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

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Abstract

I investigate the real impact of antitrust litigation on corporate acquisition and investment decisions. I exploit the random assignment of judges and use the variations in judge propensity to dismiss antitrust cases as an instrument for endogenous litigation outcomes. Judge dismissal propensity strongly predicts antitrust litigation outcomes. Compared to those dismissed from their cases, defendant firms that go through antitrust litigation experience a substantial reduction in acquisition activities and an increase in investment and R&D. There is no evidence that antitrust enforcement hinders the defendants' ability to innovate.

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

JEL: D25, G34, K21, L4

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1. Introduction

I investigate how and to what extent antitrust litigation affects corporate acquisition and investment decisions. Recent studies highlight the anti-competitive aspect of acquisitions, through which incumbent firms 'buy and bury' rival firms to preempt competition (Cunningham et al. (2021), Kamepalli et al. (2020)). Over 75% of U.S. industries became more concentrated in the past two decades (Grullon et al. (2019)), resulting in lessened competition, growing mark-ups, and shrinking wages. The acquisitions, especially those involving large technology firms, have sparked policy debates and renewed interest in antitrust enforcement. Seventy-nine percent of Americans think that mergers and acquisitions pursued by large platforms are unfair because they undermine competition and harm consumers (Raymond (2020)). The Federal Trade Commission vows to 'reactivate the full set of authorities that congress granted' 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 impact of antitrust enforcement is scarce.

Does antitrust litigation help prevent future corporate concentration and incentivize investment and R&D? On the one hand, exposure to antitrust litigation may have a negligible impact on involved firms. Specifically, most antitrust cases are either dismissed or settled, raising the concern that the penalties are weak (Coffee (2020)) and inconsistent with the merits of the case (Alexander (1990)). Moreover, acquiring innovation through acquisition avoids costly R&D races with new entrants (Phillips and Zhdanov (2013) and preempts competition (Cunningham et al. (2021), Kamepalli et al. (2020)), so the benefits may outweigh the costs. On the other hand, settling a case may cause reputation losses, which can be an important deterrent to anti-competitive behavior (Klein and Leffler (1981), Shapiro (1983)). Moreover, reputation penalties caused by legal actions far exceed the penalties imposed through the legal and regulatory system (Karpoff et al. (2008)), especially when the prohibited conduct sets losses on customers (Armour et al. (2017)).

Even if exposure to antitrust litigation deters defendant firm acquisition activities, it is not immediately clear whether the exposure incentivizes investment. Theory predictions are mixed on the direction of the effect. On the one hand, acquisitions and internal investments are natural substitutes. With a low acquisition prospect, it is intuitive for firms to ramp up internal investments and R&D efforts (Mermelstein et al. (2020)). On the other hand, 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 investments less attractive (Cortes et al. (2021)).

Empirically testing the causal impact of antitrust litigation is difficult for two reasons. First, 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 impact of antitrust litigation on corporate decisions. For example, firms that fail to dismiss antitrust cases tend to have fewer assets and spend less on R&D, which will also affect their future investment and acquisition decisions. Therefore, an identification strategy is needed to assess the impact of antitrust litigation. To mitigate the endogeneity in treatment assignment, I employ an instrumental variable (IV) approach that exploits the fact that U.S. district courts randomly assign antitrust cases to judges. Therefore, the assignment of judges is orthogonal to the defendant's characteristics, acquisition strategies, and investment decisions. The random allocation of defendants to judges results in the assignment of similar companies to judges who differ in their propensity to dismiss cases. 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 impact of antitrust litigation from potential confounds.

Second, my identification strategy requires data that combine judge information, case characteristics, and firm activities, which are not readily available. Specifically, judge-identifying information is prohibited in public statistical databases, making it onerous to link judges to cases. Moreover, there are no linkage files that connect case information with corresponding firm data. I construct a novel dataset that links case information from the Federal Judicial Center with corresponding judge information from the Lexis Nexis database and Free Law Project, as well as corporate characteristics and activities from COMPUSTAT, SDC Platinum, and the United States Patent and Trademark Office (USPTO).

