

The Real Effects of Antitrust Enforcement on Corporate Decisions: Evidence from the Courts

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Abstract

I investigate the real effects of antitrust enforcement on corporate acquisitions, investment, and innovation. I use plausibly exogenous variations in judges' propensity to dismiss antitrust cases as an instrument for endogenous exposure to antitrust enforcement. The evidence indicates that antitrust enforcement imposes behavioral constraints on firms. Specifically, defendant firms that go through antitrust litigation experience a significant decrease in future acquisitions, especially among serial acquirers. The adverse effect is economically large but transitory, disappearing after two years. Defendant firms substitute acquisitions with internal investment, resulting in no change in patent outputs. My findings highlight the importance of vigorous and continuous antitrust enforcement.

Keywords: Antitrust Litigation, Investment, Innovation, M&A

JEL: D25, G34, K21, L4

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1. Introduction

Over 75% of U.S. industries became more concentrated in the past two decades ([Grullon et al. \(2019\)](#)), resulting in lessened competition, growing markups, and shrinking wages. Recent studies highlight the anti-competitive aspect of corporate acquisitions, through which incumbent firms “buy and bury” rivals to preempt competition ([Cunningham et al. \(2021\)](#), [Kamepalli et al. \(2020\)](#)). Recent acquisitions involving large technology firms have sparked policy debates and renewed interest in antitrust enforcement. According to the survey, 79% of Americans think that mergers and acquisitions by large platforms are unfair because they undermine competition and harm consumers ([Raymond \(2020\)](#)). The Federal Trade Commission (FTC) is expanding the scope of its antitrust enforcement,¹ while Congress is drafting a new bipartisan antitrust bill.

Despite the growing interest in antitrust among consumers, regulators, and lawmakers, empirical evidence on the causal effects of antitrust enforcement is scarce. In particular, how antitrust enforcement translates to changes in the defendants’ corporate strategies, such as acquisitions and investment, is an open question. [Bizjak and Coles \(1995\)](#) argue that antitrust enforcement imposes constraints on business practices, which are the central concern of defendant firms. In this paper, I test this hypothesis by investigating the real effects of antitrust enforcement on corporate acquisitions, investment, and innovation.

Does exposure to antitrust enforcement reduce defendant acquisition activities and incentivize investment and R&D? On the one hand, most antitrust cases are brought by private parties targeting anti-competitive practices like price fixing and collusion, which are not directly tied to firms’ acquisition and investment strategies. Previous studies challenge the effectiveness of treble damages, commonly sought in private antitrust cases, in deterring antitrust violations ([Salant \(1987\)](#), [Baker \(1988\)](#)). Moreover, the majority of antitrust cases are either dismissed or settled, raising the concern that the penalties are weak ([Coffee](#)

¹For details, see the FTC’s [Press Release](#) and [Policy Statement](#).

(2020)) and inconsistent with the merits of the case (Alexander (1990)). On the other hand, antitrust litigation imposes behavioral constraints on defendant firms (Bizjak and Coles (1995)), which may have a spillover effect on other aspects of firm decisions. Additionally, legal actions may cause reputation losses far exceeding the penalties imposed by the legal system (Karpoff et al. (2008), Armour et al. (2017)), which can be an important deterrent to anti-competitive behavior (Klein and Leffler (1981), Shapiro (1983)).

Even if exposure to antitrust enforcement reduces firms' acquisition activities, it is not immediately clear whether the exposure incentivizes investment. Theory predictions are mixed on the direction of the effect. Acquisitions and internal investment are natural substitutes. With a low acquisition prospect, it is intuitive for firms to ramp up internal investment and R&D efforts (Mermelstein et al. (2020)). However, synergies from acquisitions highlight the complementary relationship between acquisitions and in-house R&D. Shutting down acquisitions prevents incumbent firms from achieving synergies, reduces their productivity, and renders internal investment less attractive (Cortes et al. (2021)).

Ultimately, how antitrust enforcement affects defendant firm decisions is an empirical question. However, testing the causal effects of antitrust enforcement is difficult. Specifically, firms that have their antitrust cases dismissed are very different from firms that do not. The difference in firm characteristics highlights the endogeneity of treatment assignment, making it challenging to assess the effects of antitrust enforcement on corporate decisions. For example, firms that have an anti-competitive business strategy may have more acquisitions and are more likely to lose antitrust suits.

To mitigate the endogeneity in treatment assignment, I employ an instrumental variable approach that exploits the plausibly exogenous variations in judges' propensity to dismiss antitrust cases. Almost all U.S. district courts have rules in place that mandate the random assignment of cases to judges.² In practice, the assignment of judges is as good as random in the sense that it is orthogonal to the defendant's characteristics, acquisition strategies,

²See 28 U.S. Code § 137.

and investment decisions, which results in the assignment of similar companies to judges who differ in their propensity to dismiss cases.³ I use the heterogeneity among judges as an instrument for the probability that a given defendant firm is dismissed from an antitrust case, which allows me to disentangle the effects of antitrust litigation from potential confounds.

This empirical strategy requires judge-identifying information, which is prohibited from being disclosed in federal statistical databases of court cases. To identify judges assigned to antitrust litigation, I scrape case filings from the Lexis Nexis database and Free Law Project. I then construct novel data that combine judge identities with case information from the Federal Judicial Center, as well as corporate characteristics and activities from COMPUSTAT, SDC Platinum, and the United States Patent and Trademark Office (USPTO).

Using novel data and exploiting the plausibly exogenous variations among judges, I show a statistically significant and economically large negative effect of antitrust enforcement on corporate acquisitions. Specifically, compared to the defendants whose cases are dismissed, those that fail to dismiss experience a 33-percentage-point decrease in their probability of acquiring another firm in the next two years. The magnitude of the effect is economically meaningful, equivalent to 82.3% of the unconditional average acquisition probability. A closer look shows that firms exposed to antitrust litigation see a 43.6% decrease in the number of acquisitions and an 84.6% decrease in the average size of acquisitions.

Tests examining the dynamics of the adverse effect show a sizable but transitory effect, taking place immediately after the litigation and persisting for two years. One potential explanation is the limited and declining public and regulatory attention after the enforcement. Importantly, the results indicate that defendant firms have strong incentives to restore their acquisition strategies. Firms with anti-competitive considerations may have more acquisitions and be susceptible to harsher punishments (Cunningham et al. (2021)). Indeed, I find that the adverse effect concentrates among serial acquirers. Overall, despite the criticism

³For evidence supporting the exogeneity of judge assignment, see Galasso and Schankerman (2015), Bernstein et al. (2019a), and Bernstein et al. (2019b).

of being weak and inconsistent, antitrust enforcement does impose constraints on defendant acquisitions. However, the short-lived effect highlights the importance of continuous and vigorous enforcement of antitrust.

Next, I empirically test the model predictions of the effect of antitrust on incumbent firms' investment and R&D. Consistent with the idea that acquisitions and internal investment are substitutes ([Mermelstein et al. \(2020\)](#)), firms exposed to antitrust litigation refrain from acquisitions and instead increase internal investment and R&D expenses. Specifically, failure to dismiss an antitrust case leads to an increase of 7 and 1.9 percentage points in the average capital intensity and R&D intensity in the following two years. As such, my results are inconsistent with [Cortes et al. \(2021\)](#), who show that acquisitions and in-house R&D are complements. A potential explanation that reconciles my empirical results with [Cortes et al. \(2021\)](#) is that the effect of antitrust litigation on acquisitions is transitory. Specifically, firms exposed to antitrust litigation expect only a temporary shutdown of acquisitions and therefore continue to invest internally to achieve future synergies.

Revealed preferences suggest that firms prefer acquisitions over internal investment. I examine the reason behind it by looking at the effect of antitrust enforcement on firm innovation. Demand for innovation is one of the main reasons behind acquisitions. Specifically, technology-driven acquisitions are cheaper than in-house R&D ([Phillips and Zhdanov \(2013\)](#)), generate synergies, and facilitate innovation ([Cortes et al. \(2021\)](#)). However, I find no evidence that antitrust litigation affects firms' patent outputs in the five years following the case filings. By highlighting firms' ability to substitute for acquisitions and maintain patent outputs, my findings suggest that demand for innovation is not the main driver of defendants' preference for acquisitions.

This paper contributes to several strands of literature. First, I contribute to the literature that studies antitrust litigation. Several articles study the stock market reaction to filing and settlement announcements ([Bhagat et al. \(1994\)](#), [Bhagat et al. \(1998\)](#)), while others debate the effectiveness and welfare implications of treble damages in deterring antitrust violations

([Block et al. \(1981\)](#), [Salant \(1987\)](#), [Baker \(1988\)](#), [Choi and Spier \(2022\)](#)). In a related study, [Bizjak and Coles \(1995\)](#) argue that the central concern of defendant firms is the potential imposition of behavioral constraints, suggesting that the debate on treble damages may be misguided. I show empirically that antitrust litigation does impose constraints on defendant firms' acquisition and investment decisions.

My paper also relates to the extensive literature in industrial organizations that studies the effects of antitrust policy. Much of the work in this area consists of formal modeling of the effects of antitrust policy on R&D and investment strategies, firm entry, and innovation of current targets ([Cunningham et al. \(2021\)](#)) or future entrants ([Chang \(1995\)](#), [Segal and Whinston \(2007\)](#), [Phillips and Zhdanov \(2013\)](#), [López and Vives \(2019\)](#), [Cavenaile et al. \(2021\)](#), [Callander and Matouschek \(2022\)](#)). In contrast, I focus on how antitrust policy affects incumbent firms, for which there is surprisingly little empirical evidence. In a related study, [Mermelstein et al. \(2020\)](#) construct a dynamic computational model and show that a stricter antitrust policy promotes R&D in incumbent firms and discourages R&D in future entrants by reducing the prospect of entry for buyouts. On the contrary, [Cortes et al. \(2021\)](#) show that shutting down the acquisition market negatively affects incumbent firms' investment and innovation. With novel data and an identification strategy, my paper is the first to empirically test these model implications.

