Are Judges Like Umpires?
Political Affiliation and Corporate Prosecutions

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Abstract

Exploiting the random assignment of cases to judges, we document that judges appointed by a Democrat president impose larger fines for corporate crimes involving environmental and labor regulations while Republican-appointed judges impose larger fines for crimes involving the hiring of illegal immigrants. These differences, which are robust to controlling for other judicial characteristics (e.g., age, race, and gender), do not appear to reflect fixed ideological differences as they become amplified during periods of greater political partisanship. The observed differences also become larger when judicial vacancies exist on a higher court, suggesting judicial career-motives might partly drive these findings. There is no evidence, however, that judges' political affiliations are associated with decisions on guilt.

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"Judges are like umpires. Umpires don't make the rules, they apply them... my job is to call balls and strikes, and not to pitch or bat."

– Chief Justice John G. Roberts, 2005

1 Introduction

The outcomes of corporate prosecutions can devastate even the largest multinational corporations and set long-lasting judicial precedents that affect how business operate. For example, the 2002 guilty verdict against Arthur Andersen (AA), one of the "Big 5" accounting firms with over 28,000 employees, resulted in the loss of AA's license to act as a certified public accountant, while the *New York Central and Hudson River Railroad v. United States* ruling of 1909 established that corporations are responsible for the actions of their employees. Increases in the sentencing fines imposed by judges, which exploded from about $500 million per year in the 1990s to over $4.5 billion in recent years (Garrett, 2014), can also shift companies' priorities, particularly if these changes are concentrated among certain types of crimes (e.g., the violation of labor regulations). In this paper, we assess whether judicial political affiliation influences the outcomes of corporate prosecutions and the monetary penalties imposed on companies.

As political polarization has increased, the potential importance of judicial political affiliations and related predispositions has received growing attention. Presidential nominations to the Federal Courts are increasingly framed in partisan terms as each political party worries that lifetime judicial appointments made by the other political party will result in future legal decisions and precedents that do not favor their political causes. Judges, however, argue that political affiliations do not affect their actions. For example, Chief Judge John G. Roberts attempted to counter concerns of judicial political bias in 2016 and 2018, when he stated, "[Judges] don't work as Democrats or Republicans" and "[W]e do not have Obama judges or Trump judges, Bush judges or Clinton judges."[1]

While concerns about judicial bias tend to focus on social issues like abortion and guns, judicial political affiliations could also be important for corporate criminal prosecutions and the broader economy. For example, if Republican-appointed judges are more likely to view the hiring of illegal workers as an important legal violation, the average outcome and resulting precedents of corporate immigration cases could be influenced by

[1]See www.nytimes.com/2018/12/23/us/politics/chief-justice-john-roberts-supreme-court.html.

the recent increase in Republican-appointed judges. Likewise, if Democrat-appointed judges are more likely to view the protection of the environment as important, the outcomes of cases involving corporate pollution could shift as well. Any such shift in the expected penalties for violating certain regulations could then influence how companies operate (e.g., by changing firms' hiring practices or investment choices).

To assess whether judicial political affiliations affect the outcomes of corporate prosecutions, we construct data on federal corporate prosecutions and the political affiliation of federal judges, which are nominated by the President for lifetime appointments. We begin by using the Corporate Prosecutions Registry, which provides information on federal criminal corporate prosecutions in the US from 2000 to 2018, and augment this data by extracting additional information from each case's docket. Our data include information on the filing date, judgement date, the type of crime being charged, outcomes (e.g., trial conviction, acquittal, plea deal, etc., and monetary damages assessed, if any), and most importantly, the judge's name. We then match each judge name to the political affiliation (Republican versus Democrat) of the president that nominated the judge. This allows us to assess whether the political affiliation of the appointing president is associated with the outcome of corporate cases judges preside over.

Our analysis focuses on whether case outcomes depend on the combination of a judge's political affiliation and how partisan political views are with respect to the underlying crime being prosecuted. We classify two types of crimes in our sample as being related to highly partisan issues: immigration crimes (e.g., a firm hired illegal immigrants) and violations of labor and environmental regulations (e.g., a firm polluted a local river). According to the PEW Research Center's Ideological Consistency Scale, liberals tend to take a more positive view of labor and environmental regulations, while conservatives tend to place a larger emphasis on enforcing immigration laws. Therefore, if judicial political affiliations matter, we might see less favorable outcomes for companies accused of labor or environmental crimes when the case is overseen by a Democrat-appointed judge, and more favorable outcomes if the case instead involves immigration crimes.