Using novel data, I find huge variations in judges' propensity to dismiss antitrust cases. I show that judge dismissal propensity is a robust predictor of antitrust litigation outcomes. A one-standard-deviation decrease in judge dismissal propensity corresponds to an increase in the defendant's probability of going through antitrust litigation by 14.5-17 percentage points, or a 35.3-41.4% increase compared to the unconditional probability of 41.1%. In addition, judge dismissal propensity explains about 11.8% of the total variation in litigation outcomes, which is equivalent to 39.6%

of the predictable variation. My findings are robust to a wide variety of alternative specifications and controls.

Next, I show that exposure to antitrust litigation translates into real economic impacts on firms. Failure to dismiss a case leads to an economically significant reduction in a defendant's subsequent acquisition activities. Compared to the defendants whose cases are dismissed, those that fail to dismiss experience a 31.4-percentage-point decrease in their probability of acquiring another firm in the following two years, which is equivalent to 78.3% of the unconditional probability of 40.1%. Moreover, I show that the negative impact of antitrust litigation begins only after the initial filing year and lasts for two years, suggesting that the effect is transient. Consistent with Mermelstein et al. (2020), defendant firms that fail to dismiss antitrust cases and cannot acquire innovation from other firms through acquisition ramp up capital investments and R&D. 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.

This paper contributes to several strands of literature. First, I contribute 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 impact 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)). I focus on how antitrust policy affects acquirers' acquisition, investment, and R&D activities. 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 buyout. On the contrary, Cortes et al. (2021) show that shutting down the acquisition market negatively impacts incumbent firms' own innovation. Relative to the abundance of theoretical work, there is surprisingly little empirical research investigating the real impact of antitrust enforcement on acquirers' investments and R&D. My paper is the first to empirically test these model implications by constructing a novel dataset and employing an identification strategy that exploits the random assignment of judges.

My paper also relates to the literature on corporate misconduct and deterrence. Starting with Klein and Leffler (1981) and Shapiro (1983), much of this literature emphasizes the role of reputation loses, measured by stock market responses to the legal actions against perpetrators, on misconduct deterrence (Karpoff et al. (2008), Armour et al. (2017)). My paper, on the other hand, investigates the direct impact of antitrust enforcement on corporate acquisition, investment, and R&D decisions. Despite the fact that antitrust litigation often ends in settlements, which are weak (Coffee (2020)) and inaccurate (Alexander (1990)), I show that exposure to antitrust litigation does have a significant impact on corporate decisions.

Last, 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 impact patent invalidation (Galasso and Schankerman (2015)), personal and corporate bankruptcy (Dobbie and Song (2015), Bernstein et al. (2019a), Bernstein et al. (2019b)), and securities class action litigation (Huang et al. (2019)). My results highlight an important channel through which the judicial appointments of judges could affect antitrust enforcement, which previously has not been documented.

The remainder of the paper is organized as follows. In Section 2, I discuss the institutional details of antitrust litigation. Section 3 discusses the data construction. I explain the details of my identification strategy in Section 4. Section 5 provides evidence on the real impact of antitrust litigation on firms, and section 6 concludes.

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. However, once a lawsuit is filed, it is randomly assigned to one of the federal judges in the division where it is filed. 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 judges in the U.S. bankruptcy court system. Notably, 16 districts have only one bankruptcy judge, and 25 districts have two bankruptcy judges. A policy recommendation provided in the study is to increase the number of judges to allow random assignment, which is exactly the case in my setup. Specifically, there are roughly 700 federal district court judges, which is more than twice as many as bankruptcy judges. As a result, most federal court divisions have at least three judges, allowing them to assign antitrust cases to judges randomly. The random assignment of judges is a key part of my identification strategy, which I elaborate 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. That said, Karpoff et al. (2008) show negative market-adjusted announcement returns on settlements of class-action litigation related to corporate misconduct and argue 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 the 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 random 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. This data contains 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 dataset covers 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. Therefore, this data does not contain information about the judge assigned to each case. I complement this data with judge information from the Free Law Project and LexisNexis. 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.

