137]

Table 3 presents the aggregated DiD results for the period starting from adoption of a poison pill statute until five years after passage, using the estimator and aggregation method from [Callaway and Sant’Anna \(2021\)](#). The outcome variables are ROA, SGA expenses, and leverage. ROA is EBITDA divided by total assets, SGA expenses are scaled by total assets, and leverage is debt divided by total assets. All outcome variables and continuous control variables are winsorized at the 0.5% and 99.5% levels. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), and Model 3 includes their “full model”. For each outcome variable / model combination, the average treatment effect on the treated, standard error, uniform confidence band based critical value, and 95% confidence interval are reported. Following [Callaway and Sant’Anna \(2021\)](#), if the uniform confidence band based critical value is less than 1.96, then 1.96 is used instead. The final two rows for each estimate report the credible interval from [Rambachan and Roth \(2023\)](#) using relative magnitude values \bar{M} of 0.5 and 1.

6 Conclusion

A series of empirical papers established a strong link between the adoption of state antitakeover statutes and a host of firm-level outcome variables, consistent with agency-theoretic models of corporate finance. The staggered nature and purported exogeneity of the laws proved a fruitful tool for empirical researchers looking for changes in the relative power of management and shareholders. However, a powerful critique of this research developed, arguing that the widely available “shadow” poison pill render such statutes legally and practically irrelevant. [Karpoff and Wittry \(2018\)](#) acknowledge aspects of the legal critique, but disagree with the “extreme view” that “any empirical result linking an outcome variable to the adoption of a state antitakeover law must be spurious.”

In this paper I demonstrate that the alleged inconsistency between the legal argument and the empirical results is largely a mirage. Nearly every paper in the empirical literature uses some variant of the standard fixed effects difference-in-differences design, which when used in its most simple form has been shown to suffer from severe limitations in settings similar to the antitakeover debate. Subjecting the standard approach to simple extensions—including studying the dynamics of the purported treatment effects around adoption, and implementing methods that restrict potentially confounded comparison firms—results in little evidence for any consistent effect of second-generation antitakeover provisions on commonly used outcome measures.

On narrow grounds, the results in this paper support the arguments provided in [Coates IV \(2000\)](#), [Klausner \(2013\)](#), and [Catan and Kahan \(2016\)](#) that antitakeover states are redundant, or vestigial, to the presence of the shadow pill. There is in reality very little empirical evidence of any effect to counter this claim, although proving a negative with empirical methods is always impossible. On the substantive merits, the conceptual rejoinder in [Karpoff and Wittry \(2018\)](#) seems difficult to maintain. Even if true that managers and directors suffer career consequences when invoking a poison pill to prevent a hostile takeover ([Johnson, Karpoff, and Wittry, 2023](#)), the potential defenses provided through antitakeover statutes similarly require recalcitrant management to “just say no” to a bidder’s offer. It is hard to imagine why investors would punish managers for actions that result in the exact same outcome through different provisions of our securities laws. The hunt for external shocks to corporate governance arrangements continues.

References

- Alchian, A. A. and H. Demsetz (1972). Production, Information Costs, and Economic Organization. *American Economic Review* 62(5), 777–795.
- Amore, M. D. and M. Bennedsen (2016). Corporate governance and green innovation. *Journal of Environmental Economics and Management* 75, 54–72.
- Angrist, J. D. and J.-S. Pischke (2009). *Mostly Harmless Econometrics*. Princeton University Press.
- Armstrong, C. S., K. Balakrishnan, and D. Cohen (2012). Corporate governance and the information environment: Evidence from state antitakeover laws. *Journal of Accounting and Economics* 53(1-2), 185–204.
- Atanassov, J. (2013). Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting. *Journal of Finance* 68(3), 1097–1131.
- Athey, S. and G. W. Imbens (2018). Design-based Analysis in Difference-In-Differences Settings with Staggered Adoption.
- Autor, D. H. (2003). Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics* 21(1), 1–42.
- Avraham, R. (2007). An empirical study of the impact of tort reforms on medical malpractice settlement payments. *Journal of Legal Studies* 36(SUPPL. 2), 183–229.
- Baer, W. J. (1997). Reflections on Twenty Years of Merger Enforcement Under the Hart-Scott-Rodino Act. *Antitrust Law Journal* 65(3), 825–863.
- Baker, A. C., D. F. Larcker, and C. C. Wang (2022, 5). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144(2), 370–395.
- Baliga, B. R., R. C. Moyer, and R. S. Rao (2016). CEO Duality and Firm Performance : What ’s the Fuss. *Strategic Management Journal* 17(1), 41–53.
- Barnhart, S. W., M. F. Spivey, and J. C. Alexander (2000). Do firm and state antitakeover provisions affect how well CEOs earn their pay? *Managerial and Decision Economics* 21(8), 315–328.
- Becker-Blease, J. R. (2011). Governance and innovation. *Journal of Corporate Finance* 17(4), 947–958.
- Bertrand, M. and S. Mullainathan (1999). Is there Discretion in Wage Setting? A Test Using Takeover Legislation. *The RAND Journal of Economics* 30(3), 535.
- Bertrand, M. and S. Mullainathan (2003, 10). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* 111(5), 1043–1075.

- Borusyak, K. and X. Jaravel (2017). Revisiting Event Study Designs, with an Application to the Estimation of the Marginal Propensity to Consume.
- Brav, A., W. Jiang, F. Partnoy, and R. Thomas (2008). Hedge Fund Activism, Corporate Governance, and Firm Performance. *The Journal of Finance* 63(4), 1729–1775.
- Brickley, J. A., J. L. Coles, and G. Jarrell (1997). Leadership structure: Separating the CEO and Chairman of the Board. *Journal of Corporate Finance* 3(3), 189–220.
- Cain, M. D., S. B. McKeon, and S. D. Solomon (2017, 6). Do takeover laws matter? Evidence from five decades of hostile takeovers. *Journal of Financial Economics* 124(3), 464–485.
- Callaway, B. and P. H. Sant’Anna (2021, 12). Difference-in-Differences with multiple time periods. *Journal of Econometrics* 225(2), 200–230.
- Catan, E. M. and M. Kahan (2016). The law and finance of antitakeover statutes. *Stanford Law Review* 68(3), 629–680.
- Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019, 8). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics* 134(3), 1405–1454.
- Cheng, S., V. Nagar, and M. V. Rajan (2005). Identifying control motives in managerial ownership: Evidence from antitakeover legislation. *Review of Financial Studies* 18(2), 637–672.
- Coates IV, J. C. (2000). Takeover Defenses in the Shadow of the Pill: A Critique of the Scientific Evidence. *Texas Law Review* 79(2), 271–382.
- Cremers, K. J., L. P. Litov, and S. M. Sepe (2017). Staggered boards and long-term firm value, revisited. *Journal of Financial Economics* 126(2), 422–444.
- Cremers, M. and A. Ferrell (2014). Thirty years of shareholder rights and firm value. *Journal of Finance* 69(3), 1167–1196.
- Daines, R. M., I. D. Gow, and D. F. Larcker (2010). Rating the ratings: How good are commercial governance ratings? *Journal of Financial Economics* 98(3), 439–461.
- Davis, J. L., R. Greg Bell, G. Tyge Payne, and P. M. Kreiser (2010). Entrepreneurial Orientation and Firm Performance: The Moderating Role of Managerial Power. *American Journal of Business* 25(2), 41–54.
- deHaan, E., D. Larcker, and C. McClure (2019). Long-term economic consequences of hedge fund activist interventions. *Review of Accounting Studies* 24(2), 536–569.
- Deshpande, M. and Y. Li (2019, 11). Who Is Screened Out? Application Costs and the Targeting of Disability Programs. *American Economic Journal: Economic Policy* 11(4), 213–248.
- Donohue, J. J. (2015). Empirical Evaluation of Law: The Dream and the Nightmare. *American Law and Economics Review* 17(2), 313–360.