To sign this potential partisanship split in views regarding the severity of the underlying crime, we assign cases involving labor or environmental crimes a *DemocratTilt* value of one, while cases involving immigration crimes are assigned a value of minus one. All other crimes that do not easily lend themselves to a partisan classification, like fraud, money laundering, and bribery, receive a *DemocratTilt* value of zero. We then assess whether outcomes vary as a function of *DemocratTilt* and judges' political affiliation.

Our identification strategy makes use of the random assignment of federal judges to cases. Once cases are assigned to a prosecution office in the US, a judge is randomly selected from the federal judges that preside over that particular jurisdiction (e.g., see Kling, 2006; Galasso and Schankerman, 2015; Dobbie and Song, 2015; Bernstein, Colonnelli, and Iverson, 2019). Consistent with random assignments, we find little evidence of differences in the distribution of crimes that Republican- and Democrat-appointed judges oversee within jurisdictions. This randomness provides us exogenous variation in our key explanatory variable of interest: judicial political affiliation. We then estimate the potential impact of this affiliation on the outcomes of corporate prosecutions using a difference-in-differences estimation that compares case outcomes as a function of differences in the political tilt of the underlying crime (i.e., *DemocratTilt*) and differences in the political affiliation of the judge (i.e., Democrat- vs. Republican- appointed judge).

Because of the granularity of our data, we are also able to control for judge, crime, and year fixed effects in our baseline difference-in-differences estimation. The judge fixed effects allow us to control for other judge-specific characteristics that might matter for the average outcome of cases overseen by a particular judge; the crime fixed effects allow us to control for average differences in the outcomes of different corporate crimes; and the year fixed effects control for any potential time trends in either judicial political affiliations or the outcomes of federal corporate prosecutions.

In our first set of findings, we document that the political affiliation of the appointing president is not associated with decisions of guilt. Specifically, we find that judicial political affiliation is not associated the likelihood of observing an acquittal, trial conviction, dismissal, plea deal, or some other pretrial agreement between the prosecutor and the accused firm, regardless of what type of crime is being prosecuted. This finding would seem to support Roberts' argument that "[W]e do not have Obama judges or Trump judges, Bush judges or Clinton judges," at least in the setting of corporate prosecutions.

These initial findings, however, do not imply that judges' political affiliations are unimportant in corporate prosecutions. Instead, they might reflect that decisions of guilt are typically decided by juries, not judges. An area where judges exert direct influence is in the amount of monetary damages that are assessed. In federal criminal cases, judges have sole discretion over the penalties imposed following a company's conviction or acceptance of a plea deal (which account for nearly 80 percent of the cases in our sample). Therefore, if judicial political affiliations matter, we might expect to observe differences in the monetary penalties imposed by judges of different political parties.

Consistent with judges having more influence over imposed penalties, we find that judicial political affiliation is associated with the level of monetary fines assessed in corporate prosecutions. For judges appointed by a Democrat, a one unit increase in the *DemocratTilt* of the underlying crime is associated with a 112 percent increase in the average fine. Given the average monetary damage attached to corporate prosecutions is $20.3 million and 62 percent of annual revenues, these changes are economically meaningful and correspond to a 0.3 standard deviation increase in the assessed damages. Moreover, the association between fines and judicial political affiliation is stronger when we exclude cases that result in a deferred prosecution (DP) or a non-prosecution (NP) agreement, which are pretrial agreements that do not require the approval of the presiding judge. Excluding these agreements, a one unit increase in *DemocratTilt* is associated with a 189 percent increase in the average fine imposed by Democrat judges. We also find suggestive evidence that judicial political affiliation is associated with the likelihood of a fine; for judges appointed by a Democrat, a one unit increase in *DemocratTilt* is associated with about a six percentage point increase in the likelihood of a fine.

The observed difference in average fines we document is being driven by both types of corporate crimes used to construct our case-level measure of *DemocratTilt*. Relative to cases with no clear partisan prediction (i.e., cases involving fraud, bribery, money laundering, etc.), assignment of a labor or environmental case to a Democrat judge results in monetary damages that are, on average, about 136 percent larger than what is observed for cases assigned to a Republican judge. For cases involving immigration, the fine is about 92 percent lower for Democrat judges relative to what is observed for Republican judges. Consistent with random assignment of cases to judges, none of our findings are affected by the inclusion of additional firm-level controls for factors that might be related to the level of monetary damages being assessed.