Lastly, my paper contributes to the literature on the economic impact of the judicial system. Previous studies have shown how legal rules and law enforcement affect a firm's external finance opportunities ([La Porta et al. \(1997\)](#), [Hail and Leuz \(2006\)](#)), corporate governance ([La Porta et al. \(2000\)](#)), and financial market development ([La Porta et al. \(2008\)](#)). A more recent series of papers document how judicial appointments affect patent invalidation ([Galasso and Schankerman \(2015\)](#)), personal and corporate bankruptcy ([Dobbie and Song \(2015\)](#), [Bernstein et al. \(2019a\)](#), [Bernstein et al. \(2019b\)](#), [Iverson et al. \(2020\)](#)), and securities class action litigation ([Huang et al. \(2019\)](#)). My results highlight an important channel through which judicial appointments of judges could affect corporate decisions.

2. Institutional Background

In the U.S., antitrust law is a collection of mostly federal laws that regulate the conduct and organization of business corporations and are generally intended to promote competition and prevent monopolies. Core U.S. antitrust law was created by three pieces of legislation, including the Sherman Antitrust Act of 1890, the Federal Trade Commission Act of 1914, and the Clayton Antitrust Act of 1914. Federal courts have exclusive jurisdiction over federal antitrust claims (28 U.S.C. §1337(a)). Public enforcement of antitrust involving the Department of Justice and the Federal Trade Commission is heard in federal courts. In practice, most state antitrust claims are also heard in federal courts unless a state attorney general is suing under state law. Private enforcement of antitrust laws also relies on federal courts. Under federal law, private parties such as direct purchasers and rivals who suffer antitrust injury may bring private lawsuits for antitrust violations.

A typical civil litigation case goes through several stages and has multiple potential exit points. See Figure 1 for a breakdown of antitrust cases by outcome and year. First, during the pleading stage, the plaintiff can file an official antitrust complaint with any of the 276 divisional offices pertaining to the 94 United States district courts, as long as it is where the defendant is incorporated, where the defendant is headquartered, or where the defendant conducts the bulk of its business. The defendant has the opportunity to reply after receiving the official complaint. However, if the defendant chooses not to respond, the case is terminated with a default judgment in favor of the plaintiff.

It is worth noting that the discretion in court choice allows venue shopping by the plaintiffs to some extent, especially when the defendant is a large national firm.⁴ However, most U.S. district courts have rules in place that mandate the random assignment of cases to judges once a lawsuit is filed. In practice, there are a few other court-based rules that can

⁴To address the concern of venue shopping, I include division fixed effects and exploit within division variations.

make the assignment of antitrust cases not completely random.⁵ That said, these rules are generally exogenous to the cases.⁶ For my purposes, the assignment of judges is as good as random in the sense that it is orthogonal to the defendant’s characteristics, acquisition strategies, and investment decisions. The exogeneity of judge assignment is a key part of my identification strategy, which I elaborate on and test in Section 4.

Next, during the pretrial stage, parties involved in the case hold meetings before the trial judge or a magistrate judge. An important part of these meetings is the discovery process, in which the parties obtain evidence from each other by conducting legal research, reviewing documents, and interviewing witnesses. With a better understanding of the case from both perspectives, either party could file dispositive motions during the pretrial stage, including motions to dismiss and motions for summary judgment. These motions, if granted, could terminate the litigation and end the dispute before trial. In practice, these dispositive motions are almost always filed in antitrust cases. 61% of the cases are dismissed for reasons including lack of jurisdiction, failure to state a claim, and want of prosecution. A case dismissal is generally regarded as a ‘win’ for the defendants in the sense that they no longer need to carry on the expensive legal fights or face any potential punishments. Meanwhile, plaintiffs win in 2% of the cases through default judgment or summary judgment.

Another common practice of the involved parties during these meetings is to negotiate and potentially settle the dispute. One way of doing so is to enter a consent judgment with a settlement contract that is signed by the parties and approved by the judge. However, a consent judgment makes the details of the settlement public information. Therefore, for confidentiality purposes, the parties often enter private settlements and dismiss the case voluntarily. In my sample, 36% of the cases end in settlements. It is widely believed that settlements are weak punishments (Coffee (2020)). That said, Karpoff et al. (2008) argue

⁵The most common rule is that senior judges may elect not to draw any new cases. For example, see the [Order for Assignment of Cases](#) at the U.S. District Court, District of Minnesota.

⁶For evidence supporting the exogeneity of judge assignment, see [Galasso and Schankerman \(2015\)](#), [Bernstein et al. \(2019a\)](#), and [Bernstein et al. \(2019b\)](#).

that the reputation penalties far exceed the settlement amounts.

In practice, a common strategy among defendants is to try their best to dismiss the case in its early stage and push for a settlement if they fail to do so. Unless the defendant has compelling confidence in winning the case, it is very rare for an antitrust case to reach the trial stage. In my sample, fewer than 1% of the cases make it to trial. Among these cases, a jury is demanded in 67% of the cases, and plaintiffs win 33% of the time.

With very few cases reaching trial, the outcomes of antitrust litigation can be broadly categorized into two groups. First, the defendants win in the form of case dismissal, which happens in 61% of the cases. Second, the plaintiffs receive favorable treatment in the form of default judgment, summary judgment, or settlement, which makes up 38% of my sample. With the current practice of law and strategic responses by the firms, judge discretion plays an essential role in the forming of these outcomes. Importantly, while there are uniform criteria by which a judge may dismiss an antitrust case, there is significant variation in the interpretation of these criteria across the judges ([Kirkwood and Lande \(2008\)](#), [Waller \(2009\)](#), [Kovacic \(2020\)](#)). The exogenous allocation of judges thus results in the assignment of similar defendants to judges who differ in their propensity to dismiss antitrust cases. As I outline in [Section 4](#), I exploit this heterogeneity among judges to instrument for the probability that a given defendant is dismissed from the antitrust case.

3. Data

I gather data on antitrust filings from the Federal Judicial Center’s Integrated Database, which contains data on all federal, civil, criminal, bankruptcy, and appellate court cases reported by the courts to the Administrative Office of the U.S. courts. The data contain legal information about each filing, including the plaintiff and defendant, the date when the case was filed, the court in which it was filed, the docket number, the nature of the suit, and the final judgment. The Federal Judicial Center data cover cases as early as 1969, with better coverage and more comprehensive data fields in later years as courts transitioned to an electronic records system. My sample consists of 14,031 case filings from 2000 to 2020,

for which the nature of the suit is antitrust. Sometimes, there are multiple plaintiffs suing the same defendant firm over the same antitrust violation. These cases are often transferred and consolidated into one case, while the duplicate filings remain in the data. Occasionally, the cases are consolidated for pretrial hearings only, meaning that the combined case filing will be remanded after the conclusion of the hearings. Dropping duplicate cases that are transferred or remanded reduces my sample to 10,466 unique antitrust cases. See Figure 2 for the number of antitrust cases filed by year. It is worth noting that the number of filings has been in a steady decline over the past two decades.

Importantly, the Judicial Conference of the U.S. prohibits the Administrative Office from releasing judge-identifying information from statistical databases, except to the extent required by law.⁷ Therefore, this database does not contain information about the judge assigned to each case. I complement this database with judge information from the Free Law Project and Lexis Nexis. The Free Law Project is a public repository of legal opinions and filings, with the largest free collection of federal court documents and dockets gathered from the Public Access to Court Electronic Records (PACER) database. I gather data on antitrust related case filings during my sample period. Lexis Nexis is a search engine that features more than 17,000 news, business, and legal sources. I scrape all the search results of federal case filings dated from 2000 to 2020 with keywords related to antitrust.⁸ For each of the filings collected from the Free Law Project and Lexis Nexis, I identify the plaintiff and defendant, the date of the filing, the court in which it was filed, the docket number, and the name of the judge. I then manually merge the judge names with the original case data using the case-identifying information collected. The merged data contain 6,882 antitrust cases of which I could identify the presiding judge’s name. Judge names that appear on case filings are often short-hands, including initials, nicknames, and sometimes only last names.

⁷In March 1995, the Judicial Conference (JCUS) announced a policy “prohibiting the disclosure (except to the extent required by law) of judge-identifying information from statistical databases” (JCUS-MAR 95, pp. 21–22). The policy was reaffirmed by the JCUS at a meeting in September 1995 and again in March 2003.

⁸The keywords I use include ‘antitrust’, ‘anti-competitive’, ‘Clayton Act’, and ‘Sherman Act.’

I manually match the names that appear on case filings to judges’ official names and merge the filings with judge biographical data from the Federal Judicial Center. 902 federal district judges are identified.

Moreover, I match the defendants of antitrust filings with their financial reports from COMPUSTAT, acquisition activities from Refinitiv SDC Platinum, and patent registration activities from the United States Patent and Trademark Office (USPTO). It is worth noting that not all antitrust litigation defendants are large public firms. Due to the limitations of these data sources on small or private firms, the sample size is further reduced. Specifically, I am able to match acquisition activities from Refinitiv SDC Platinum to 3,930 cases, financial reports from COMPUSTAT to 2,558 cases, and patent registration activities from the USPTO to 1,903 cases.⁹

Table 1 presents summary statistics for my sample. Panel A shows the characteristics of the judges that are assigned to the antitrust cases. 46% of the judges are appointed by Republican presidents. 62% of the judges are rated “well qualified” by the American Bar Association.¹⁰ 81% of the judges are white, and 64% of the judges are male. An average judge in my sample is 62 years old with approximately 12 years of experience as a district judge. These judges dismissed roughly 59% of the antitrust cases in my sample prior to trial. Panel B of Table 1 shows the characteristics of the defendant firms. An average defendant firm in my sample acquires a firm every two years and spends \$1.3 billion on acquisitions every year. A firm in the merged sample with COMPUSTAT has approximately \$153 billion of assets, a leverage ratio of 0.28, and a market-to-book ratio of 2.22. These are overall large and successful firms that play an important role in the American economy.