LexisNexis 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.[1] For each of the filings collected from the Free Law Project and LexisNexis, 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 contains 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. 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.[2]

Table 1 presents summary statistics for my sample. Panel A shows the charac-

[1] The keywords I use include 'antitrust', 'anti-competitive', 'Clayton Act', and 'Sherman Act.'

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

teristics 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.[3] 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 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. It is worth noting the differences between defendant firms that are dismissed from antitrust cases and those that are not dismissed. For example, the average defendant in a dismissed case has more assets and engages in larger acquisitions. The differences between dismissed and non-dismissed defendant firms highlight the endogeneity in antitrust litigation outcomes. It is, therefore important that I employ an identification strategy in assessing the real impact of the litigation outcomes.

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

[3]The 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 the Article III and Article IV federal courts.

by estimating the following baseline specification:

$$Y_{i,t+k} = \alpha + \beta FailToDismiss_{cit} + \gamma X_{cijt} + \theta_t + \delta_d + \mu_k + \epsilon_c \,, \tag{1}$$

where the dependent variable $Y_{i,t+m}$ is a measure of post-litigation defendant firm outcomes such as acquisition activities and investment intensity at firm i in year $t+k$. I am interested in estimating β, which captures the impact of going through antitrust litigation on $Y_{i,t+m}$ 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 fail to dismiss antitrust cases tend to have fewer assets and spend less on R&D, which will also affect their future investment and acquisition decisions. Therefore, to identify the causal impact of antitrust litigation on firm decisions, I rely on the random assignment of judges to antitrust cases and use judge heterogeneity in their 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:

$$NonDismissalRate_{cj} = \frac{NonDismissal_{cj}}{N_{cj}} - \frac{NonDismissal_{cd}}{N_{cd}}, \tag{2}$$

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 rejected 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. By subtracting the average non-dismissal rate of the division, $NonDismissalRate_{cj}$ 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, the case is randomly assigned to one of the federal judges in the division where it 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 judges in the U.S. bankruptcy court system. 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, allowing cases to be randomly assigned even when certain judges are busy. I further show evidence supporting the random assignment of judges in Section 4.2.2.

Next, I rely on the random assignment 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:

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

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) 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 5.4, 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:

$$Y_{i,t+k} = \alpha + \beta \widehat{FailToDismiss}_{cit} + \gamma X_{cijt} + \theta_t + \delta_d + \mu_k + \epsilon_c \,, \tag{4}$$

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, an 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 $NonDismissalRate_{cj}$ 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 14.5-17 percentage points, which is equivalent to a 35.3-41.4% increase from the unconditional probability of 41.1%. Depending on the control variables included, the F-statistic ranges between 11.158 and 101.4, 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, $NonDismissalRate_{cj}$, explains about 11.8% of the total variation in antitrust litigation outcome, 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 16.8% 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 probability of case dismissal by 18.2 percentage points, 15.4 percentage points, and 6.3 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 firm 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 most of these control variables are not statistically different from zero, except for $Male$. Specifically, male federal district judges are less likely to dismiss antitrust cases, compared to their female counterparts, by 5.1 percentage points. 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. Although it is not possible to empirically test this assumption, the random assignment of judges strongly supports it. In Table 3, 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 0.159 shows that differences among divisions and over time explain a substantial amount of variation in judge non-dismissal propensity. Recently, (Hüther and Kleiner (2022)) find evidence that sophisticated investors can predict the assignment of bankruptcy judges by exploiting the small number of judges in the U.S. bankruptcy court system. Therefore, it is essential to examine whether the plaintiffs in my setup can influence judge assignments. 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 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 Impact of Antitrust Litigation

5.1. Antitrust Litigation and Firm Acquisition Activities

Table 4 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 random 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 101.4 to 21.088, but the coefficient estimates in columns 2 and 3 are very close in magnitude. Specifically, failure to dismiss an antitrust case causes a 31.4 percentage points reduction in the likelihood of acquisition. Overall, the results in Table 4 indicate that going through an antitrust case dramatically reduces the prospect of acquisition.