Our findings are not driven by just a small subset of judges. We continue to find large differences even after removing a random 20 percent of the judges from the sample. Nor are the observed differences driven by a handful of cases with particularly large monetary fines. The observed difference in penalties remains even when drop cases that exhibited a fine that was in the top five percent for a given year. Combined, these findings suggest a systematic difference in the outcome of cases as a function of judicial political affiliation.

We next analyze whether the importance of judicial political affiliation increases in the run-up to a congressional or presidential election. Elections are typically associated with increased partisanship as political candidates seek to distinguish themselves from their opponent and win elections (Gulen and Ion, 2015; Autor, Dorn, Hanson, Majlesi et al., 2016). If our findings are being driven by judges' political affiliation rather than fixed ideological differences between judges appointed by different political parties, we might expect the observed differences between Democrat- and Republican-appointed judges to increase during time periods of greater partisanship. This is exactly what we find.

Differences in the outcomes of corporate prosecutions are amplified during time periods of higher partisanship. In the four months prior to a national congressional or presidential election, a one unit increase in the *DemocratTilt* of a crime is associated with, on average, an additional 326 percent increase in the fine for cases assigned to Democrat-appointed judges. Because of our inclusion of judge fixed effects, these findings indicate individual judges are imposing different fines during periods of higher partisanship than in other time periods. We also find large differences during time periods of high and low political polarization, as calculated by Gallup's PEW Research Center. Specifically, only during periods of above average political polarization do we observe differences in the monetary fines assessed by Democrat- and Republican-appointed judges.

We next analyze whether career motives might influence penalties imposed by judges. Judges that seek an appointment to a higher, more prestigious court could use the magnitude of assessed penalties to signal their ideological compatibility to a nominating president (Savchak, Hansford, Songer, Manning, and Carp, 2006). To assess this possibility, we analyze whether the observed difference in penalties are amplified during months where there exists a vacancy on an appellate court that oversees a judge's current jurisdiction. About three-fourths of such vacancies occur in our sample because of a death, and presidential appointments to appellate courts are often made by nominating a federal judge that sits on a district court (the level of our analysis) that resides within the jurisdiction of the appellate court. Therefore, if judges seek to signal their political views through the magnitude of penalties they assess, their incentive to do so might be larger when a higher court vacancy exists for their jurisdiction.

While not as robust as our other findings, we find evidence that the observed differences in monetary penalties is larger when there exists a vacancy on a higher court that oversees a judge's jurisdiction. For judges appointed by a Democrat, a one unit increase in the *DemocratTilt* of the underlying crime is associated with an additional 295 percent increase in the average fine for cases decided during a vacancy on the higher court. Unlike our other findings, however, these estimates are not identified using within-judge variation and are instead estimated using cross-sectional variation across judges.

The estimates are quantitatively similar when including judge fixed effects but no longer statistically significant as we have very few judges that assess penalties for crimes of different *DemocratTilt* in both periods where there exists a vacancy and not.

A potential concern with our identification strategy is the possibility that political affiliation is associated with other judge-level characteristics that drive differential predispositions. While the average differences in outcomes associated with other judicial characteristics, like age, gender, and experience, would be controlled for by our inclusion of judge fixed effects, there still exists the possibility that these characteristics matter differently as a function of *DemocratTilt*. For example, if Democrat-appointed judges are more likely to be female and if females have a predisposition that labor crimes are serious for reasons that are unrelated to political affiliation, then our difference-in-differences findings could reflect differences in gender rather than differences in political affiliation.

However, we find no evidence that our findings are driven by other judicial characteristics that could be correlated with judicial political affiliations. In particular, we find no evidence that a judge's gender or experience is associated with differences in monetary damages assessed across cases with different levels of *DemocratTilt*. Nor does controlling for other judge-level characteristics, like age and gender, and their interaction with the underlying type of crime affect our estimates. It is also unclear why these, or other, judicial characteristics, would exhibit differential predispositions in the months prior to national elections or during periods where there exists a vacancy on a higher court. The estimates are also not sensitive to excluding districts where more than 75 percent of the judges were appointed by a particular political party, suggesting that forum shopping by prosecutors seeking a favorable judge is unlikely to explain our findings.