- DuBois, C. (2016). The impact of "soft" affirmative action policies on minority hiring in executive leadership: The case of the NFL's Rooney rule. *American Law and Economics Review* 18(1), 208–233.
- Easterbrook, F. H. and D. R. Fischel (1981). The Proper Role of a Target's Management in Responding to a Tender Offer. *Harvard Law Review* 94(6), 1161–1204.
- Fama, E. F. and K. R. French (1997). Industry costs of equity. *Journal of Financial Economics* 43(2), 153–193.
- Gao, M., H. Leung, and B. Qiu (2021, 2). Organization capital and executive performance incentives. *Journal of Banking & Finance* 123, 106017.
- Garvey, G. T. and G. Hanka (1999). Capital structure and corporate control: The effect of antitakeover statutes on firm leverage. *Journal of Finance* 54(2), 519–546.
- Gelman, A. and H. Stern (2006). The difference between "significant" and "not significant" is not itself statistically significant. *American Statistician* 60(4).
- Giroud, X. and H. M. Mueller (2010). Does corporate governance matter in competitive industries? *Journal of Financial Economics* 95(3), 312–331.
- Gompers, P., J. Ishii, and A. Metrick (2003). Corporate governance and equity prices. *Quarterly Journal of Economics* 118(1), 107–155.
- Goodman-Bacon, A. (2021, 12). Difference-in-differences with variation in treatment timing. *Journal of Econometrics* 225(2), 254–277.
- Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? corporate responses to liability risk. *Review of Financial Studies* 24(8), 2781–2821.
- Grossman, S. J. and O. Hart (1982). Corporate financial structure and managerial incentive. In J. J. McCall (Ed.), *The Economics of Information and Uncertainty*, Volume I, pp. 107–140. Chicago, IL: University of Chicago Press.
- Hart, B. O. and J. Moore (1995). Debt and Seniority : An Analysis of the Role of Hard Claims in Constraining Management Author. *The American Economic Review* 85(3), 567–585.
- Heath, D., M. C. Ringgenberg, M. Samadi, and I. M. Werner (2019). Reusing Natural Experiments.
- Imai, K. and I. S. Kim (2020, 11). On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data. *Political Analysis*, 1–11.
- Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics* 86(1), 4–29.
- Jarrell, G. A. and M. Bradley (1980). The Economic Effects of Federal and State Regulations of Cash Tender Offers. *The Journal of Law and Economics* 23(2), 371–407.

- Jennings, J., J. M. Kim, J. Lee, and D. Taylor (2020). Measurement Error and Bias in Causal Models in Accounting Research.
- Jensen, M. C. and W. H. Meckling (1976). Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. *Journal of Financial Economics* 3, 305–360.
- John, K., A. Knyazeva, and D. Knyazeva (2015). Governance and Payout Precommitment. *Journal of Corporate Finance* 33, 101–117.
- John, K. and L. Litov (2010). Managerial Entrenchment and Capital Structure: New Evidence. *Journal of Empirical Legal Studies* 7(4), 693–742.
- Johnson, L. and D. Millon (1989). Misreading the Williams Act. *Michigan Law Review* 87(7), 1862–1923.
- Johnson, W. C., J. M. Karpoff, and M. D. Wittry (2023, 5). The Consequences to Directors for Deploying Poison Pills. *SSRN Electronic Journal*.
- Johnson, W. C., J. M. Karpoff, and S. Yi (2015). The bonding hypothesis of takeover defenses: Evidence from IPO firms. *Journal of Financial Economics* 117(2), 307–332.
- Karpoff, J. M. and P. H. Malatesta (1995). State takeover legislation and share values: The wealth effects of Pennsylvania’s Act 36. *Journal of Corporate Finance* 1(3-4), 367–382.
- Karpoff, J. M., R. J. Schonlau, and E. W. Wehrly (2017). Do takeover defense indices measure takeover deterrence? *Review of Financial Studies* 30(7), 2359–2412.
- Karpoff, J. M. and M. D. Wittry (2018). Institutional and Legal Context in Natural Experiments: The Case of State Antitakeover Laws. *Journal of Finance* 73(2), 657–714.
- Kershaw, D. and E.-P. Schuster (2021). The Purposive Transformation of Company Law. *American Journal of Comparative Law* 68.
- Kim, E. H. and P. Ouimet (2014). Broad-based employee stock ownership: Motives and outcomes. *Journal of Finance* 69(3), 1273–1319.
- Klausner, M. (2013, 7). Fact and fiction in corporate law and governance. *Stanford Law Review* 65(6), 1325–1370.
- Larcker, D. F., P. C. Reiss, and Y. Xiao (2015). Corporate Governance Data and Measures Revisited.
- Ludwig, J. (1998). Concealed-gun-carrying laws and violent crime: Evidence from state panel data. *International Review of Law and Economics* 18(3), 239–254.
- Macey, J. R. (1998). The Legality and Utility of the Shareholder Rights Bylaw. *Hofstra Law Review* 26(4), 835–872.
- Manne, H. G. (1965). Mergers and the Market for Corporate. *Journal of Political Economy* 73(3), 110–120.