⁹The reduced sample size is partly due to the need to track defendant firms over a two-to-five-year period after the case filing.

¹⁰The Standing Committee on the Federal Judiciary of the American Bar Association provides the Senate Judiciary Committee, the administration, and the public with its independent, nonpartisan peer evaluation of the professional qualifications of every judicial nominee to Article III and Article IV federal courts.

4. Identification Strategy

4.1. Empirical Design

The final dataset is a cross-section where the unit of observation is an antitrust case. I quantify the impact of failure to dismiss antitrust cases on defendant firms by estimating the following baseline specification:

$$Y_{ci,t+m} = \alpha + \beta FailToDismiss_{cit} + \gamma X_{cijt} + \theta_t + \delta_d + \mu_k + \epsilon_{ci,t+m}, \quad (1)$$

where the dependent variable $Y_{ci,t+m}$ is a measure of post-litigation defendant firm outcomes such as acquisition activities and investment intensity at firm i in year $t+m$. I am interested in estimating β , which captures the impact of going through antitrust litigation on $Y_{ci,t+m}$ after controlling for a set of judge-, plaintiff-, and defendant-level variables, X_{cijt} , such as judge tenure and firm size. Because dispositive motions are typically filed and decided in the year of initial case filing, $FailToDismiss_{cit}$ is indexed by the filing year t . Under the null hypothesis that going through antitrust litigation has no impact on future defendant firm decisions, β should not be statistically different from zero.

Identifying the effect of going through antitrust litigation, relative to being dismissed from the case, on firm decisions is challenging due to the inherent endogeneity of court decisions. For example, firms that have an anti-competitive business strategy may have more acquisitions and are more likely to lose antitrust suits. Therefore, to identify the causal impact of antitrust litigation on firm decisions, I rely on the plausibly exogenous variations in judges' propensity to dismiss antitrust cases as an instrumental variable. Importantly, antitrust laws are uniform at the federal level, meaning that this instrument does not rely on differences in antitrust laws. Rather, the instrument exploits the fact that interpretation of the law varies significantly among federal district judges ([Kirkwood and Lande \(2008\)](#), [Waller \(2009\)](#), [Kovacic \(2020\)](#)).

My complete sample of antitrust cases involves 425 distinct federal district judges. To

quantify a judge’s propensity to dismiss antitrust cases, I construct the measure:

$$\begin{aligned} \text{ExcessNonDismissalRate}_{cj} &= \text{NonDismissalRate}_{cj} - \text{NonDismissalRate}_{cd} \\ &= \frac{\text{NonDismissal}_{cj}}{N_{cj}} - \frac{\text{NonDismissal}_{cd}}{N_{cd}}, \end{aligned} \quad (2)$$

where N_{cj} (N_{cd}) is the total number of antitrust cases that judge j (judges in division d) receive(s), excluding the current case c . NonDismissal_{cj} (NonDismissal_{cd}) is the number of antitrust cases for which judge j (judges in division d) do(es) not receive dispositive motions or reject(s) such motions, excluding the current case c . Note that the decision for the focal antitrust case does not enter into the quantification of judge non-dismissal propensity for that case, which follows the previous literature (Doyle (2007), Maestas et al. (2013), Galasso and Schankerman (2015), Bernstein et al. (2019b), Bernstein et al. (2019a)). Specifically, dropping the focal case avoids the mechanical relationship that would otherwise appear between the judge non-dismissal propensity measure and litigation outcomes.¹¹ By subtracting the average non-dismissal rate of the division, $\text{ExcessNonDismissalRate}_{cj}$ captures the propensity that judge j rejects the dismissal of case c relative to the other judges in the same division. There is substantial variation among judges within the same division in their non-dismissal propensities, with a mean of 0% and a standard deviation of 26.8%.

Antitrust cases can be filed in any of the 276 United States district court divisions. Plaintiffs can file antitrust claims where the defendant is incorporated, where the defendant is headquartered, or where the defendant conducts the bulk of its business. Although plaintiffs have some leeway in the choice of court venue, most U.S. district courts have rules in place that mandate the random assignment of cases to judges once a lawsuit is filed, allowing me to exploit variation among judges within the same division. Recently, researchers find evidence that large debtors (Levitin (2022)) and sophisticated investors (Hüther and Kleiner (2022)) can predict the assignment of bankruptcy judges by exploiting the small number of

¹¹Following the literature, I confirm judge propensity is very persistent and show similar results when I calculate the measure using prior cases only. See Section 5.5 for details.

judges in the U.S. bankruptcy court system.¹² My setup, on the other hand, does not share the same concern for two reasons. First, firms that file for bankruptcy can choose where to build a presence to establish jurisdiction (Merle and Bernstein (2019), Randles (2020)), thereby having more discretion in the choice of venue than the plaintiffs in antitrust cases. Second, there are more than twice as many federal district judges as bankruptcy judges, making it more difficult to time the case filing when a particular judge is busy. In practice, there are a few other court-based rules that can make the assignment of antitrust cases not completely random. That said, these rules are generally exogenous to the cases. For my purposes, the assignment of judges is as good as random in the sense that it is orthogonal to the defendant’s characteristics, acquisition strategies, and investment decisions. I further show evidence supporting the exogeneity of judge assignment in Section 4.2.2.

Next, I rely on the plausibly random assignment of judges to generate exogenous variation in the likelihood that the defendant firm fails to dismiss an antitrust case. To implement the instrumental variable approach, I estimate the following specification as my first-stage regression:

$$FailToDismiss_{cit} = \rho + \pi ExcessNonDismissalRate_{cj} + \lambda X_{cijt} + \theta_t + \delta_d + \mu_k + \sigma_{cit}, \quad (3)$$

where antitrust case c is filed against firm i in year t . d denotes the division where the case is filed, and k denotes the industry of the defendant firm i . The dependent variable $FailToDismiss_{cit}$ is an indicator variable that equals one when the defendant firm i fails to dismiss case c . I am interested in estimating π , which captures the impact of judge non-dismissal propensity on $FailToDismiss_{cit}$, after controlling for a set of judge-, plaintiff-, and defendant-level variables, X_{cijt} . Note that I include division fixed effects, δ_d , to control for potential venue shopping and ensure that I exploit judge variation within a division. I also include year fixed effects, θ_t , and defendant two-digit Standard Industrial Classification (SIC)

¹²Notably, 16 districts have only one bankruptcy judge, and 25 districts have two bankruptcy judges, prompting a policy recommendation to increase the number of judges to allow random assignment.

industry fixed effects, μ_k , to control for time trends and unobserved industry heterogeneity. Because some firms are litigated more than once, I report standard errors clustered at the defendant firm level to account for any correlation among cases targeting the same defendant. I also confirm significance using standard errors clustered at the division level.

Recall that the focal case is removed from the calculation of my instrument, which prevents the mechanical relationship that would otherwise exist between the instrument and the outcome for a given case. In a robustness check in Section 5.5, I show that the results are unchanged if I calculate the instrument for each case using only the precedent cases prior to the focal case. This alternative instrument avoids any potential look-ahead bias introduced by the standard leave-one-out measure. I also confirm that judge non-dismissal propensity is quite consistent over time, as judge decisions in the first half of their tenure strongly predict their decisions in the second half of their tenure with a coefficient close to one.

The second stage equation estimates the effect of going through antitrust litigation on defendant firm outcomes:

$$Y_{ci,t+m} = \alpha + \beta \widehat{FailToDismiss}_{cit} + \gamma X_{cijt} + \theta_t + \delta_d + \mu_k + \epsilon_{ci,t+m}, \quad (4)$$

where $\widehat{FailToDismiss}_{cit}$ is the predicted values from the first stage regression. Because some firms are litigated more than once, I report standard errors clustered at the defendant firm level in all regressions to account for any correlation among cases targeting the same defendant. I also confirm significance using standard errors clustered at the division level.

4.2. Identifying Assumptions

For the instrumental variable regressions to correctly identify the causal relationship between litigation outcomes and firm decisions, the instrument must satisfy several conditions. First, the instrument must strongly affect the likelihood of case dismissal in antitrust litigation. Second, the instrument needs to be unrelated to the future decisions of defendant firms other than through the outcomes of their cases. Moreover, the instrument must have a monotonic impact on the probability of case dismissal in antitrust litigation. In the following

section, I discuss each of the conditions.

4.2.1. Determinants of Antitrust Litigation Outcome

Table 2 presents evidence of a strong relationship between judge non-dismissal propensity and antitrust litigation outcomes. In all five specifications, the estimated coefficients on $ExcessNonDismissalRate_{cj}$ suggest an economically large and statistically significant correlation between judge non-dismissal propensity and the outcomes of antitrust litigation cases. Depending on the specification, a one standard deviation increase in my measure of judge non-dismissal propensity increases the likelihood of non-dismissal by 14.3-16.9 percentage points, which is equivalent to a 34.8-41.1% increase from the unconditional probability of 41.1%. Depending on the control variables included, the F-statistic ranges between 68.1 and 107.9, which is well above the $F = 10$ threshold of [Staiger and Stock \(1994\)](#) and the critical values of [Stock and Yogo \(2002\)](#).