Our findings contribute to the growing literature on judicial biases, including those related to racial bias (e.g., see Arnold, Dobbie, and Yang, 2018). Whereas prior work has looked at the importance of judicial political affiliation on individual sentence lengths (e.g., Cohen and Yang, 2019; Schanzenbach and Tiller, 2007) and decisions pertaining to administrative law (Smith and Tiller, 2002), we study the implications for corporate prosecutions, which have the potential to impact the broader economy. Monetary damages assessed in these cases can bankrupt firms, resulting in a reorganization of companies' assets, liabilities, and workforce.[2] The outcomes of these corporate prosecutions can also

[2]For example, Insys Therapeutics, an Opiod manufacturer with over 300 employees, filed for Chapter 11 bankruptcy protection just five days after agreeing to pay $225 million as part of a plea deal with federal prosecutors over criminal charges related to bribery. See www.npr.org/2019/06/10/731363225/insys-files-for-chapter-11-days-after-landmark-opioid-settlement-of-225-million.htm.

influence the future operations of other businesses. For example, the imposition of large monetary damages for the willful hiring of illegal immigrants can deter future companies from hiring such workers, whereas smaller fines might not.[3] A back-of-the-envelope calculation using our estimates suggest that Donald Trump's election in 2016 will result in the average fine for immigration-related crimes being about 30.9% higher by the end of 2020 relative to what it would have been if Hillary Clinton had instead won the election.

The importance of judicial political affiliations we document is also connected to recent papers that analyze the importance of uncertainty on firms' choices. Political uncertainty negatively affects corporate investment (e.g., see Julio and Yook, 2012; Gulen and Ion, 2015; Bonaime, Gulen, and Ion, 2018; Kaviani, Kryzanowski, Maleki, and Savor, 2019), and uncertainty about economic policy negatively affects both investment and employment (e.g., see Baker, Bloom, and Davis, 2016). Our findings suggest that firms also face uncertainty about the penalties they may face for breaking various laws. If this uncertainty affects firms' incentives to abide by existing regulations and laws, our findings suggest a novel channel through which politics can affect real economic outcomes, which may be increasingly important given recent increases in political polarization (e.g., see Iyengar, Sood, and Lelkes, 2012; Mason, 2013; Mason, 2015; Gentzkow, 2016; Boxell, Gentzkow, and Shapiro, 2017), which amplifies the judicial uncertainty we document.

Finally, we contribute to the recent literature on how partisanship can influence economic behavior. Whereas previous work has documented the impact of political partisanship on credit analysts (Kempf and Tsoutsoura, 2019), economic expectations and spending (e.g., Gerber and Huber, 2009; Mian, Sufi, and Khoshkhou, 2018), portfolio holdings (Meeuwis, Parker, Schoar, and Simester, 2018), and stock returns (Addoum and Kumar, 2016), we document that partisanship also affects how companies fare in the courts. Because federal judicial appointments are for life, these findings show that a shift in the political party holding the presidency and senate can have a long-lasting impact on the extent to which different corporate laws are enforced through the courts.

[3]Prosecutors, judges, and regulators are very cognizant of these potential future ramifications. For example, following the 2017 guilty plea of Asplundh, a tree-trimming company of 30,000 employees accused of willfully hiring illegal immigrants, regulators held out the $95 million in record fines as sending a "strong, clear message to employers who scheme to hire and retain a workforce of illegal workers." See www.ice.gov/news/releases/asplundh-tree-experts-co-pays-largest-civil-settlement-agreement-ever-levied-ice and www.usatoday.com/story/money/2017/09/29/tree-company-asplundh-pay-record-fine-immigration-practices/715729001/.

2 Data and Summary Statistics

To analyze the importance of judicial political affiliations on corporate prosecutions, we begin by collecting information on federal corporate prosecutions concluded in the US from 2000 to 2018. The list of corporate prosecutions is obtained from the Corporate Prosecutions Registry (see Garrett and Ashley, 2017), which is produced jointly by Legal Data Lab at the University of Virginia School of Law and Duke University School of Law and made available at the University of Virginia Law School website. The registry contains a list of 3,354 cases that were concluded between 2000 and 2018.[4] For each prosecution case, the registry provides us information on a number of variables, including the case name, name of the corporation involved, outcome of the case (e.g., plea, trial conviction, acquittal, etc.), crime code (i.e., the type of crime being prosecuted), docket number, judgement date, and the amount of monetary damages assessed, if any.

Because the registry does not provide us full details about each case, including the assigned judge's name, we extract additional information about each case from the official dockets using the available docket number. The dockets of each case are made available by Public Access to Court Electronic Records (PACER) and available at `www.pacer.gov`. Using a Python algorithm, we extract information from the dockets for some of our key variables, including the assigned judge's name and jurisdiction.[5] Of the original 3,354 federal corporate prosecutions obtained from the Corporate Prosecutions Registry, we are able to obtain the judge's name for 2,795 cases, which are overseen by 741 unique judges.[6] The median number of cases observed per judge is three.