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 4, 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 the antitrust filing, consistent with the random 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, indicating a dramatic yet transient effect.

Table 5 presents two alternative dependent variables that capture firm acquisition activities. 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 4. 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. 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 42.9%. 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 -1.798 implies a reduction in average acquisition size by 83.4%. Overall, the results are consistent with my findings in Table 4.

5.2. Antitrust Litigation and Firm Investment Activities

External acquisitions and internal investments are often considered substitutes for each other (Mermelstein et al. (2020)). Ideally, by preventing 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 6 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 4, 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 transient, as shown in Figure 3, whereas Cortes et al. (2021) model a complete shut down of the acquisition market. Therefore, the incumbent firms exposed to antitrust litigation, knowing that the negative impact is transient, continue to invest in R&D in hopes of achieving synergies through future acquisitions.

5.3. Antitrust Litigation and Firm Access to Innovation

Accessing innovation through investments and R&D instead of acquisitions can be costly to big firms (Phillips and Zhdanov (2013)). Does antitrust litigation affect defendant firms' ability to access innovation in the long run? Table 7 examines the impact of the failure to dismiss an antitrust case on a defendant firm's patenting activities. The regression specifications follows those in Table 4. 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. The coefficient estimates of the IV-2SLS regressions are close to zero and statistically insignificant. In other words, there is no evidence that antitrust enforcement hinders the defendant's ability to access innovation in the long run. While defendant firms that go through antitrust litigation face a lower prospect for acquisition, it seems that the firms can substitute acquisition with internal investments.

5.4. 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 judgment or summary judgment 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 8 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 their 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 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 9 presents the regression estimates using the alternative instrument. The regression specifications follow those in Tables 4 and 6. 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. In rare occasions, the Federal Trade Commission and Department of Justice bring antitrust litigation to the court to stop proposed acquisitions. In practice, an 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 10 shows that the regression estimates are almost identical to my previous results.

6. Conclusion

In this paper, I investigate the real impact of antitrust litigation on corporate acquisition and investment decisions. 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 random assignment of judges and uses the variations in judge propensity to dismiss antitrust cases as an instrument for the endogenous litigation outcomes.

There are a few key empirical findings. First, I show that judge 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. Last but not least, I find no evidence that antitrust enforcement hinders the defendant's ability to innovate. The results show the impact of antitrust enforcement on firm decisions and highlight an important channel through which the judicial appointments of judges could affect the antitrust enforcement. Lawmakers need to carefully consider the amount of judge discretion allowed in current antitrust policies for them to be enforced effectively and fairly.

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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.