Column 1 reports the regression without any control variables or fixed effects. Note that my measure, $ExcessNonDismissalRate_{cj}$, explains about 11.8% of the total variation in antitrust litigation outcomes, as indicated by the adjusted R^2 . In column 2, I verify my results with the inclusion of division fixed effects, year fixed effects, and industry fixed effects. These fixed effects control for time trends, unobserved heterogeneity among divisions and industries, and venue shopping. Adding the fixed effects explains an additional 16.3% of the total variation in antitrust litigation outcomes.

The plaintiffs of antitrust cases range from individual customers to rival public firms and governments. Previous studies show that the differences in available resources and quality of counsel may explain litigation outcomes ([Eisenberg \(1988\)](#)). In an attempt to capture the advantages of certain plaintiffs, in column 3, I add indicator variables for federal or state plaintiffs, public firm plaintiffs, and class action litigation. Consistent with the literature, the coefficient estimates for all three variables are positive and statistically significant, highlighting the ability of these plaintiffs to prevent defendants from dismissing the case. Specifically, federal or state plaintiffs, public firm plaintiffs, and class action litigation reduce the proba-

bility of case dismissal by 18.5 percentage points, 15.2 percentage points, and 6.4 percentage points, respectively. Analogously, defendant firms with a track record of large acquisitions may be subject to higher scrutiny. In column 4, I further include control variables that characterize the defendant firms' acquisition activities prior to the litigation. Interestingly, past acquisition activities of the defendant firms are not correlated with litigation outcomes.

Column 5 adds control variables for judge characteristics. In particular, I control for a judge's political ideology, professional qualification, demographics, tenure, and prior work experience. It is worth noting that the coefficient estimates on all of these control variables are not statistically different from zero. While many of these variables have been shown to be important predictors of litigation outcomes ([Tate \(1981\)](#)), adding them only slightly improves the adjusted R^2 . The small improvement in predictability highlights the measure's ability to capture judge variations and predict litigation outcomes.

4.2.2. Exclusion Restriction

Importantly, for the instrument to be valid, it must satisfy the exclusion restriction condition. Specifically, it is required that the instrument, judge non-dismissal propensity, has no direct effect on future defendant firm behavior other than through the effect on litigation outcomes. The random assignment of judges strongly supports the exclusion restriction. However, there are several concerns regarding the randomness of judge assignments. I further investigate the concerns and show that the assignment of judges is as good as random for my purposes. Specifically, the assignment is orthogonal to the characteristics of plaintiffs and defendants.

There are a few court-based rules that can make the assignment of antitrust cases not completely random. An example of such rules is that senior judges may elect not to draw any new cases.¹³ Consistent with this rule, in [Table 3](#) I show that judges with a below-median abnormal case share tend to be much older.¹⁴ However, judges with high and low abnormal

¹³For example, see the [Order for Assignment of Cases](#) at the U.S. District Court, District of Minnesota.

¹⁴Measured as the share of cases assigned to the judge within the division subtracting the share of cases she should receive if cases were split equally.

case shares are otherwise similar in characteristics. Importantly, judges with a low dismissal rate, which is favored by plaintiffs, do not seem to receive more cases than their counterparts.

Additionally, [Hüther and Kleiner \(2022\)](#) find evidence that unsecured hedge funds can predict the assignment of bankruptcy judges by venue shopping and timing the bankruptcy filing when unfavorable judges are busy. However, my setup does not share the same concern. First, firms that file for bankruptcy can choose where to build a presence to establish jurisdiction ([Merle and Bernstein \(2019\)](#), [Randles \(2020\)](#)), thereby having much discretion in the choice of venue. On the contrary, it is much more difficult for plaintiffs in antitrust cases to establish jurisdiction in specific court divisions. More importantly, my empirical specifications include division fixed effects to control for venue shopping, effectively comparing judges within the same division. Second, there are more than twice as many federal district judges as bankruptcy judges, making it more difficult to time the case filing when a particular judge is busy. Moreover, I confirm that being assigned an antitrust case in the previous period does not prevent a judge from being assigned a new case in the next period. Last but not least, in Table 4, I show that the instrument is uncorrelated with plaintiff sophistication and defendant historical acquisition activities.

In Column 1, I regress the measure of judge non-dismissal propensity on division fixed effects and year fixed effects. The adjusted R^2 of 0.160 shows that differences among divisions and over time explain a substantial amount of variation in judge non-dismissal propensity. Given the findings in [Hüther and Kleiner \(2022\)](#), it is essential to examine whether the plaintiffs in my setup can influence the assignment of judges. In column 2, I test whether my instrument is correlated with plaintiff characteristics conditional on the division and year fixed effects. I do so by adding indicator variables for federal or state plaintiffs, public firm plaintiffs, and class action litigation. Importantly, these are strong predictors of antitrust litigation outcomes, as shown in Table 2, suggesting that these plaintiffs have better resources and are potentially more sophisticated. However, the coefficient estimates on these variables are small and statistically insignificant, and the R^2 is unaffected by their addition. The fact

that plaintiff sophistication is uncorrelated with judge non-dismissal propensity is consistent with the random assignment of antitrust cases to judges. In columns 3 and 4, I include lagged measures of defendant acquisition activities and industry fixed effects. Note that there is no evidence of a correlation between judge non-dismissal propensity and defendant past acquisition records.

4.2.3. Monotonicity

The monotonicity assumption requires that the instrument has a monotonic impact on the probability of case dismissal. The assumption will be violated if I observe negative first-stage estimates for some subsamples. I split my sample by the median of total assets, leverage, market-to-book ratio, capital intensity, and R&D intensity and estimate the first-stage regression on each subsample. I also estimate the first stage regression separately for different types of plaintiffs, such as governments and class action. Consistent with the monotonicity assumption, I confirm that the first-stage estimates are positive and sizable in all sample splits.

5. Real Effects of Antitrust Enforcement

5.1. Antitrust Enforcement and Firm Acquisition Activities

Table 5 presents the main results on how going through antitrust litigation affects defendant acquisition activities in the future relative to dismissing the case. The dependent variable is an indicator variable that equals one if the defendant performs an acquisition within the two-year period following the antitrust case filing. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant acquisition activities in the year prior to antitrust case filing, such as an indicator variable for acquisition, the number of acquisition deals, and the average size of acquisition deals. All regressions include the division fixed effects, year fixed effects, and industry fixed effects. Column 1 shows the ordinary least squares (OLS) estimate, which does not account for the endogeneity of litigation outcomes. The coefficient estimate suggests that failure to dismiss an antitrust case is associated with a 4 percentage

points reduction in the likelihood of acquisition. Columns 2 and 3 report IV-2 stage least squares (2SLS) estimates, which rely on the exogenous assignment of judges. Column 2 controls for division fixed effects, year fixed effects, and industry fixed effects, while column 3 adds additional controls for plaintiff and defendant characteristics. Including additional controls reduces the first stage F-statistic from 103.5 to 22.1, but the coefficient estimates in columns 2 and 3 are very close in magnitude. Specifically, failure to dismiss an antitrust case causes a 33 percentage points reduction in the likelihood of acquisition. Overall, the results in Table 5 indicate that going through an antitrust case dramatically reduces acquisition prospects.

In Figure 3, I examine the dynamics of acquisition deterrence among defendant firms. Specifically, I estimate variants of the regression in column 2 of Table 5, where the dependent variables are indicators of acquisitions for each year from three years before the antitrust filing until three years after. I plot the coefficients pertaining to the annual acquisition regressions. Importantly, I find no difference in acquisition dynamics among dismissed and non-dismissed defendants prior to the antitrust filing, consistent with the plausibly exogenous assignment of judges. Moreover, the plot rules out the concern that a confounding pre-trend exists in acquisition dynamics. The difference in acquisition probabilities becomes sizable and statistically significant immediately after the year of initial filing and disappears after two years. One potential explanation of the dramatic yet transitory effect is the limited and declining public and regulatory attention after the enforcement. Judging by the revealed preference, acquisitions are the dominant strategy even after recent antitrust enforcement, and defendant firms have strong incentives to restore their acquisition strategies. The lack of long-term or permanent changes in acquisition strategies is consistent with the increased concentration in U.S. industries. As a policy implication, regulators should bring up antitrust cases vigorously and continuously if they want to create a long-term effect.

Table 6 presents two alternative dependent variables that capture the level of firm acquisition activities instead of the likelihood. Specifically, I decompose acquisition activities

into intensive and extensive margins. I measure the extensive margin by the number of acquisitions by the defendant firm in the two years following the antitrust litigation. I measure the intensive margin by the average size of acquisition in the same time window. The regression specifications are analogous to those in Table 5. In columns 1-3, I present results on how antitrust litigation affects the extensive margin. The dependent variable in these regressions is the logarithm of one plus the number of acquisitions in the two years following the litigation.¹⁵ While the coefficient estimates in all three regressions are negative, IV-2SLS estimates in columns 2 and 3 are much larger in magnitude. Specifically, failure to dismiss an antitrust case reduces the number of acquisitions in the near future by 43.6%. Columns 4-6 report how antitrust litigation affects the intensive margin. The dependent variable is the logarithm of one plus the average size of acquisition deals in the two years following the litigation. Again, the IV-2SLS estimates are larger in magnitude than the OLS estimate. The estimated coefficient of -1.870 implies a reduction in average acquisition size by 84.6%. Overall, the results are consistent with my findings in Table 5.

5.2. *Heterogeneous Effects of Antitrust Enforcement*

To this point, I have assumed that the effect of antitrust litigation on defendant acquisition activities is constant across firms. Firms with anti-competitive considerations may have more acquisitions and be susceptible to harsher punishments (Cunningham et al. (2021)). As such, I hypothesize that serial acquirers face more adverse effects when targeted by antitrust litigation. To test this hypothesis, I split my sample based on the defendant firm's prior acquisition activities, where serial acquirers are defined as those with at least one acquisition deal in the year prior to the antitrust case filing.