- Medcof, J. W. (2001). Resource-based strategy and managerial power in networks of internationally dispersed technology units. *Strategic Management Journal* 22(11), 999–1012.
- Pi, L. and S. G. Timme (1993). Corporate control and bank efficiency. *Journal of Banking and Finance* 17(2-3), 515–530.
- Qiu, J. and F. Yu (2009). The market for corporate control and the cost of debt. *Journal of Financial Economics* 93(3), 505–524.
- Rambachan, A. and J. Roth (2023, 2). A More Credible Approach to Parallel Trends. *The Review of Economic Studies*.
- Romano, R. (1987). The Political Economy of Takeover Statutes. *Virginia Law Review* 73, 111–199.
- Sant’Anna, P. H. and J. Zhao (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics* 219(1), 101–122.
- SEC (2020). Control Share Acquisition Statutes. Technical report, SEC Division of Investment Management.
- Smiley, R. (1981). the Effect of State Securities Statutes on Tender Offer Activity. *Economic Inquiry* 19(3), 426–435.
- Snipes, W. (1983). Corporate Battles for Control-Edgar v . Mite and the Constitutionality of State Takeover Legislation-The Continuing Saga. *Howard Law Journal* 26(4), 1425–1484.
- Spamann, H. (2019). On Inference When Using State Corporate Laws for Identification.
- Spamann, H. and C. Wilkinson (2020). A New Dataset of Historical States of Incorporation of U.S. Stocks 1994-2019.
- Strezhnev, A. (2018). Semiparametric weighting estimators for multi-period difference-in-differences designs.
- Stulz, R. M. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics* 26(1), 3–27.
- Sun, L. and S. Abraham (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* (xxxx), 1–25.
- Tirole, J. (2001). Corporate governance. *Econometrica* 69(1), 1–35.
- Wald, J. K. and M. S. Long (2007). The effect of state laws on capital structure. *Journal of Financial Economics* 83(2), 297–319.

Internet Appendix A: Tables and Figures

State
Alabama
Alaska
Arizona

State

South Carolina

South Dakota

This table lists the adoption dates for control share acquisition statutes (CS), business combination statutes (BC), fair price laws (FP), directors' duties laws (DD), and poison pill laws (PP), as reported in Table II of [Karpoff and Wittry \(2018\)](#). Overall 153 different second-generation laws were passed by a total of 43 states.

Table A.2

Replication of DiD Results With Data (2)

	Dependent Variable													
	(1) ROA		(2) Capex		(3) PPE Growth		(4) Asset Growth		(5) Cash		(6) SGA Expense		(7) Leverage	
	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model
Business combination law (BC)	-0.015 (0.016)	0.000 (0.015)	0.004* (0.002)	0.003 (0.002)	-0.023*** (0.009)	-0.016 (0.017)	-0.061*** (0.023)	-0.064*** (0.023)	-0.007*** (0.003)	-0.005 (0.003)	0.017 (0.013)	0.012 (0.013)	0.045*** (0.017)	0.029** (0.014)
First-generation law		-0.048*** (0.018)		0.002 (0.003)		-0.011 (0.014)		-0.029 (0.028)		0.001 (0.007)		0.031** (0.015)		-0.020 (0.033)
Poison Pill law (PP)		-0.025*** (0.008)		0.002 (0.001)		-0.009 (0.016)		-0.032* (0.020)		-0.001 (0.003)		0.022** (0.010)		0.035*** (0.011)
Control share acquisition law (CS)		-0.039** (0.018)		0.002 (0.003)		-0.017 (0.022)		0.033 (0.027)		0.006 (0.005)		0.033** (0.014)		0.033* (0.018)
Directors' duties law (DD)		0.024 (0.017)		-0.001 (0.001)		0.006 (0.013)		0.014 (0.024)		0.004 (0.004)		-0.021 (0.018)		-0.002 (0.018)
Fair price law (FP)		-0.014 (0.019)		0.002 (0.002)		-0.013 (0.014)		0.022 (0.020)		-0.002 (0.003)		-0.007 (0.017)		-0.011 (0.015)
CS x CTS		0.000 (0.017)		0.000 (0.002)		0.005 (0.019)		-0.050** (0.025)		0.001 (0.006)		0.037** (0.016)		0.005 (0.026)
BC x Amanda		-0.046*** (0.017)		0.002 (0.002)		-0.015 (0.035)		-0.019 (0.031)		-0.003 (0.006)		0.036*** (0.013)		0.053* (0.027)
BC x MF (motivating firms)		0.324*** (0.082)		0.012 (0.010)		0.053 (0.037)		0.250*** (0.064)		-0.041*** (0.012)		-0.237*** (0.061)		-0.160*** (0.048)
Observations	88,072	88,072	87,014	87,014	79,690	79,690	80,733	80,733	88,253	88,253	81,145	81,145	88,043	88,043
R2	0.525	0.525	0.439	0.439	0.059	0.059	0.234	0.234	0.575	0.575	0.597	0.598	0.439	0.439

Note: Table A.2 replicates the estimates from Table IV of [Karpoff and Wittry \(2018\)](#) using an identical code but with current header information. The table reports results of the impact of business combination laws on seven different outcome variables, and tests for the effects of including controls for other types of states, court decisions, and motivating firms. The outcome variables are ROA, Capex, PPE growth, asset growth, cash, SGA expenses, and leverage. ROA is EBITDA divided by total assets, Capex, PPE, cash, and SGA expenses are scaled by total assets; PPE and asset growth are the percentage change in PPE and total assets, respectively; and leverage is debt divided by total assets. All outcome variables and continuous control variables are winsorized at the 0.5% and 99.5% levels. Control variables include size, size squared, age, and age squared. All regressions include firm, state-year, and industry-year fixed effects. Robust standard errors are clustered at the state of incorporation level. *, **, and *** denote two-tailed significance tests at the 10%, 5%, and 1% levels, respectively.

Table A.3

Replication of DiD Results With Data (3)

	Dependent Variable													
	(1) ROA		(2) Capex		(3) PPE Growth		(4) Asset Growth		(5) Cash		(6) SGA Expense		(7) Leverage	
	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model
Business combination law (BC)	-0.013** (0.005)	-0.009** (0.004)	0.004*** (0.001)	0.003*** (0.001)	-0.011 (0.008)	-0.007 (0.014)	-0.046** (0.023)	-0.048*** (0.015)	-0.005** (0.002)	-0.003 (0.002)	0.016*** (0.005)	0.014*** (0.004)	0.011* (0.006)	0.011 (0.008)
First-generation law		-0.025*** (0.006)		0.002 (0.003)		-0.001 (0.009)		-0.011 (0.024)		0.001 (0.004)		0.011 (0.007)		0.010 (0.009)
Poison Pill law (PP)		-0.002 (0.005)		0.001 (0.001)		-0.022** (0.010)		-0.003 (0.011)		-0.002 (0.002)		0.009 (0.006)		0.021*** (0.007)
Control share acquisition law (CS)		-0.010 (0.011)		0.002 (0.003)		-0.053*** (0.014)		0.008 (0.029)		0.002 (0.005)		0.016** (0.008)		0.017 (0.016)
Directors' duties law (DD)		-0.010 (0.007)		-0.002 (0.002)		0.043*** (0.014)		0.012 (0.020)		-0.001 (0.004)		0.004 (0.007)		-0.005 (0.008)
Fair price law (FP)		0.003 (0.008)		0.001 (0.002)		-0.012 (0.012)		0.031 (0.020)		0.001 (0.003)		-0.001 (0.007)		0.007 (0.010)
CS x CTS		0.000 (0.010)		0.000 (0.004)		0.002 (0.015)		-0.017 (0.027)		0.006 (0.005)		0.009 (0.009)		-0.010 (0.015)
BC x Amanda		-0.016* (0.009)		0.002 (0.002)		-0.014 (0.027)		-0.013 (0.024)		-0.002 (0.005)		0.014* (0.008)		0.002 (0.010)
BC x MF (motivating firms)		0.121*** (0.020)		0.020 (0.013)		0.033 (0.030)		0.170*** (0.054)		-0.034** (0.014)		-0.038* (0.023)		-0.083** (0.038)
Observations	90,387	90,387	89,279	89,279	81,845	81,845	82,280	82,280	90,535	90,535	83,763	83,763	90,320	90,320
R2	0.657	0.657	0.448	0.448	0.070	0.070	0.291	0.291	0.592	0.592	0.760	0.760	0.520	0.520