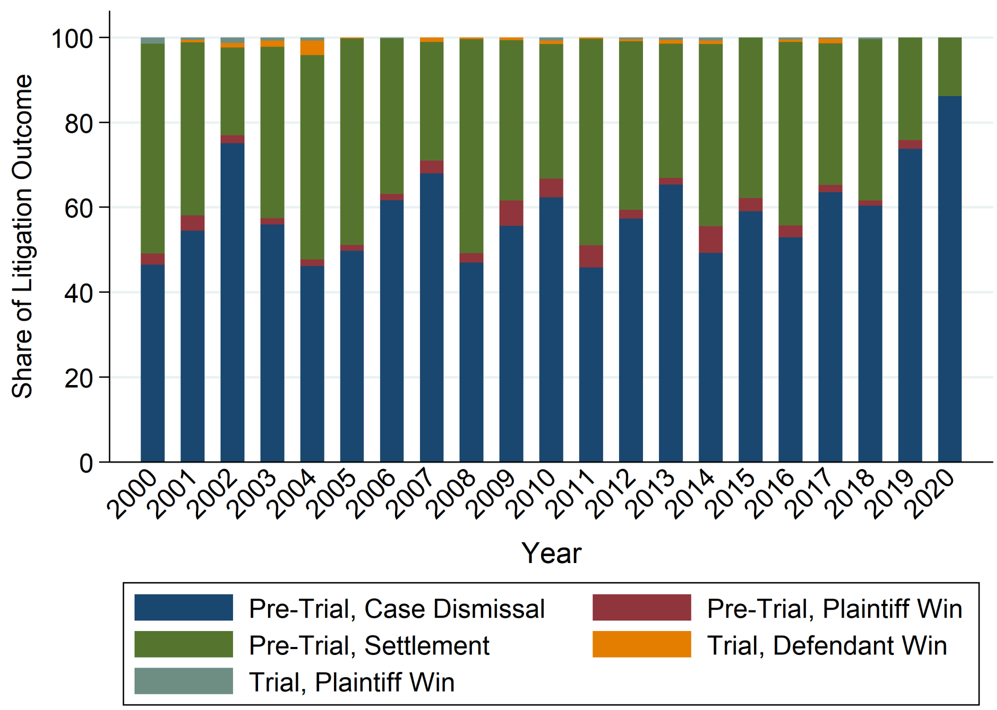

Figure 2: Number of Filings by Year

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.

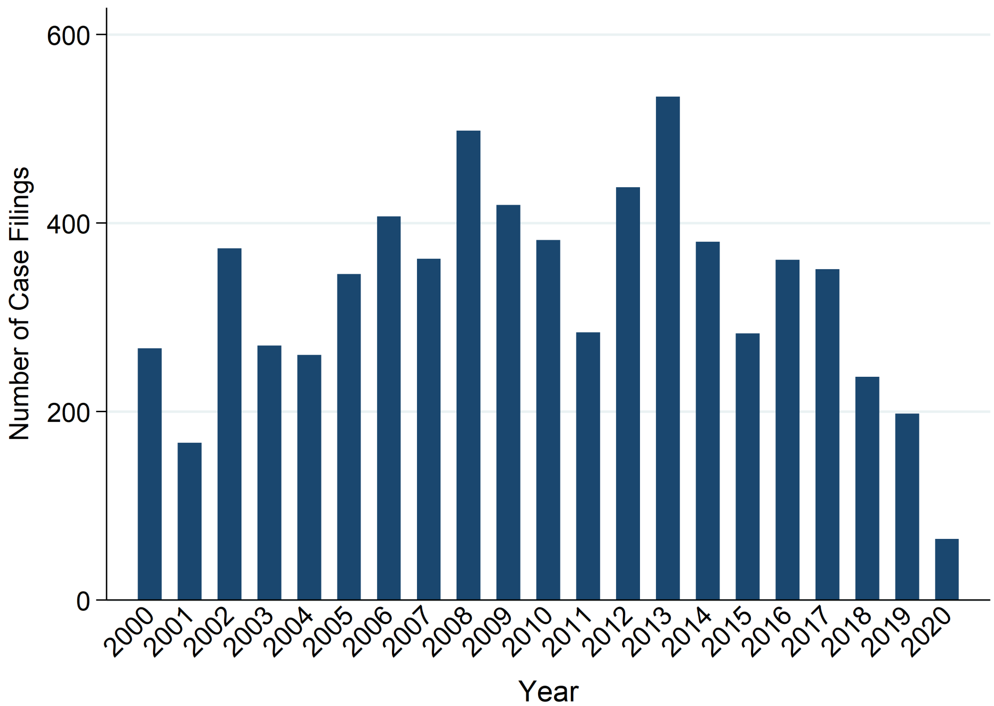

Figure 3: Dynamics of Acquisition Deterrence

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.