To identify the political affiliation of each federal judge in our sample, we rely on judicial biographies provided on the United States Courts' website. In particular, we define the political affiliation of the judge using the information provided on the US Courts' website regarding the president that appointed the judge. Judges appointed

[4]Legal Data Lab only claims to provide complete coverage beginning in 2001, but because we observe a similar number of cases in 2000 as in other years, we retain these cases for our analysis. We do not, however, include the 15 cases from 1992-1999 as it is clear the registry is incomplete in these years. We also exclude six cases that are missing a date. See http://lib.law.virginia.edu/Garrett/corporate-prosecution-registry for more details about the registry data and its coverage.

[5]While the registry does provide information on case jurisdictions, many of them are missing or recorded with error. Therefore, we update all jurisdiction information using the official dockets.

[6]Cases without a judge's name were those assigned to a magistrate, which are judges appointed to assist a district court. Unlike district judges, which are nominated by the President, confirmed by the US Senate, and appointed for life, magistrates are appointed for set term by the federal judges of that district. It is unclear why some cases are missing the jurisdiction, but our subsequent findings are robust to using the smaller sample that excludes cases with incomplete jurisdiction information.

by a Republican president are assigned a Republican political affiliation, while judges appointed by a Democrat president are assigned a Democrat political affiliation.

The judicial biographies also allow one to illustrate the importance of presidential elections for proportion of judges appointed by each political party. This is shown in Figure 1, where we plot the yearly fraction of active district-level Federal judges appointed by a Democrat next to indicators for when a new president was elected by each party. On average, the share of judges appointed by the winning political party increases by about nine percentage points over the first 4-year term of a newly-elected president.

The types of federal crimes being prosecuted in our final sample of cases are wide-ranging. The frequency of different crimes is presented in Table 1. The most common type of crime, accounting for 18.3 percent of our cases, are those involving general fraud. The second and third most common are environmental crimes and antitrust cases, accounting for 15.8 and 9.7 percent respectively. Immigration violations account for a smaller 4.5 percent (125 cases), but the frequency of such cases has increased almost threefold in recent years. In total, there are 24 crime types covered in our database.

There are six possible prosecution outcomes in our sample: trial conviction, acquittal, plea deal, deferred- or non-prosecution agreement (DP or NP agreements), declination, or dismissal. The first two reflect cases that reach a trial verdict, while the next two reflect cases that end with an agreement being reached between the prosecuting office and the accused company that negates the need for a trial. Plea bargains are when a company admits guilt and the terms of the punishment are set by the presiding judge. DP and NP agreements, however, reflect a negotiated agreement between the defendant and the government that is imposed and monitored outside the judicial system. In these agreements, the defendant may or may not admit guilt but agrees to certain conditions, which can include fines, in exchange for the government agreeing to not move forward with the formal charges and eventually dropping the charges once these conditions are met.[7] The remaining cases either result in the prosecutor declining to pursue the case (i.e., a declination) or the judge dismissing the charges (i.e., a dismissal).

Descriptive statistics on the outcomes of the cases in our sample are provided in

[7]One reason firms might accept DP/NP agreements and pay fines while maintaining their innocence is because they likely avoid higher penalties that would be imposed if they proceed to trial and are eventually convicted. For example, in one DP case in our sample, the fines were only $45,000 while the docket states that the expected penalty in a trial would be more than 1.5 million dollars. Prosecutors might also offer DP/NP agreements in cases where they think proving their case in court might be difficult. See http://www.mololamken.com/news-knowledge-18.html for more details.

Table 2. Only 0.43 percent of cases result in a trial conviction, and 0.39 percent of cases result in an acquittal at trial. The large majority of cases never reach a trial because of an agreement being reached between the prosecuting office and the accused company. About 79.79 percent of cases result in a plea deal while DP and NP agreements account for 14.96 percent of outcomes. The charges are dismissed by the judge in 3.72 percent of cases, and prosecutors decline to pursue charges in the remaining 0.72 percent of cases.

The fines imposed in corporate prosecutions can be quite large and wide-ranging. This is shown in Table 3. Fines are only observed in trial convictions, plea deals, and DP/NP agreements, and 1,925 of our 2,795 cases report a fine. The average monetary damages imposed in this sample is $20.30 million, and there is considerable variation in fines across cases, as seen by the large standard deviation of $103.94 million. When DP/NP agreements are excluded, the average monetary damages imposed by judges are $17.19 million. For the 165 companies that we can match to Compustat and obtain data on annual revenues, we find that the average fine is about 62 percent of a firm's revenues for that year, while the median fine is about 1 percent of annual revenues.