Table 7 presents the split sample regressions, where the specifications are analogous to column 2 in Table 5. In column 2, I show that the adverse effect of antitrust litigation

¹⁵The outcome variable, the number of acquisitions in the two years following the litigation, is potentially skewed with a mass at zero, for which Cohn et al. (2022) recommend estimating a Poisson regression. Table A.2 presents the results estimated by Poisson regressions, and the results are overall consistent with those of Table 6.

is more severe for serial acquirers. On the one hand, serial acquirers have a much higher unconditional probability of future acquisitions. On the other hand, the higher likelihood is partially offset by the severe adverse effect. Specifically, serial acquirers that fail to dismiss antitrust cases face a 66.1-percentage-point decrease in acquisition prospects when compared to their counterparts who managed to dismiss their cases. In column 3, I show that the effect of antitrust litigation is small and statistically insignificant among defendant firms that are not serial acquirers.

5.3. Antitrust Enforcement and Firm Investment Activities

External acquisitions and internal investments are often considered substitutes for each other (Mermelstein et al. (2020)). Ideally, by placing constraints on anti-competitive practices in acquisition, antitrust enforcement should encourage investment and R&D efforts. That said, Cortes et al. (2021) highlight the synergies from acquisitions and show evidence of a complementary relationship between acquisitions and in-house R&D. Consequently, shutting down acquisitions prevents incumbent firms from achieving synergies, reduces their productivity, and renders internal investments less attractive.

Table 8 investigates the causal impact of having antitrust litigation on defendant firm investment decisions relative to being dismissed from the case. The dependent variables I use to measure investments are the average capital intensity and R&D intensity over the two years following the antitrust filing. In particular, capital intensity is measured by the ratio between capital expenditure and property, plant, and equipment, and R&D intensity is measured by the ratio between R&D expenses and total assets. The regression specifications are analogous to those in Table 5, except that the control variables now include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and measures of defendant investments in the year prior to antitrust case filing. Columns 1-3 present results on the impact of antitrust litigation on defendant firms' capital intensity. Specifically, going through an antitrust case, relative to being dismissed from the case, increases the capital intensity of defendant firms by 7 percentage points, which

is equivalent to a 34.1% increase from the unconditional mean of 20.5%. Similarly, columns 4-6 show that failure to dismiss an antitrust case increases R&D intensity by roughly 1.9 percentage points, which is equivalent to a 44.2% increase from the unconditional mean of 4.3%. Again, the IV-2SLS estimates are significant at the 1% level for both dependent variables.

The results highlight the positive impact of antitrust litigation on defendant firm investment strategies, which are consistent with [Mermelstein et al. \(2020\)](#) but contradict with [Cortes et al. \(2021\)](#). A potential explanation is that the impact of antitrust litigation on corporate acquisitions is transitory, as shown in Figure 3, whereas [Cortes et al. \(2021\)](#) model a complete shutdown of the acquisition market. Therefore, the incumbent firms exposed to antitrust litigation, knowing that the negative impact is transitory, continue to invest in R&D in hopes of achieving synergies through future acquisitions.

5.4. *Antitrust Enforcement and Firm Innovation*

What explains the defendant firms' revealed preference for acquisitions? One of the main motives behind acquisitions is the demand for innovation. Technology-driven acquisitions create synergies and facilitate innovation ([Cortes et al. \(2021\)](#)). Moreover, accessing innovation through investment and R&D instead of acquisitions can be costly to big firms ([Phillips and Zhdanov \(2013\)](#)). As such, the natural question to ask is whether antitrust enforcement affects defendant firms' ability to produce innovation.

Table 9 examines the impact of the failure to dismiss an antitrust case on a defendant firm's patenting activities. The regression specifications follow those in Table 5. Analogously, the control variables now include measures of defendant patenting activities in the prior year. In columns 1-3, the dependant variable is an indicator variable that equals one if the defendant firm registers a new patent in the five-year window following the antitrust case. In columns 4-6, the dependent variable is the logarithm of one plus the number of new patents in the five years following the litigation.¹⁶ The coefficient estimates of the IV-2SLS

¹⁶The outcome variable, the number of new patents in the five years following the litigation, is potentially

regressions are close to zero and statistically insignificant.

In other words, there is no evidence that antitrust litigation hinders the defendant’s ability to produce patents in the next five years. While defendant firms that go through antitrust litigation face a lower prospect for acquisitions, my results suggest that the firms can substitute acquisitions with internal investment. The ability of defendant firms to maintain patent outputs indicates that the demand for innovation is not the main driver behind these firms’ revealed preferences for acquisitions over internal investment. Instead, my findings are more consistent with the anti-competitive motives of acquisitions.

5.5. Robustness Tests

I perform a variety of tests to confirm the robustness of my findings. First, a concern people may have is that my results are driven by the rare cases in which the plaintiffs win through default judgment or summary judgment. As I discussed in Section 2, 2% of the cases end in default judgments or summary judgments in favor of the plaintiff, 36% of the cases are settled, and 61% of the cases are dismissed. If settlements are weaker punishments than default judgment and summary judgment, as many people may believe, it is possible that my results on the impact of antitrust litigation rely purely on the small subset of cases that end in default judgment and summary judgment. I address the concern by running the same regressions with these cases dropped from my sample. Table A.4 presents the coefficient estimates of these regressions. All my results remain statistically significant, and the magnitude of the coefficients is almost identical to those reported in the original tables.

Moreover, there is the concern that the standard leave-one-out measure may cause look-ahead bias and violate the exclusion restriction. Although judge non-dismissal propensity is very persistent in the data, it is possible that judges learn from the impact of their past rulings and adjust their future rulings accordingly. Specifically, the realized impact of antitrust litigation on firm decisions may influence a judge’s future thinking on similar

skewed with a mass at zero, for which [Cohn et al. \(2022\)](#) recommend estimating a Poisson regression. Table A.3 presents the results estimated by Poisson regressions, and the results are overall consistent with those of Table 9.

cases, therefore creating a relationship between the instrument and defendant outcomes. To address the concern, I show that the results are unchanged if I calculate my measure of judge non-dismissal propensity using only the precedent cases prior to the focal case. Table A.5 presents the regression estimates using the alternative instrument. The regression specifications follow those in Tables 5 and 8. Note that the estimates have the same sign as their counterparts in the original regressions, are statistically significant, and are larger in magnitude.

Public antitrust claims make up roughly 6% of my sample. On rare occasions, the Federal Trade Commission and Department of Justice bring antitrust litigation to the court to stop proposed acquisitions. In practice, outstanding litigation does not automatically block a proposed acquisition, and acquirers often rush to complete the acquisition to exploit the benefits. That said, it is possible that failure to dismiss antitrust cases mechanically leads to a reduction in acquisition activities. In a robustness test, I rerun my main regressions on the subsample of private antitrust cases. Table A.6 shows that the regression estimates are almost identical to my previous results.

Last but not least, there is the concern that the measure of judge dismissal propensity is noisy for judges with only a few cases. However, judge dismissal propensity is very persistent over time. Nonetheless, I address the concern by rerunning my main regressions on a sample excluding judges with fewer than five cases. Table A.7 shows the regression estimates, which are almost identical to those reported in the original tables.

6. Conclusion

In this paper, I investigate the real impact of antitrust litigation on corporate acquisitions, investment, and innovation. I construct a novel dataset that combines multiple data sources, including the Federal Judicial Center’s Integrated Database, the Free Law Project, LexisNexis, COMPUSTAT, Refinitiv SDC Platinum, and USPTO. The identification strategy exploits the plausibly exogenous variations in judges’ propensity to dismiss antitrust cases as an instrument for endogenous litigation outcomes.

There are a few key empirical findings. First, I show that judges' propensity to dismiss antitrust cases is a robust predictor of antitrust litigation outcomes. Second, failure to dismiss an antitrust case leads to significant changes in defendant acquisition and investment decisions. Going through an antitrust case, relative to dismissing it, causes a substantial reduction in acquisition activities and an increase in investment and R&D expenses. However, the adverse effect is transitory, indicating strong incentives among defendant firms to restore their acquisition strategies. Last but not least, I find no evidence that antitrust enforcement hinders the defendant's patent output. The ability of defendant firms to maintain patent outputs indicates that demand for innovation is not the main driver behind these firms' revealed preferences for acquisitions over internal investment. My results show the impact of antitrust enforcement on firm decisions and highlight the importance of continuous and vigorous antitrust enforcement. Moreover, I document an important channel through which the judicial appointments of judges could affect antitrust enforcement. Lawmakers need to carefully consider how much judicial discretion is allowed in current antitrust policies and practices, which may create unwanted inefficiencies and costs.

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Figure 1: Share of Litigation by Outcome and Year

This figure shows the share of antitrust cases by outcome and year. Blue represents cases that are dismissed for reasons including lack of jurisdiction, failure to state a claim, and want of prosecution. Red represents cases in which the plaintiffs win through default judgment or summary judgment. Green represents cases that are settled. Orange represents cases in which the defendants win in trial. Teal represents cases in which the plaintiffs win in trial. The sample consists of 10,466 cases filed during the sample period from 2000 to 2020. Note that the sample excludes cases that are remanded or transferred.