Note: Table A.3 replicates the estimates from Table IV of [Karpoff and Wittry \(2018\)](#) using but fixing data quality issues, including the use of stale header information. The table reports results of the impact of business combination laws on seven different outcome variables, and tests for the effects of including controls for other types of states, court decisions, and motivating firms. The outcome variables are ROA, Capex, PPE growth, asset growth, cash, SGA expenses, and leverage. ROA is EBITDA divided by total assets, Capex, PPE, cash, and SGA expenses are scaled by total assets; PPE and asset growth are the percentage change in PPE and total assets, respectively; and leverage is debt divided by total assets. All outcome variables and continuous control variables are winsorized at the 0.5% and 99.5% levels. Control variables include size, size squared, age, and age squared. All regressions include firm, state-year, and industry-year fixed effects. Robust standard errors are clustered at the state of incorporation level.

*, **, and *** denote two-tailed significance tests at the 10%, 5%, and 1% levels, respectively.

Table A.4

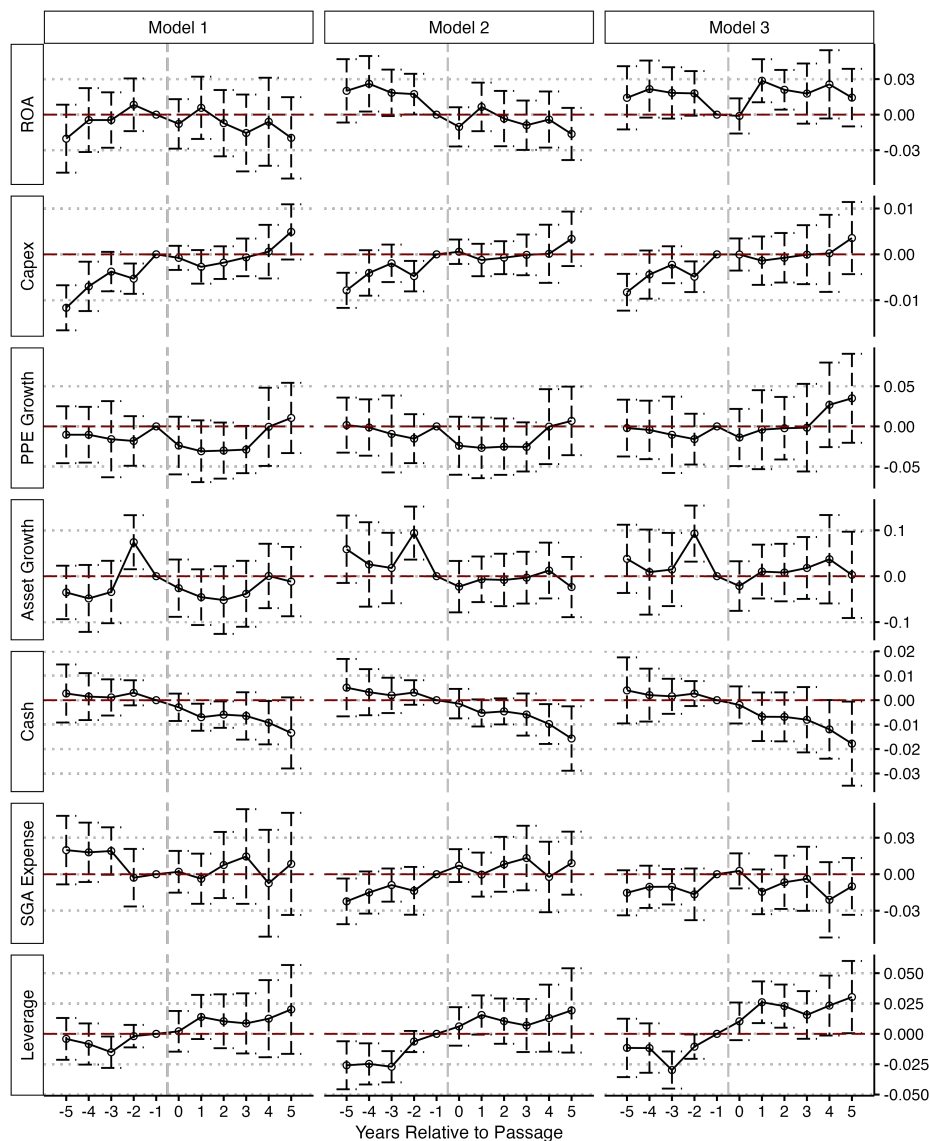
Replication of DiD Results With Data (4)