There is a roughly even split in the proportion of cases overseen by Democratic and Republican judges. Judges appointed by a Democratic president preside over 53.4 percent of cases, and judges appointed by a Republican president account for the remaining 46.6 percent of cases. We now turn to providing more details on the process by which federal judges are assigned to cases and our identification strategy.

3 Identification Strategy

In the US, corporate cases are not assigned to federal prosecutors' offices under any hard and fast rule. There can be multiple offices that have a claim to jurisdiction. An office may have jurisdiction because of the place where alleged illegal activities occurred, because of where the targeted company is headquartered, and in the case of public companies, because of where the company's shares are listed. In practice, the first federal prosecutor's office to file a case tends to retain jurisdiction, even if other offices are potentially interested in pursuing the matter (see Chemerinsky, 2018).

In total, there are 94 geographic-based district court jurisdictions, which each fall within one of twelve geographic-based appellate court jurisdictions. In addition to these district courts, there are a few specialized federal courts that have nationwide jurisdiction over certain cases. In total, our sample spans 94 different jurisdictions, 89 of which reflect geographic district court jurisdictions. The remaining five jurisdictions, "US Antitrust," "US Criminal," "US Tax," "US Environmental," and "US National Security" likely refer to cases that are overseen by judges from one of the nationwide specialized federal courts.[8]

Our identification strategy makes use of the random assignment of federal judges to cases filed in their jurisdiction. This assignment process is overseen by each district court and its chief judge and has been used in previous studies of judicial impact (e.g., see Abrams, Bertrand, and Mullainathan, 2012; Anwar, Bayer, and Hjalmarsson, 2012; Chang and Schoar, 2013; Cohen and Yang, 2019). The random allocation is used to ensure an equal allocation of cases to judges and to prevent prosecutors or defendants from seeking favorable judges, and as noted on the US Courts' website, "[t]he majority of courts use some variation of random drawing" to allocate cases to judges.[9] This random assignment of judges provides the exogenous variation in our key explanatory variable of interest, judicial political affiliation, and allows us to test whether judicial political affiliation affects the outcomes of cases. For example, do companies in cases randomly assigned to a Democrat judge receive harsher (smaller) penalties when the underlying crime involves a political issue that Democrats tend to care more (less) about?

Consistent with a random assignment of cases to judges, the cases overseen by Democrat and Republican judges are similar in variety of dimensions. This is shown in Table 4. The proportion of cases that involve environmental and labor crimes are similar for judges appointed by Republican and Democrat presidents and account for about 17 percent of all cases for both types of judges. Additionally, the characteristics of firms being prosecuted is similar for Republican and Democrat judges. About 11 percent of firms are publicly-listed for both types of judges, and 11 percent of the firms have a criminal record. In neither case, can we reject the null hypothesis that the average characteristics of firms assigned to judges varies as a function of political affiliation.

While there is evidence that Republican-appointed judges see a higher proportion of immigration cases, this difference disappears when we control for jurisdiction, which is the level at which the random assignment of cases supposedly occurs. This is shown in Appendix Table A.1, where we regress indicators for the ten most frequent crime types onto jurisdiction fixed effects and an indicator for the judge being appointed by

[8]Because the assignment process for judges in these non-geographic distributions is less clear, we will later show that our subsequent findings are robust to excluding the 333 cases in these five jurisdictions. Our findings are also robust to dropping 57 cases where we are only able to identify the state where the case was held but not the district court jurisdiction within that state.

[9]See http://www.uscourts.gov/faqs-filing-case for more details on this allocation process.

a Democrat. We find little evidence that the distribution of cases within jurisdictions is systematically different for Democrat- and Republican-appointed judges. In further support of a random assignment process, we also find no evidence that the partisan tilt of the underlying crime or other characteristics of the prosecuted company predict the political affiliation of the presiding judge. This is shown in Appendix Table A.2.

3.1 Difference-in-differences estimation

For our main tests, we analyze the impact of judicial political affiliation on the outcomes of cases using a difference-in-differences type of estimation. The first difference is with respect to the political affiliation of the randomly assigned judge: Democrat versus Republican. The second difference is with respect to whether the alleged corporate crime involves a political issue where Democrats and Republicans tend to exhibit sharply different views versus cases involving crimes that are less related to partisan issues. The underlying assumption of our test is that in the absence of partisan predispositions, there would not be any observed difference in outcomes for cases assigned to Democrat judges that touch upon partisan issues relative to that of other cases.