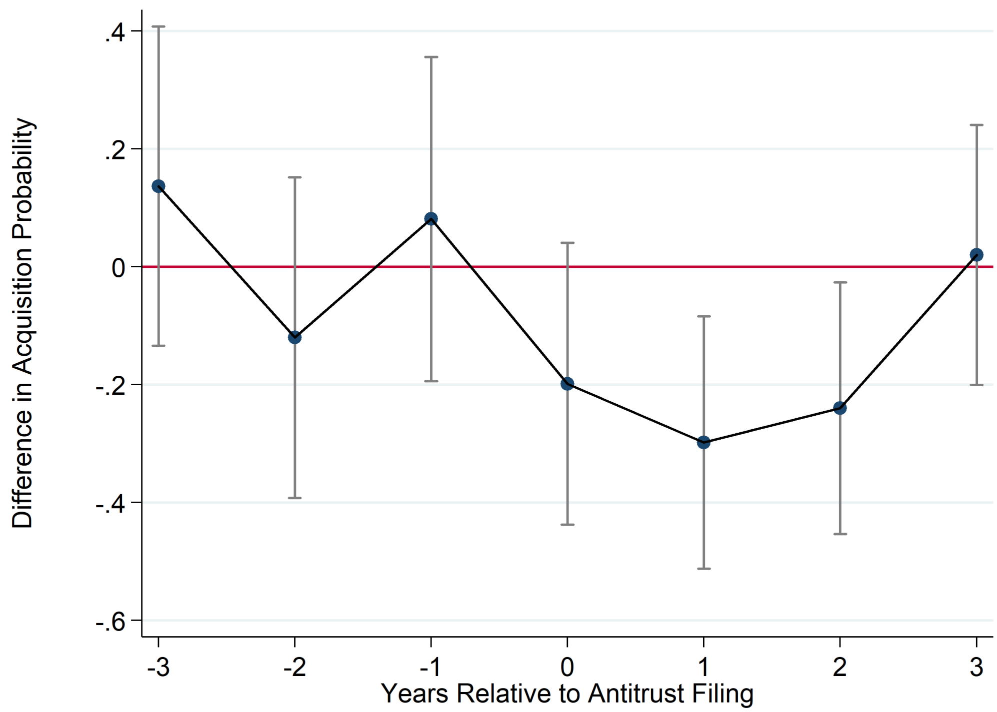

Table 1: Summary Statistics

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 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.
a. Judge			
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
b. Plaintiff			
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.
a. Acquisition Activities									
Acquisition Dummy	3930	0.33	0.47	2314	0.33	0.47	1616	0.33	0.47
Number of Acquisitions	3930	0.52	0.95	2314	0.52	0.93	1616	0.52	0.99
Total Acquisition Size, ($mm.)	3930	1329.17	6458.28	2314	1527.23	7241.46	1616	1045.55	5121.74
Average Acquisition Size, ($mm.)	3930	989.96	4547.52	2314	1111.84	4822.29	1616	815.44	4117.48
b. Financial Information									
Total Assets, ($bn.)	2558	153.04	443.75	1502	164.40	464.96	1056	136.88	411.39
Leverage	2558	0.28	0.23	1502	0.28	0.21	1056	0.28	0.24
Market-to-Book Ratio	2558	2.22	1.66	1502	2.26	1.57	1056	2.17	1.78
Capital Intensity	2558	0.22	0.13	1502	0.22	0.13	1056	0.22	0.13
R&D Intensity	2558	0.04	0.05	1502	0.05	0.06	1056	0.04	0.05
c. Patenting Activities									
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 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 include 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)
Non-Dismissal Rate	0.631***	0.547***	0.547***	0.546***	0.541***
	(0.076)	(0.054)	(0.053)	(0.054)	(0.053)
Federal or State Plaintiff			0.182***	0.187***	0.183***
			(0.056)	(0.057)	(0.057)
Public Firm Plaintiff			0.154***	0.154***	0.155***
			(0.031)	(0.031)	(0.031)
Class Action			0.063**	0.063**	0.066**
			(0.031)	(0.030)	(0.031)
Acquisition Dummy$_{t-1}$				0.025	0.034
				(0.077)	(0.074)
Log(Number of Acquisitions$_{t-1}$)				-0.016	-0.017
				(0.052)	(0.049)
Log(Average Acquisition Size$_{t-1}$)				-0.005	-0.007
				(0.010)	(0.010)
Republican					-0.029
					(0.030)
Well Qualified by ABA Rating					0.043
					(0.033)
White					0.029
					(0.034)
Male					0.051*
					(0.029)
Age					-0.001
					(0.003)
Tenure					0.002
					(0.003)
Army Experience					-0.007
					(0.054)
Private Practice Experience					-0.047
					(0.041)
Public Service Experience					-0.053*
					(0.031)
Division FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
F-Stat	68.230	101.400	36.555	21.088	11.158
Observations	3930	3930	3930	3930	3930
Adjusted R^2	0.118	0.286	0.296	0.296	0.298