	Dependent Variable													
	(1) ROA		(2) Capex		(3) PPE Growth		(4) Asset Growth		(5) Cash		(6) SGA Expense		(7) Leverage	
	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model	Short Regres- sion	Full Model
Business combination law (BC)	-0.014*** (0.005)	-0.011*** (0.003)	0.004** (0.001)	0.003** (0.001)	-0.008 (0.007)	-0.007 (0.016)	-0.048** (0.020)	-0.051*** (0.012)	-0.005** (0.002)	-0.004 (0.002)	0.018*** (0.005)	0.017*** (0.003)	0.014* (0.007)	0.011 (0.008)
First-generation law		-0.026*** (0.007)		0.003 (0.003)		-0.003 (0.009)		-0.006 (0.023)		0.004 (0.004)		0.011 (0.008)		0.005 (0.009)
Poison Pill law (PP)		-0.003 (0.004)		0.001 (0.001)		-0.018 (0.011)		-0.004 (0.011)		-0.002 (0.002)		0.009 (0.006)		0.019*** (0.006)
Control share acquisition law (CS)		-0.011 (0.011)		0.004 (0.004)		-0.067*** (0.020)		0.008 (0.040)		0.009** (0.004)		0.013 (0.011)		-0.002 (0.015)
Directors' duties law (DD)		-0.012** (0.006)		-0.002* (0.001)		0.046*** (0.014)		0.001 (0.018)		0.000 (0.004)		0.004 (0.007)		-0.008 (0.007)
Fair price law (FP)		0.004 (0.007)		0.001 (0.002)		-0.011 (0.014)		0.032 (0.020)		0.001 (0.003)		-0.004 (0.006)		0.008 (0.010)
CS x CTS		0.001 (0.011)		-0.003 (0.004)		0.019 (0.021)		-0.009 (0.033)		-0.001 (0.004)		0.010 (0.009)		0.010 (0.016)
BC x Amanda		-0.014 (0.010)		0.002 (0.002)		-0.006 (0.030)		-0.009 (0.024)		-0.001 (0.004)		0.013 (0.009)		0.007 (0.009)
BC x MF (motivating firms)		0.136*** (0.037)		0.012 (0.010)		0.032 (0.021)		0.163*** (0.041)		-0.036** (0.014)		-0.045 (0.038)		-0.086*** (0.030)
Observations	90,387	90,387	89,279	89,279	81,845	81,845	82,280	82,280	90,535	90,535	83,763	83,763	90,320	90,320
R2	0.659	0.659	0.443	0.443	0.075	0.075	0.298	0.298	0.592	0.592	0.758	0.758	0.516	0.516

Note: Table A.4 replicates the estimates from Table IV of [Karpoff and Wittry \(2018\)](#) using but fixing data and design issues, including using less granular industry definitions. The table reports results of the impact of business combination laws on seven different outcome variables, and tests for the effects of including controls for other types of states, court decisions, and motivating firms. The outcome variables are ROA, Capex, PPE growth, asset growth, cash, SGA expenses, and leverage. ROA is EBITDA divided by total assets, Capex, PPE, cash, and SGA expenses are scaled by total assets; PPE and asset growth are the percentage change in PPE and total assets, respectively; and leverage is debt divided by total assets. All outcome variables and continuous control variables are winsorized at the 0.5% and 99.5% levels. Control variables include size, size squared, age, and age squared. All regressions include firm, state-year, and industry-year fixed effects. Robust standard errors are clustered at the state of incorporation level. *, **, and *** denote two-tailed significance tests at the 10%, 5%, and 1% levels, respectively.