To bolster our underlying identification assumption, we augment the standard difference-in-differences estimation by allowing case outcomes to vary as a function of the crime, judge, and year. Specifically, we will include crime fixed effects to control for the average outcome of different types of crimes and the possibility that, even after the random assignment of cases, Democrat (or Republican) judges happen to end up being assigned more of a particular type of crime, though, as shown in Table 4 and Appendix Table A.1, we find a relative similar distribution of crime types across judges. We also include judge fixed effects to control for the average difference in outcomes one might observe across judges for other reasons (like gender, race, and experience), and we include year fixed effects to control for any potential time trends in average case outcomes.

3.2 Classifying the partisan tilt of corporate crimes

We identify crimes likely to involve issues strongly associated with an individual's political predispositions using the PEW Research Center's Ideological Consistency Scale, which PEW uses to quantify the share of Americans who hold "ideologically consistent" liberal or conservative views across a range of topics.[10] The PEW ideology scale identifies important issues for individuals with liberal and conservative political views in the US. For example, according to PEW's Ideological Consistency Scale, liberals are much more likely to think businesses make too much profit and should be regulated and that protecting the environment is important, while conservatives are more likely to think immigrants are a burden on the country and take US jobs.

Looking over the list of crimes in our sample (see Table 1), there are three broad types of crimes connected to highly partisan topics found in PEW's scale: those involving environmental damages and regulations (i.e., crime types "Environmental," "Act to Prevent Pollution from Ships," and "Wildlife"), those involving labor regulations and the protection of workers (i.e., crime type "OSHA / Workplace Safety / Mine Safety"), and those involving violations of immigration laws and the hiring of illegal workers (i.e., crime type "Immigration"). According to PEW's consistency scale, we might expect Democrat judges to view environmental and labor crimes as more serious, while Republican judges might view immigration crimes as more serious. The remaining types of crimes in our sample, such as those related to fraud, antitrust, money laundering, etc., have no clear association with any of the questions used by PEW to classify an individual's ideology.[11]

We next create a variable, *DemocratTilt*, to classify how seriously a Democrat is likely to view the underlying crime based on where partisan viewpoints for that particular topic usually fall. Specifically, we set *DemocratTilt* equal to one for corporate prosecutions involving environmental or labor crimes and equal to minus one for prosecutions involving immigration crimes. All other crime types, which have no clear connection to a partisan issue on PEW's scale, receive a *DemocratTilt* value of zero.

[10] See www.people-press.org/2014/06/12/appendix-a-the-ideological-consistency-scale/. This is also sometimes referred to as "ideological constraint" or "ideological sorting" by political scientists and other researchers. The concept of ideological constraint refers to the existence of psychological and logical pressures upon an individual to make decisions and respond to political stimuli in a way consistent with his perceived interest (see Jackson and Marcus, 1975; Jackson, 1975; Green, Palmquist, and Schickler, 2004; Bordalo, Coffman, Gennaioli, and Shleifer, 2016).

[11] Consistent with these crimes being potentially less partisan in nature, we find little evidence of a Republican versus Democrat difference in fines for the ten other most common crime types. In particular, we find no difference in the average fine of these other crimes, except for crimes involving the Foreign Corrupt Practices Act, which tend to exhibit larger fines when assigned to a Democrat judge.

3.3 Empirical specification

The main specification we estimate is

$$\begin{aligned} Outcome_{i,j,k,l,t} =& \beta Democrat_j \times DemocratTilt_k \\ &+ Judge_j + Crime_k + Year_t + \epsilon_{i,j,k,l,t}, \end{aligned} \tag{1}$$

where $Outcome_{i,j,k,l,t}$ is the outcome in case i that was assigned to judge j involving crime code k in jurisdiction district l and decided in year t, $Democrat_j$ is an indicator that equals one when the assigned judge was nominated by a Democrat president, and $Judge_j$, $Crime_k$, and $Year_t$ are judge, crime type, and year fixed effects, respectively. We double cluster our standard errors at the levels of the crime and judge, but our findings are robust to clustering at other levels (e.g., judge, crime, or judge and jurisdiction) or to just using standard errors that are robust to heteroskedasticity.[12]

The coefficient on the interaction $Democrat_j \times DemocratTilt_k$ reflects our difference-in-differences estimate. β will capture the average difference in case outcomes for Democrat- versus Republican-appointed judges for a one unit increase in the assumed partisan tilt of the underlying crime, *DemocratTilt*, after controlling for the judge, crime, and year. We do not include the separate controls for *Democrat* and *DemocratTilt* as they are co-linear with the judge and crime fixed effects, respectively. In subsequent tests, we will also separately report the differences in outcomes for environmental and labor cases (i.e., cases with a *DemocratTilt* value of 1) and immigration cases (i.e., cases with a *DemocratTilt* value of -1) relative to the difference for all other cases (i.e., cases with a *DemocratTilt* value of zero) so as to better understand what type of cases contribute to our estimate.