Table 3: Random Assignments of Judges

This table illustrates the random 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	Non-Dismissal Rate			
	(1)	(2)	(3)	(4)
Federal or State Plaintiff		-0.012	-0.011	-0.024
		(0.034)	(0.034)	(0.031)
Public Firm Plaintiff		0.011	0.010	-0.009
		(0.022)	(0.022)	(0.017)
Class Action		0.030	0.030	0.023
		(0.020)	(0.019)	(0.018)
Log(Number of Acquisitions$_{t-1}$)			-0.023	0.012
			(0.053)	(0.041)
Log(Average Acquisition Size$_{t-1}$)			0.003	-0.002
			(0.007)	(0.006)
Division FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes
Observations	3930	3930	3930	3930
Adjusted R^2	0.159	0.161	0.160	0.271

Table 4: 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 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	-0.039*	-0.327***	-0.314***
	(0.023)	(0.122)	(0.114)
Control Variables	Yes	No	Yes
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	.401	.401	.401
First Stage F-Stat		101.400	21.088
Observations	3930	3930	3930
Adjusted R^2	0.342	0.301	0.347

Table 5: 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 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(Number of Acquisitions)			Log(Avg Acquisition Size)		
	OLS	IV-2SLS	IV-2SLS	OLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)	(4)	(5)	(6)
Fail to Dismiss	-0.048*	-0.569***	-0.560***	-0.103	-1.887**	-1.798**
	(0.029)	(0.151)	(0.136)	(0.165)	(0.768)	(0.729)
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		101.400	21.088		101.400	21.088
Observations	3930	3930	3930	3930	3930	3930
Adjusted R^2	0.463	0.429	0.474	0.333	0.304	0.338

Table 6: 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 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*	0.070***	0.070***	-0.001	0.025*	0.019***
	(0.007)	(0.025)	(0.024)	(0.002)	(0.013)	(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	.205	.205	.205	.043	.043	.043
First Stage F-Stat		67.475	19.056		67.475	19.056
Observations	2558	2558	2558	2558	2558	2558
Adjusted R^2	0.638	0.621	0.641	0.858	0.547	0.860

Table 7: 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 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 Dummy			Log(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**	0.004	-0.064	-0.049	0.083	-0.534
	(0.026)	(0.196)	(0.187)	(0.164)	(1.155)	(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	.808	.808	.808	3.332	3.332	3.332
First Stage F-Stat		35.798	10.784		35.798	10.784
Observations	1903	1903	1903	1903	1903	1903
Adjusted R^2	0.478	0.377	0.475	0.695	0.594	0.695

Table 8: Robustness - Settlements Only

This table addresses the concern that the my 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 4 and columns 2 and 5 in Table 6, 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
	IV-2SLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)
Fail to Dismiss	-0.299**	0.073***	0.028**
	(0.128)	(0.025)	(0.014)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	.405	.205	.043
First Stage F-Stat	95.192	62.558	62.558
Observations	3803	2532	2532
Adjusted R^2	0.308	0.620	0.548

Table 9: 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 4 and columns 2 and 5 in Table 6. 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
	IV-2SLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)
Fail to Dismiss	-0.576**	0.157***	0.041
	(0.249)	(0.059)	(0.037)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	.42	.201	.041
First Stage F-Stat	20.672	16.900	16.900
Observations	3311	2066	2066
Adjusted R^2	0.322	0.592	0.525

Table 10: Robustness - Private Claims

This table addresses the concern that the my 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 4 and columns 2 and 5 in Table 6, 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
	IV-2SLS	IV-2SLS	IV-2SLS
Model	(1)	(2)	(3)
Fail to Dismiss	-0.344***	0.081***	0.032**
	(0.129)	(0.027)	(0.015)
Division FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	.401	.205	.045
First Stage F-Stat	95.716	56.704	56.704
Observations	3686	2443	2443
Adjusted R^2	0.321	0.636	0.553

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 through 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
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