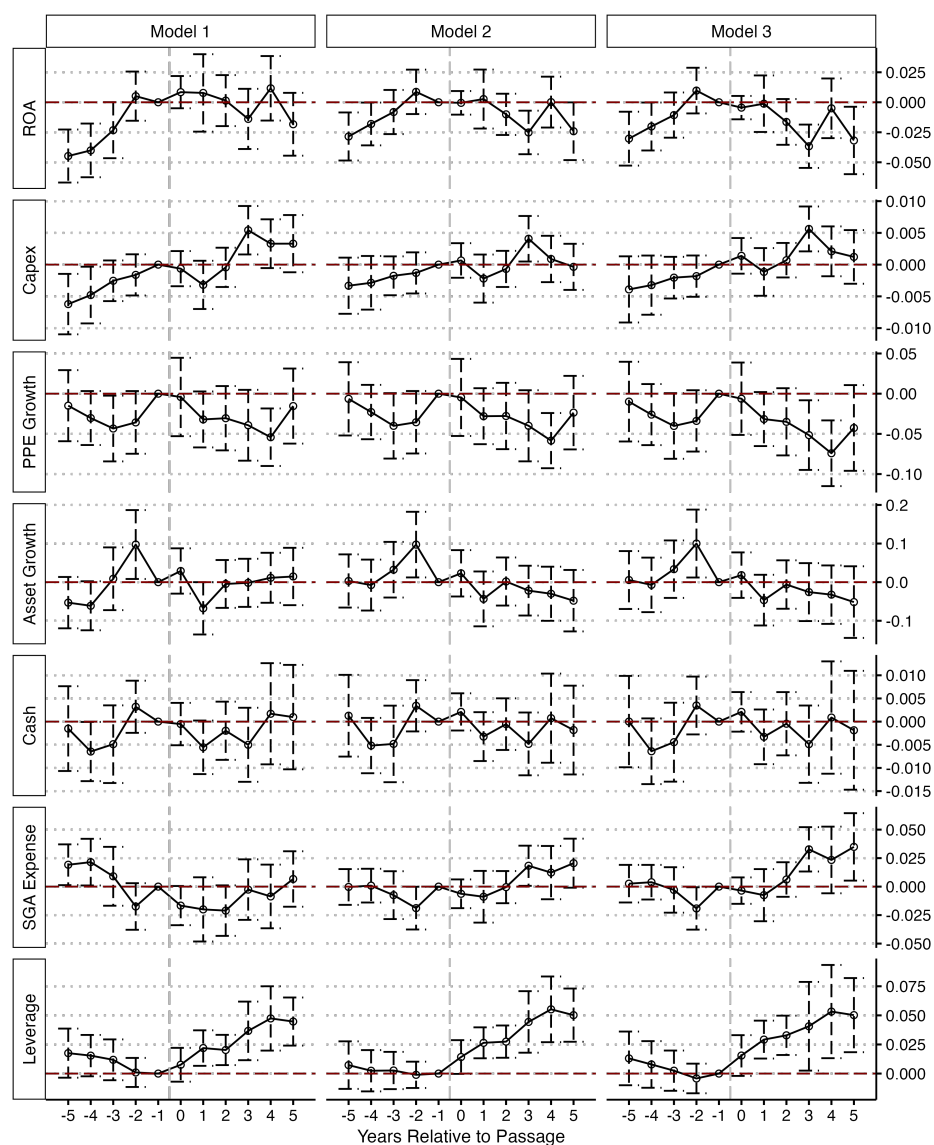
Internet Appendix B: Figures

Fig. B1 Event Study Estimates - Business Combination Statutes



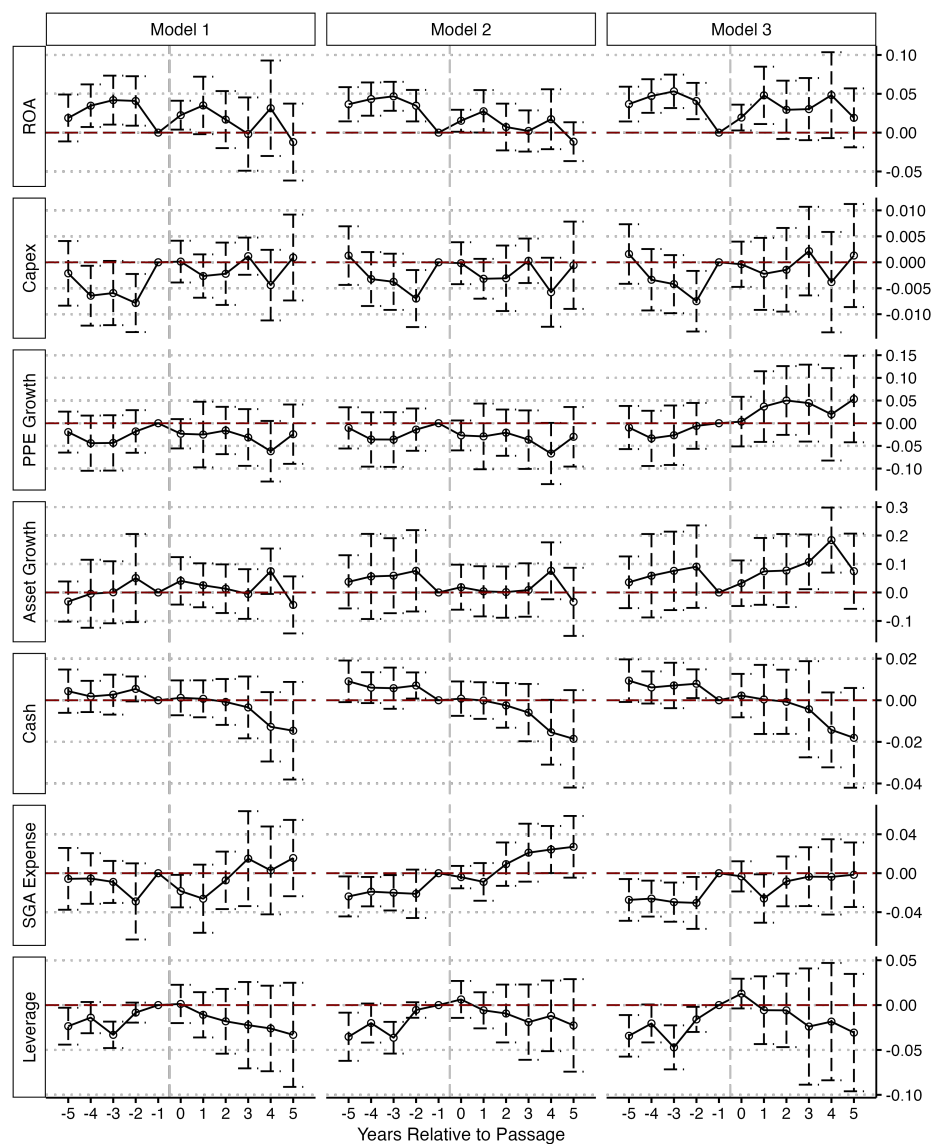
Note: Figure B1 reports the event study estimates of the impact of business law changes using the data from [Karpoff and Wittry \(2018\)](#). Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), while Model 3 includes the full model.

Fig. B2 Event Study Estimates - Poison Pill Laws



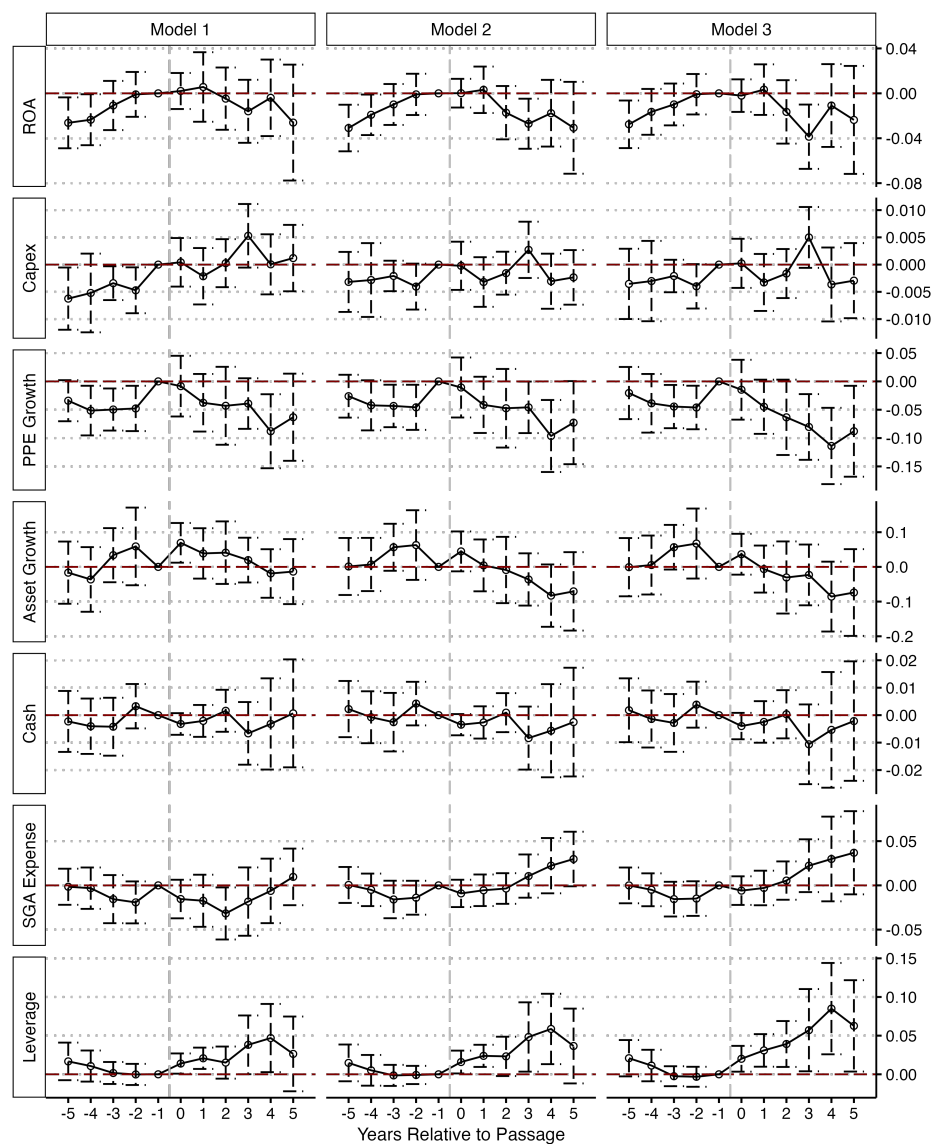
Note: Figure B2 reports the event study estimates of the impact of poison pill law changes using the data from [Karpoff and Wittry \(2018\)](#). Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), while Model 3 includes the full model.