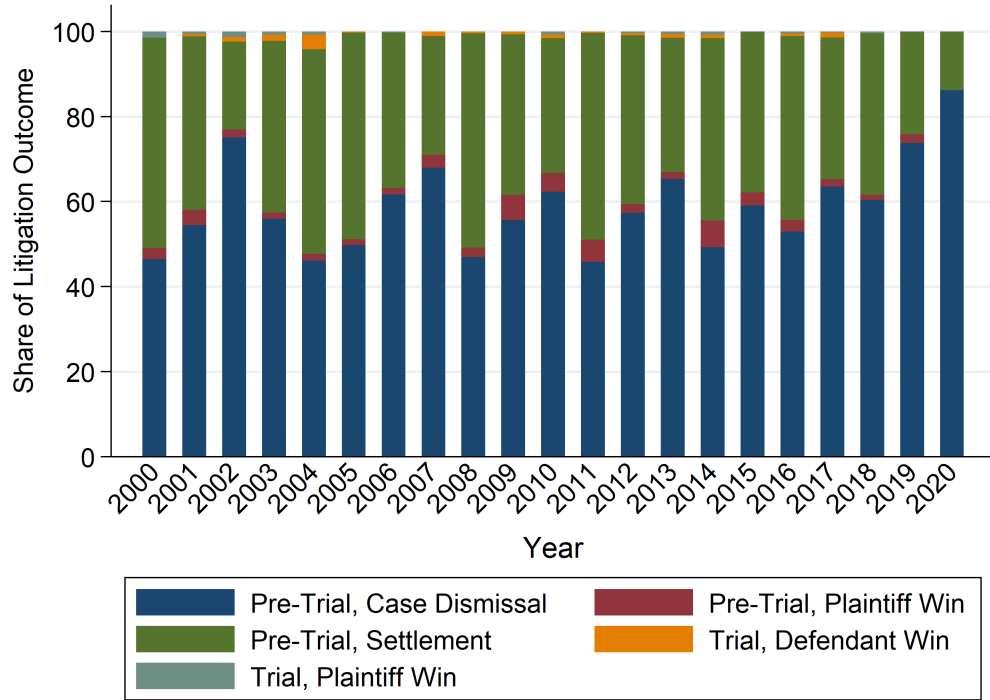


Figure 2: Number of Filings by Year

This figure shows the number of antitrust case filings by year. The sample consists of 10,466 cases filed during the sample period from 2000 to 2020. Note that the sample excludes cases that are remanded or transferred.

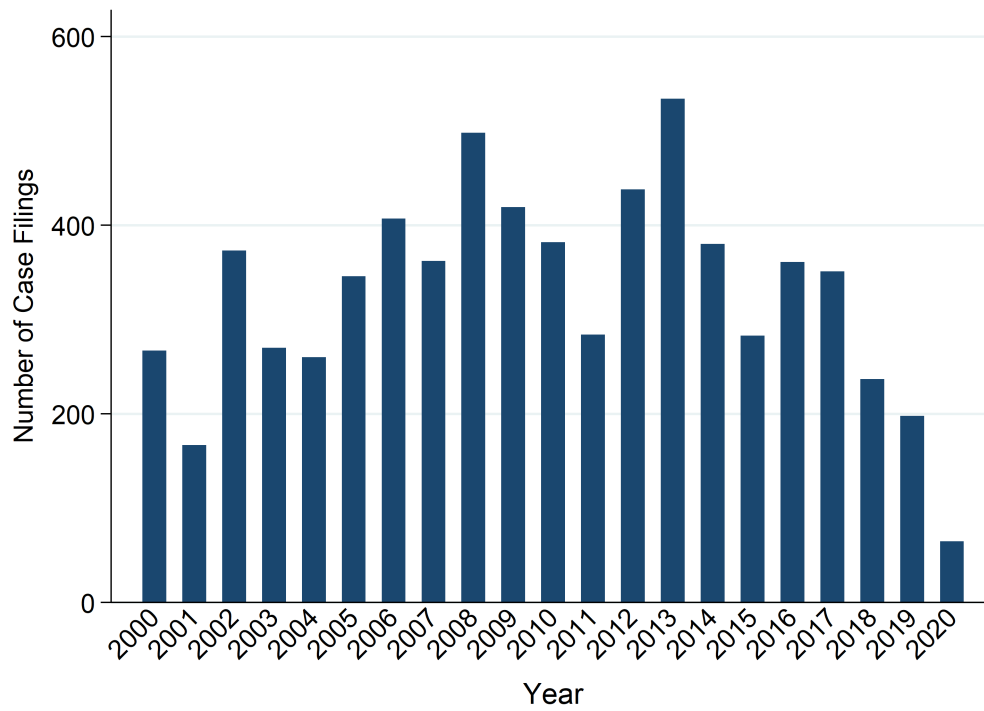


Figure 3: Dynamics of Acquisition Deterrence

This figure plots the dynamics of acquisition deterrence among defendants that fail to dismiss antitrust cases compared to the defendants that are able to dismiss their cases from three years before the antitrust filing until three years after. The y-axis indicates the difference in the probability of acquisition. The x-axis indicates the year relative to the antitrust filing. Error bars show the 95% confidence intervals.

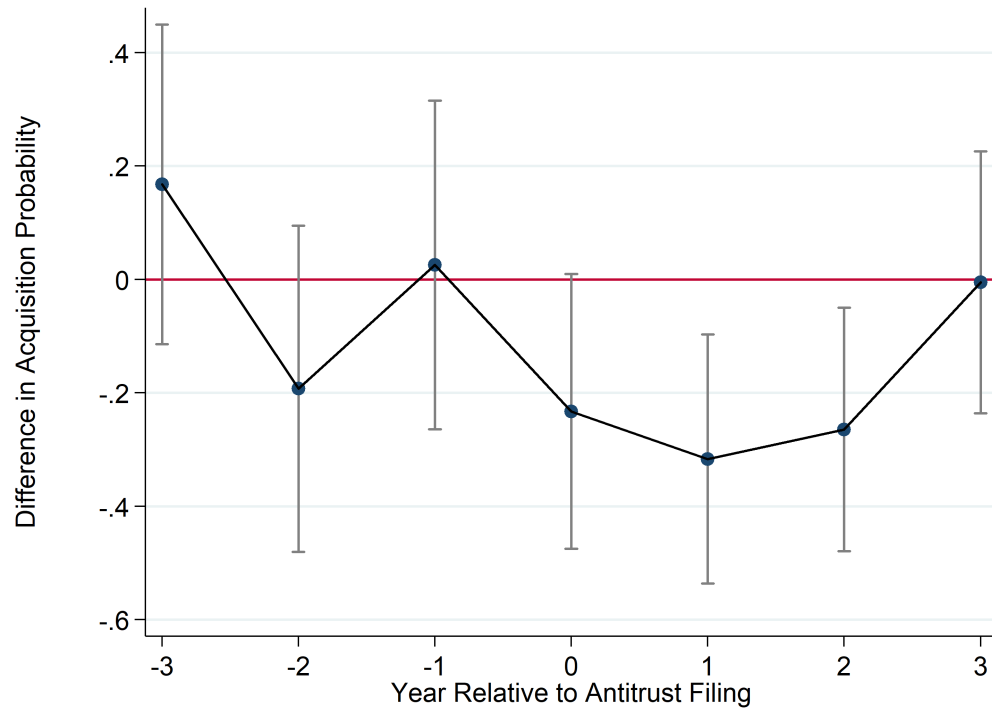


Table 1: Summary Statistics

Panel A of this table presents summary statistics of judge- and plaintiff-level characteristics on the antitrust cases in my sample. Panel B describes the characteristics of the defendant firms, including firm financial information, measures of acquisition activities, and measures of patenting activities. Statistics are reported for all defendant firms and separately for defendants of cases that are dismissed and settled. See Section 3 for dataset description and Table A.1 in the Appendix for details of variable construction.

Panel A. Judge and Plaintiff Characteristics

	N	Mean	Std. Dev.
<i>a. Judge</i>			
Fail to Dismiss	6882	0.41	0.49
Republican	6882	0.46	0.50
Well Qualified by ABA Rating	6882	0.62	0.49
White	6882	0.81	0.39
Male	6882	0.64	0.48
Age	6882	62.21	9.35
Tenure	6882	11.55	8.31
Army Experience	6882	0.15	0.36
Private Practice Experience	6882	0.87	0.34
Public Service Experience	6882	0.52	0.50
<i>b. Plaintiff</i>			
Federal or State Plaintiff	6882	0.06	0.24
Class Action	6882	0.28	0.45
Public Firm Plaintiff	6882	0.06	0.24

Panel B. Defendant Characteristics

	All			Dismissal			Settlement		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
<i>a. Acquisition Activities</i>									
Acquisition Dummy	3928	0.33	0.47	2312	0.33	0.47	1616	0.33	0.47
Number of Acquisitions	3928	0.52	0.95	2312	0.52	0.93	1616	0.52	0.99
Total Acquisition Size, (\$mm.)	3928	1329.17	6458.28	2312	1527.23	7241.46	1616	1045.55	5121.74
Average Acquisition Size, (\$mm.)	3928	989.96	4547.52	2312	1111.84	4822.29	1616	815.44	4117.48
<i>b. Financial Information</i>									
Total Assets, (\$bn.)	2557	153.04	443.75	1501	164.40	464.96	1056	136.88	411.39
Leverage	2557	0.28	0.23	1501	0.28	0.21	1056	0.28	0.24
Market-to-Book Ratio	2557	2.22	1.66	1501	2.26	1.57	1056	2.17	1.78
Capital Intensity	2557	0.22	0.13	1501	0.22	0.13	1056	0.22	0.13
R&D Intensity	2557	0.04	0.05	1501	0.05	0.06	1056	0.04	0.05
<i>c. Patenting Activities</i>									
New Patent Dummy	1903	0.51	0.50	1170	0.51	0.50	733	0.52	0.50
Number of New Patents	1903	53.81	219.72	1170	54.31	220.71	733	53.01	218.28