Fig. B3 Stacked Regression Event Study Estimates
Business Combination Statutes



Note: Figure B3 reports the stacked regression event study estimates and 95% confidence interval of the impact of business combination law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from [Karpoff and Wittry \(2018\)](#), and Model 3 includes their “full model”.

Fig. B4 Stacked Regression Event Study Estimates
Poison Pill Laws



Note: Figure B4 reports the stacked regression event study estimates and 95% confidence interval of the impact of poison pill law changes using the data and design changes described in Section 5.1. Model 1 includes only the fixed effects without any covariates, Model 2 includes the covariates in the short regression model from Karpoff and Wittry (2018), and Model 3 includes their “full model”.

Internet Appendix C: Dataset Construction

In this section I detail how the datasets used in the paper are constructed. Corporate law and corporate finance papers frequently use similar publicly available data sources but “clean” the data in different and often unclear ways. For increased transparency I list in this appendix the detailed routine used to create the different datasets (besides Data (1) which comes directly from Professors Jonathan Karpoff and Michael Wittry). The code used to create the data will also be publicly posed on the code repository GitHub.

- Download the historical incorporation files from Bill McDonald here and Holger Spamann and Colby Wilkinson here.
 - Load the enactment dates by state from Table II of [Karpoff and Wittry \(2018\)](#).
 - Download the full Compustat file from WRDS (file name = **comp.funda**), with the standard filters: *indfmt* = INDL, *datafmt* = STD, *popsrc* = D, and *consol* = C. Require that the fiscal year variable *fyear* is not missing and that firm assets (*at*) and sales (*sale*) are also non-missing and non-negative.
 - Make one measure for the historical state of incorporation which is the first non-missing value from the Bill McDonald header file, the Spamann/Wilkinson header file, Compustat’s historical header information (from file **crsp.comphist**), or the present header information (which comes from the file **comp.company**) based on the firm’s fiscal year date. If the value is still missing, then use the most recent available value from the McDonald file, the Spamann/Wilkinson file, or the historical header file, in that order. If still missing then use the present header information.
 - For headquarter state (*state*), get the correct historical values from Mingze Gao’s website (<https://mingze-gao.com/posts/firm-historical-headquarter-state-from-10k/>) ([Gao, Leung, and Qiu, 2021](#)).
 - Headquarter country (*fic*) is imputed based on the *state* variable.
 - Firm cusip (*cusip*) comes from CRSP daily stock events file (**crsp.dsenames**), which is merged to the Compustat data using the CRSP-Compustat linking file (**crsp.ccmxpf.lnkhist**). The final value is identified using the same process as described with the firm’s state of incorporation.
- Do a similar exercise for information from the header file—including headquarter state (*state*), country (*fic*), and security identifier (*cusip*).
- For industry, use Compustat’s historical industry identifier *sich* rather than the header file value *sic*. Here fill the value “down-up”. That is, assume that missing values are equal to the most recent non-missing value. For missing values before any non-missing entries (at the firm level) then fill up - using the closest non-missing value. If still missing then use the header info value.
 - Drop all firms not in the United States, with missing values of state of incorporation, or incorporated outside of the 50 states (i.e. in a territory or Washington D.C.). In addition drop financial firms and utilities (SIC code between 6000 and 6999 or between 4000 and 4949), or where the industry or headquarter state is missing.
 - Merge each firm-year observation into one of the 48 industry identifiers identified by Eugene Fama and Ken French, located on Ken French’s website here. This will be used in Data (4) for the industry-year fixed effects.

- Create firm age variables which are equal to the natural logarithm of the fiscal year less the first fiscal year for a given firm (*age*), and the square of that value (*age2*). In addition firm size variables are the natural logarithm of firm assets *at* (*size*) and the square of that value (*size2*).

- Calculate the dependent variables as follows:

- PPE growth (*ppe*) = $(p_t - p_{t-1})/p_{t-1}$ where $p_t = ppent_t/at_t$, if $at > 0$ otherwise missing.
- Asset growth (*assetgrowth*) = $(at_t - at_{t-1})/at_{t-1}$ if lagged assets are greater than 0, otherwise missing.
- Leverage ratio (*leverage*) = $(dltt + dlc)/at$ if $at > 0$ otherwise missing.
- Capital Expenditure (*capex*) = $capx/at$ if $at > 0$ otherwise missing.
- SG&A Expense (*sga*) = $xsga/at$ if $at > 0$ otherwise missing.
- Return on assets (*roa*) = $ebitda/at$ if $at > 0$ otherwise missing.
- Cash (*cash*) = che/at if $at > 0$ otherwise missing.

- Winsorize all of the values for those variables at the 0.5 and 99.5 level. [Karpoff and Wittry \(2018\)](#) do this over the full dataset while I do so within fiscal year, so that the value doesn't depend on how many years you arbitrarily choose to have in your data.

- Merge in the enactment date values from Table II of [Karpoff and Wittry \(2018\)](#). Code variables (*bc*, *pp*, *cs*, *fp*, *dd*) for those laws if the firm is incorporated in a state where the law is in place. Data (3) and (4) use the fiscal year period date to do this merge, while Data (1) and (2) follow [Karpoff and Wittry \(2018\)](#) and use the year of the enactment date and the fiscal year from Compustat.

- Generate variables for the legal cases:

- *CTS* decision (*cts*) = the firm fiscal year period is after April 21, 1987 when the decision was issued.
- *Amanda* decision (*amanda*) = the firm fiscal year period is after May 24, 1989 when the decision was issued.
- *csXcts* = the firm fiscal year period is after the *CTS* decision and the firm is covered by a control share acquisition statute.
- *bcXamanda* = the firm fiscal year period is after the *Amanda* decision and the firm is covered by a business combination statute.

- Identify the firms that opt-out of the laws from the ISS risk metrics dataset (**risk.gset** and **risk.rmgobernance**). The specifics of this identification are explained in the code. Merge into the Compustat dataset based on *cusip* and *year*. Data (1) and (2) remove these firms from coverage while Data (3) and (4) do not.

- Following [Karpoff and Wittry \(2018\)](#) remove coverage for firms incorporated in Georgia for business combination and fair price laws, and Tennessee for control share acquisition statute, because they require firms to opt-in.
- [Karpoff and Wittry \(2018\)](#) identify a set of firms (by *cusip*) that lobbied for the passage of each type of law. Create variables that are set to 1 for these firms and 0 otherwise for each type of law. Create additional variables that are equal to the interaction of these motivating firms and the periods when they have the law in place.

Appendix D: Stacked Regression Method

In Section 5.3 I use a “stacked regression” approach to circumvent some of the pitfalls identified in the literature on difference-in-differences with panel data and staggered treatment adoption. In this appendix I more fully explain how the stacked regression estimates are implemented. For other papers that have used a stacked regression approach, see [Cengiz et al. \(2019\)](#); [Deshpande and Li \(2019\)](#); [Gormley and Matsa \(2011\)](#).

The first steps for the stacked approach is to generate stacked data:

- For each dataset and law, identify the “switch” years for each firm, which are the years when they go from not being covered by a statute to being covered.
- Make “stacked” datasets. For each unique treatment year (years when firms begin coverage by either a business combination or poison pill statute), keep only treatment years with at least 10 treated firms.
- For each treatment year identify all firms treated in that year with full data from the year before to the year after coverage begins. Do the same thing for all control firms—i.e. they are not treated in that year and also have full coverage for three years surrounding the coverage year in question.
- Generate a sub-dataset for each treatment year which contains only observations from the identified treated and control firms for the years from five years before to five years after coverage begins. Require that control firms do not begin coverage in that relevant window, and if they do drop the observations when they are covered. If the treated firms somehow become uncovered by the statute (e.g. because they reincorporate) then also drop those uncovered observations. Generate a variable in the sub-dataset identifying the relevant treatment year.
- Generate relative time indicators for the treated firms in each sub-dataset which identify whether the fiscal year is t years from the coverage start year, for years $t \in \{-5, \dots, -2, 0, \dots, 5\}$.
- Create sub-datasets for each treatment year and stack them (i.e. bind them by rows).

With the stacked datasets (these are specific to the law in question—so here we have one for business combination statutes and another for poison pill statutes), estimate the event study regression model:

$$y_{itk} = \alpha_{ik} + \lambda_{ltk} + \eta_{jtk} + \sum_{l \neq -1} \delta_l \mathbb{1}\{t - E_i = l\} + \Omega X_{itk} + \epsilon_{itk}$$

The only difference between the stacked regression model and Equation 4 is that we now interact the fixed effects with an identifier for the specific sub-dataset (i.e. specific treatment year for those observations). This stacking prevents the negative-weighting issues (by using past treated units to enter as controls) identified in the literature. See [Baker et al. \(2022\)](#) for confirmation that this removes the bias in simulated examples.

Appendix E: Callaway & Sant’Anna Estimator

The estimator in [Callaway and Sant’Anna \(2021\)](#) is an alternative to standard fixed effect designs that avoids the common issues with staggered DiD, including using past-treated units as controls and undesirable attributes of OLS-based weighting that moves treatment effect estimates away from the usual estimands of interest. Their estimator is very intuitive, and accords with what most studies *allege* that their DiD estimate does in practice. In addition, it allows for multiple time periods, with treatment timing variation, and for the parallel trends assumption to only hold conditional on unit-level covariates.

The key attribute of this estimator is that it identifies granular treatment effects at the treatment-year/relative time period level, which the authors call group-time average treatment effects. Denoted $ATT(g, t)$, these estimates are the average treatment effect for group g at time t , which can then be aggregated to an overall estimate at relative times $e = t - g$ to accord with the commonly used event-study designs. In addition, “the group-time average treatment effect parameters do not directly restrict heterogeneity with respect to observed covariates, the period in which units are first treated, or the evolution of treatment effects over time. As a consequence, these easy-to-interpret causal parameters can be directly used for learning about treatment effect heterogeneity, and/or to construct many other more aggregated causal parameters.”

Although the estimator allows for both inverse-probability weighted and doubly-robust methods, I use the standard outcome-regression approach, in keeping with the spirit of the standard DiD approach. In addition, I use “not-yet treated” units as potential control units. With outcome-regression models, the $ATT(g, t)$ estimate is calculated as:

$$ATT(g, t) = \mathbb{E} \left[\frac{G_g}{\mathbb{E}[G_g]} (Y_t - Y_{g-1} - m_{g,t}^{ny}(X)) \right]$$

where G_g is a binary variable that is equal to one if a firm is first treated in year g , Y_t is the value of the outcome variable in year t , Y_{g-1} is the value of the outcome variable in the year prior to treatment, and $m_{g,t}^{ny}(X) = \mathbb{E}[Y_t - Y_{g-1} \mid X, D_t = 0, G_g = 0]$. In words, $m_{g,t}^{ny}(X)$ are population outcome regressions for the not yet treated group by relative time period t .

With the $ATT(g, t)$ estimates we aggregate up to event-time (i.e. the effect of the policy adoption two years out across treatment cohort groups) by weighting each estimate by its sample share. That is $\delta_e^* = \sum_{g \in G} w(g) \cdot ATT(g, t - g = e^*)$ where the weights $w(g)$ sum to 1 and are equal to the number of firms with an estimate for $e = e^*$ in group g as a percentage of all firms with an estimate for $e = e^*$. As noted in [Callaway and Sant’Anna \(2021\)](#), this simple combination of sub-estimates immediately rules out troubling issues due to negative weights. For example, when the effect of participating in the treatment is always positive then this aggregated parameter cannot be negative, unlike with regression-based methods. The standard errors for the estimate is calculated using a multiplier bootstrap method with the influence functions from each $ATT(g, t)$ estimate.

While the CS estimator is open source (available on CRAN with package named **did**), unique attributes of my implementation require me to code the method by hand (in particular firms change states of incorporation and/or states drop the law). Below I describe the exact steps used to provide the estimates in Figure 9.

- Identify a list of valid treatment years where firms go from being uncovered to covered by a poison pill statute.
- For each treatment year t , get a list of all treated units with full observations for $t - 1$ to $t + 1$, and the same for control years. The treated units must have treatment indicators of the form $\{0, 1, 1\}$ and the control units must be of the form $\{0, 0, 0\}$.
- Make a smaller dataset with just the treated and control units for years in $\{t - 5, t + 5\}$.
- Require that the treatment variable stays constant in the relative periods. For treated units the variable pp must be equal to 0 for years in $\{t - 5, t - 1\}$ and 1 in $\{t, t + 5\}$ and for control units pp must be 0 for all years in $\{t - 5, t + 5\}$. Any observation that does not fit this restriction is dropped.
- For each relative time period e in $\{-5, 5\}$, calculate the ATT. Keep observations in year $t + e$ and $t - 1$ where $t - 1$ is the reference year (the year prior to enactment).
- Calculate the simple two period DiD ATT using the outcomes and covariates for years $t + e$ and $t + e^*$ and Equation 2.2 from [Sant'Anna and Zhao \(2020\)](#). Store the efficient influence functions from the estimate.
- With each treatment year/relative time period estimate, calculate the overall relative period \hat{e} which is simply the weighted average of all ATTs for each treatment group year, weighted by the number of treated firms in each group.
- Generate the standard errors for \hat{e} with a multiplier bootstrap and 1,000 iterations using the saved influence functions.

For each outcome variable this process results in a set of coefficients and standard errors for $e \in \{-5, 5\}$ which are then plotted in Figures 9.