Table 2: Determinants of Case Outcome

This table shows results from a regression of a dummy for whether a defendant fails to dismiss an antitrust case on the measure of judge excess non-dismissal propensity and a set of judge-, plaintiff-, and defendant-level controls. See Table A.1 in the Appendix for details of variable construction. The sample includes antitrust cases for which all data fields are available. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Fail to Dismiss				
	(1)	(2)	(3)	(4)	(5)
Excess Non-Dissmissal Rate	0.631*** (0.076)	0.544*** (0.053)	0.544*** (0.052)	0.542*** (0.053)	0.535*** (0.052)
Federal or State Plaintiff			0.185*** (0.058)	0.189*** (0.058)	0.189*** (0.059)
Public Firm Plaintiff			0.152*** (0.032)	0.151*** (0.032)	0.156*** (0.032)
Class Action			0.064** (0.031)	0.064** (0.031)	0.067** (0.031)
Acquisition Dummy _{t-1}				0.037 (0.073)	0.045 (0.072)
Log(Number of Acquisitions _{t-1})				-0.003 (0.052)	-0.008 (0.049)
Log(Average Acquisition Size _{t-1})				-0.008 (0.010)	-0.009 (0.010)
Republican					-0.027 (0.032)
Well Qualified by ABA Rating					0.016 (0.033)
White					0.040 (0.035)
Male					0.044 (0.029)
Age					0.000 (0.003)
Tenure					0.000 (0.003)
Army Experience					0.011 (0.055)
Private Practice Experience					-0.045 (0.040)
Public Service Experience					-0.046 (0.030)
Division FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
F-Stat	68.091	103.532	107.835	105.807	107.951
Observations	3928	3928	3928	3928	3928
Adjusted R^2	0.118	0.281	0.291	0.291	0.293

Table 3: Comparison of Judges

This table compares the characteristics of judges in my sample. Panel A reports statistics separately for judges with an overall dismissal rate above and below the median. Panel B reports statistics separately for judges with an overall abnormal case share above and below the median. See Table A.1 in the Appendix for details of variable construction.

Panel A. Above and Below Median Dismissal Rate

Sample	Dismissal Rate<p50		Dismissal Rate≥p50		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Number of Cases	7.01	18.27	8.32	17.69	-1.31
Number of Cases per Year	0.46	1.06	0.58	1.10	-0.13
Abnormal Case Share	0.07	0.13	0.06	0.12	0.00
Republican	0.48	0.50	0.47	0.50	0.01
Well Qualified by ABA Rating	0.61	0.49	0.57	0.50	0.04
White	0.80	0.40	0.76	0.43	0.04
Male	0.75	0.44	0.71	0.45	0.03
Age	75.21	11.70	71.87	11.83	3.34***
Tenure	21.29	10.81	19.05	10.73	2.24**
Army Experience	0.26	0.44	0.18	0.39	0.07**
Private Practice Experience	0.89	0.31	0.89	0.32	0.01
Public Service Experience	0.54	0.50	0.56	0.50	-0.02

Panel B. Above and Below Median Abnormal Case Share

Sample	Abnormal Case Share<p50		Abnormal Case Share≥p50		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	
Dismissal Rate	0.52	0.42	0.57	0.33	-0.05
Republican	0.47	0.50	0.48	0.50	-0.00
Well Qualified by ABA Rating	0.59	0.49	0.60	0.49	-0.01
White	0.77	0.42	0.79	0.40	-0.03
Male	0.76	0.43	0.70	0.46	0.07*
Age	74.85	12.91	72.24	10.59	2.61***
Tenure	20.52	11.64	19.83	9.95	0.68
Army Experience	0.24	0.43	0.20	0.40	0.05
Private Practice Experience	0.90	0.29	0.88	0.33	0.03
Public Service Experience	0.58	0.49	0.52	0.50	0.06

Table 4: Exogeneity of Judge Assignment

This table illustrates the exogenous assignment of judges to antitrust cases. The dependent variable, *Non-Dismissal Rate*, is the measure of judge non-dismissal propensity constructed according to Equation 2. See Table A.1 in the Appendix for details on the construction of independent variables. All regressions include division fixed effects and year fixed effects. Column 5 further adds two-digit SIC industry fixed effects. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Excess Non-Dismissal Rate			
	(1)	(2)	(3)	(4)
Federal or State Plaintiff		-0.017 (0.034)	-0.016 (0.034)	-0.032 (0.031)
Public Firm Plaintiff		0.010 (0.022)	0.010 (0.022)	-0.004 (0.018)
Class Action		0.030 (0.020)	0.030 (0.019)	0.027 (0.017)
Log(Number of Acquisitions _{<i>t</i>-1})			-0.023 (0.053)	0.007 (0.040)
Log(Average Acquisition Size _{<i>t</i>-1})			0.003 (0.007)	-0.003 (0.006)
Division FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Observations	3928	3928	3928	3928
Adjusted R^2	0.160	0.162	0.162	0.270

Table 5: Impact on Acquisition Activities

This table shows the impact of going through antitrust litigation on defendant firm acquisition activities. The dependent variable is an indicator variable that equals one if the defendant performs an acquisition within the two-year period following the antitrust case filing. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant acquisition activities in the year prior to the antitrust case filing, such as an indicator variable for acquisition, the logarithm of one plus the number of acquisition deals, and the logarithm of one plus the average size of acquisition deals. See Table A.1 in the Appendix for details of variable construction. The regression in column 1 is estimated by OLS; the regressions in columns 2 and 3 are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator		
	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)
Fail to Dismiss	-0.041* (0.024)	-0.353*** (0.127)	-0.330*** (0.120)
Control Variables	Yes	No	Yes
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.401	0.401	0.401
First Stage F-Stat		103.532	105.807
Observations	3928	3928	3928
Adjusted R^2	0.328	0.289	0.333

Table 6: Impact on Acquisition Activities - Intensive and Extensive Margins

This table decomposes the impact of going through antitrust litigation on defendant firm acquisition activities into intensive and extensive margins. The dependent variable in columns 1-3 is the logarithm of one plus the number of acquisitions in the two years following the litigation. The dependent variable in columns 4-6 is the logarithm of one plus the average size of acquisition deals in the two years following the litigation. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant acquisition activities in the year prior to the antitrust case filing, such as an indicator variable for acquisition, the logarithm of one plus the number of acquisition deals, and the logarithm of one plus the average size of acquisition deals. See Table A.1 in the Appendix for details of variable construction. The regressions in columns 1 and 4 are estimated by OLS; the regressions in columns 2, 3, 5, and 6 are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Log(1+Number of Acquisitions)			Log(1+Avg Acquisition Size)		
	OLS	IV-2SLS	IV-2SLS	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	-0.045 (0.029)	-0.597*** (0.151)	-0.573*** (0.136)	-0.128 (0.168)	-2.021** (0.801)	-1.870** (0.774)
Control Variables	Yes	No	Yes	Yes	No	Yes
Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat		103.532	105.807		103.532	105.807
Observations	3928	3928	3928	3928	3928	3928
Adjusted R^2	0.456	0.421	0.467	0.319	0.292	0.324

Table 7: Heterogeneity, Past Acquisition Activities

This table shows the heterogeneous impact of going through antitrust litigation on defendant firms that are serial acquirers and non-serial acquirers. The dependent variable is an indicator variable that equals one if the defendant performs an acquisition within the two-year period following the antitrust case filing. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. See Table A.1 in the Appendix for details of variable construction. The regressions are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator		
	All	Serial Acquirer	Non-Serial Acquirer
Sample			
Model	IV-2SLS	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Fail to Dismiss	-0.353*** (0.127)	-0.661*** (0.150)	0.059 (0.168)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.401	0.583	0.304
First Stage F-Stat	103.532	58.912	54.161
Observations	3928	1349	2547
Adjusted R^2	0.289	0.552	0.261

Table 8: Impact on Investments and R&D

This table shows the impact of going through antitrust litigation on defendant firm investment and R&D activities. The dependent variables are *Capital Intensity*, measured by the ratio between capital expenditure and property, plant, and equipment, and *R&D Intensity*, measured by the ratio between RD expenses and total assets. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant investment and R&D activities in the year prior to the antitrust case filing, such as lagged capital intensity and R&D intensity. See Table A.1 in the Appendix for details of variable construction. The regressions in columns 1 and 4 are estimated by OLS; the regressions in columns 2, 3, 5, and 6 are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Capital Intensity			R&D Intensity		
	OLS	IV-2SLS	IV-2SLS	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	0.012* (0.007)	0.070*** (0.025)	0.070*** (0.024)	-0.001 (0.002)	0.025* (0.013)	0.019*** (0.007)
Control Variables	Yes	No	Yes	Yes	No	Yes
Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.205	0.205	0.205	0.043	0.043	0.043
First Stage F-Stat		67.475	66.484		67.475	66.484
Observations	2557	2557	2557	2557	2557	2557
Adjusted R^2	0.638	0.621	0.641	0.858	0.547	0.860

Table 9: Impact on Patenting Activities

This table shows the impact of going through antitrust litigation on defendant firm patenting activities. The dependent variable in columns 1-3 is an indicator variable that equals one if the defendant firm registers a new patent in the five-year window following the antitrust case. The dependent variable in columns 4-6 is the logarithm of one plus the number of new patents in the five years following the litigation. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant patenting activities in the year prior to the antitrust case filing, such as an indicator variable for new patent and the logarithm of one plus the number of new patents. See Table A.1 in the Appendix for details of variable construction. The regressions in columns 1 and 4 are estimated by OLS; the regressions in columns 2, 3, 5, and 6 are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	New Patent Indicator			Log(1+Number of New Patents)		
	OLS	IV-2SLS	IV-2SLS	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	-0.051** (0.026)	0.004 (0.196)	-0.064 (0.187)	-0.049 (0.164)	0.083 (1.155)	-0.534 (1.051)
Control Variables	Yes	No	Yes	Yes	No	Yes
Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.808	0.808	0.808	3.332	3.332	3.332
First Stage F-Stat		35.798	36.506		35.798	36.506
Observations	1903	1903	1903	1903	1903	1903
Adjusted R^2	0.478	0.377	0.475	0.695	0.594	0.695

**Appendix to
The Real Impact of Antitrust Litigation on Corporate Decisions: Evidence
from the Courts**

Table A.1: Variable Construction

This table defines each of the variables used throughout the paper. For clarification, I use the following subscripts: i for firms, j for judges, c for antitrust case, and t for year.

Variable	Definition	Source
Republican $_j$	Indicator variable that equals one if the judge is appointed by a Republican president.	FJC
Well Qualified by ABA Rating $_j$	Indicator variable that equals one if the judge is rated ‘Well Qualified’ by the standing committee of the American Bar Association.	FJC
White $_j$	Indicator variable that equals one if the judge is white.	FJC
Male $_j$	Indicator variable that equals one if the judge is male.	FJC
Age $_{jt}$	The age of judge.	FJC
Tenure $_{jt}$	The number of years serving as a federal district judge.	FJC
Army Experience $_j$	Indicator variable that equals one if the judge has military service experience.	FJC
Private Practice Experience $_j$	Indicator variable that equals one if the judge has private practice experience.	FJC
Public Service Experience $_j$	Indicator variable that equals one if the judge has public service experience, such as work experience as a prosecutor.	FJC
Number of Cases $_j$	The total number of cases assigned to the judge.	FJC
Number of Cases per Year $_j$	The average number of cases per year assigned to the judge.	FJC
Dismissal Rate $_j$	The overall share of cases dismissed by the judge.	FJC
Abnormal Case Share $_j$	The share of cases assigned to the judge within the division subtracts the share of cases she should receive if cases were split equally.	FJC
Federal or State Plaintiff $_c$	Indicator variable that equals one if the plaintiff is federal or state government or agencies.	FJC
Class Action $_c$	Indicator variable that equals one if the case is a class action suit.	FJC
Public Firm Plaintiff $_c$	Indicator variable that equals one if the plaintiff is a public firm.	FJC
Total Assets $_{it}$	Book value of assets (AT).	COMPUSTAT
Log(Size) $_{it}$	The logarithm of total assets (AT).	COMPUSTAT
Leverage $_{it}$	The sum of long-term debt (DLTT) and current liabilities (DLC) divided by total assets (AT).	COMPUSTAT

Table A.1: cont'd

Variable	Definition	Source
Market-to-Book _{it}	Market-to-book ratio calculated as market equity divided by book equity. Book equity is defined as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (TXDITC) if available, minus the book value of preferred stock. Depending on the data's availability we use SEQ as stockholders' equity, the book value of common equity (CEQ) plus the par value of preferred stock (PSTK), or the book value of assets (item AT) minus total liabilities (LT), in that order. Book value of preferred stock is defined depending on data availability as redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK) of preferred stock. Market equity is equal to the shares outstanding (CSHO) times the absolute value of price (PRCC). I winsorize the market-to-book ratio at the 1% and the 99% of their empirical distributions.	COMPUSTAT
Capital Intensity _{it}	Capital expenditure (CAPX) divided by property, plant, and equipment (PPENT)	COMPUSTAT
R&D Intensity _{it}	R&D expenses (XRD) divided by total assets (AT).	COMPUSTAT
Acquisition Dummy _{it}	Indicator variable that equals one if the defendant engages in an acquisition.	SDC Platinum
Number of Acquisitions _{it}	The number of acquisition deals.	SDC Platinum
Total Acquisition Size _{it}	The total deal value of acquisitions.	SDC Platinum
Average Acquisition Size _{it}	The average acquisition deal size.	SDC Platinum
New Patent Dummy _{it}	Indicator variable that equals one if the defendant registers a new patent.	USPTO
Number of New Patents _{it}	The number of new patents registered.	USPTO

Table A.2: Impact on Acquisition Activities - Intensive and Extensive Margins

This table decomposes the impact of going through antitrust litigation on defendant firm acquisition activities into intensive and extensive margins. The dependent variable in columns 1-3 is the number of acquisitions in the two years following the litigation. The dependent variable in columns 4-6 is the logarithm of one plus the average size of acquisition deals in the two years following the litigation. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant acquisition activities in the year prior to the antitrust case filing, such as an indicator variable for acquisition, the logarithm of one plus the number of acquisition deals, and the logarithm of one plus the average size of acquisition deals. See Table A.1 in the Appendix for details of variable construction. The regression in column 1 is estimated by Poisson; the regressions in columns 2 and 3 are estimated by IV where the second stage is a Poisson regression; the regression in column 4 is estimated by OLS; the regressions in columns 5 and 6 are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Number of Acquisitions			Log(1+Avg Acquisition Size)		
	Poisson	IV-Poisson	IV-Poisson	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	-0.088 (0.094)	-1.332*** (0.472)	-1.267** (0.498)	-0.128 (0.168)	-2.021** (0.801)	-1.870** (0.774)
Control Variables	Yes	No	Yes	Yes	No	Yes
Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat		103.532	105.370		103.532	105.807
Observations	3776	3776	3776	3928	3928	3928
Adjusted R^2				0.319	0.292	0.324

Table A.3: Impact on Patenting Activities

This table shows the impact of going through antitrust litigation on defendant firm patenting activities. The dependent variable in columns 1-3 is an indicator variable that equals one if the defendant firm registers a new patent in the five-year window following the antitrust case. The dependent variable in columns 4-6 is the number of new patents in the five years following the litigation. *Fail to Dismiss* is a dummy variable that indicates whether the defendant fails to dismiss the antitrust case. The control variables include plaintiff characteristics, such as indicator variables for government plaintiffs, public firm plaintiffs, and class action, and defendant patenting activities in the year prior to the antitrust case filing, such as an indicator variable for new patent and the logarithm of one plus the number of new patents. See Table A.1 in the Appendix for details of variable construction. The regression in column 1 is estimated by OLS; the regressions in columns 2 and 3 are estimated by IV-2SLS; the regression in column 4 is estimated by Poisson; the regressions in columns 5 and 6 are estimated by IV where the second stage is a Poisson regression. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	New Patent Indicator			Number of New Patents		
	OLS	IV-2SLS	IV-2SLS	Poisson	IV-Poisson	IV-Poisson
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	-0.051** (0.026)	0.004 (0.196)	-0.064 (0.187)	-0.028 (0.108)	-0.245 (0.823)	-0.235 (0.774)
Control Variables	Yes	No	Yes	Yes	No	Yes
Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.808	0.808	0.808	496.966	496.966	496.966
First Stage F-Stat		35.798	36.506		35.798	35.794
Observations	1903	1903	1903	1870	1870	1870
Adjusted R^2	0.478	0.377	0.475			

Table A.4: Robustness - Settlements Only

This table addresses the concern that the results are driven by the rare cases in which the plaintiffs win through default judgment or summary judgment. The regression specifications are analogous to those in column 2 of Table 5 and columns 2 and 5 in Table 8, except that the sample now excludes cases in which the plaintiffs win through default judgment or summary judgment. See Table A.1 in the Appendix for details of variable construction. All regressions are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator	Capital Intensity	R&D Intensity
Model	IV-2SLS	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Fail to Dismiss	-0.328** (0.134)	0.073*** (0.025)	0.028** (0.014)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.405	0.205	0.043
First Stage F-Stat	97.502	62.558	62.558
Observations	3802	2532	2532
Adjusted R^2	0.296	0.620	0.548

Table A.5: Robustness - Alternative Instrument Based on Precedents

This table addresses the concern that the standard leave-one-out measure may cause look-ahead bias and violate the exclusion restriction. The instrument is replaced by the alternative measure of judge non-dismissal propensity using only the precedent cases prior to the focal case. The regression specifications are analogous to those in column 2 of Table 5 and columns 2 and 5 in Table 8. See Table A.1 in the Appendix for details of variable construction. All regressions are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator	Capital Intensity	R&D Intensity
Model	IV-2SLS	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Fail to Dismiss	-0.653** (0.254)	0.157*** (0.059)	0.041 (0.037)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.420	0.201	0.041
First Stage F-Stat	21.070	16.900	16.900
Observations	3307	2066	2066
Adjusted R^2	0.308	0.592	0.525

Table A.6: Robustness - Private Claims

This table addresses the concern that the results are driven by the public antitrust claims in which the Federal Trade Commission or Department of Justice tries to block proposed acquisitions. The regression specifications are analogous to those in column 2 of Table 5 and columns 2 and 5 in Table 8, except that the sample now excludes public antitrust cases. See Table A.1 in the Appendix for details of variable construction. All regressions are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator	Capital Intensity	R&D Intensity
Model	IV-2SLS	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Fail to Dismiss	-0.373*** (0.135)	0.081*** (0.027)	0.032** (0.015)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.401	0.205	0.045
First Stage F-Stat	98.137	56.704	56.704
Observations	3682	2443	2443
Adjusted R^2	0.309	0.636	0.553

Table A.7: Robustness - Judges with More Than Five Cases

This table addresses the concern that the measure for judge propensity is noisy and inaccurate for judges with only a few cases. The regression specifications are analogous to those in column 2 of Table 5 and columns 2 and 5 in Table 8, except that the sample now excludes judges with fewer than five cases. See Table A.1 in the Appendix for details of variable construction. All regressions are estimated by IV-2SLS. Standard errors, clustered at the defendant firm level, are shown in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Dependent Variable	Acquisition Indicator	Capital Intensity	R&D Intensity
Model	IV-2SLS	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Fail to Dismiss	-0.365*** (0.131)	0.076*** (0.029)	0.025* (0.015)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	0.403	0.205	0.044
First Stage F-Stat	111.586	48.736	48.736
Observations	3659	2438	2438
Adjusted R^2	0.307	0.640	0.569