The key assumption of our difference-in-differences estimation is that in the absence of biases related to political affiliations, we would not observe any differential outcomes across cases based on the underlying nature of the crime and its connection to the average views of the two political parties. This assumption, however, would be violated if a judge's political affiliation is correlated with other judge-level characteristics that drive differential outcomes for cases we assign as being more likely partisan in nature. For example, if Democrat judges are more likely to be female and females tend to have a

[12] In our setting, it is not obvious what the appropriate level of clustering, if any, is since our key explanatory variable is measured at the judge-crime level. In our subsequent findings, we present standard errors double clustered by judge and crime as these tend to give more conservative standard errors for our coefficient of interest, β, relative to other clustering choices or to not clustering at all, but in later tests we show that our findings are robust to alternative clustering choices.

predisposition that environmental crimes are more serious for reasons that are unrelated to political affiliation, then our difference-in-difference estimates could reflect differences in gender rather than differences in political affiliation. In our later tests, we show the robustness of our findings to including controls for other judge-level characteristics and their interaction with *DemocratTilt*. We now turn to our empirical findings.

4 Empirical Findings

In this section, we begin by documenting average differences in outcomes for Democrat- and Republican-appointed judges. We then move to our main difference-in-differences specification to assess whether there exist differential outcomes as a function of the political affiliation of the appointing president and the underlying partisan nature of the case. We also test for whether any observed differences in judicial outcomes vary over time in ways that might suggest a potential political bias rather than fixed ideological differences between judges appointed by a particular party. Specifically, we assess whether outcomes vary based on the extent of overall partisanship in the time period where the case is decided, as proxied by there being an upcoming congressional or presidential election, and in time periods where judicial career motives might be greater, as proxied for using the existence of a vacancy in a higher court to which a judge might seek to serve. Finally, we test the robustness of our findings and explore the possibility of alternative explanations.

4.1 Political affiliation and average outcomes

Before estimating our main difference-in-differences specification, as given in Equation (1), we begin by assessing whether a judge's political affiliation is associated with the average outcome in corporate prosecutions. We do this by estimating

$$\begin{aligned} Outcome_{i,j,k,l,t} =& \eta Democrat_j + \gamma X_j + \delta Z_i \\ & + Crime_k + Jurisdiction_l + Year_t + \mu_{i,j,k,l,t}, \end{aligned} \tag{2}$$

where $Outcome_{i,j,k,l,t}$ is the outcome of case i that was assigned to judge j involving crime code k located in jurisdiction l in year t, $Democrat_j$ is an indicator that equals one when the assigned judge was nominated by a Democrat president, X_j are other characteristics of the judge (e.g., age, race, and gender) that might matter for prosecution outcomes, Z_i are characteristics of the defendant (e.g., public firm, firm with criminal history), and $Crime_k$, $Jurisdiction_l$, and $Year_t$ are crime, jurisdiction, and year fixed effects, respectively. Unlike our main specification, we include jurisdiction rather than judge fixed effects here because the *Democrat* indicator is co-linear with the judge fixed effects.

We find little evidence of a difference in the average outcome of cases assigned to Democrat- and Republican-appointed judges. This is shown in Table 5. Controlling for the jurisdiction, crime, and year, we find no difference in the proportion of cases that result in a plea deal, trial conviction, acquittal, etc. This is shown in Columns 1-6 of Table 5, where we use an indicator for each potential case outcome as our dependent variable. We also find no difference in the average level of fines, as shown in Column 7 where we use the natural log of assessed fines as our dependent variable. The sample size drops from 2,737 to 1,885 in this last regression because *Ln(Fine)* is not defined for cases with no fine.[13] We continue to find little association between case outcomes and judicial political affiliation when we add additional controls for other judicial characteristics, like gender, age, race, and experience, and firm-level characteristics, like whether the firm is public or has a criminal history [see Appendix Table A.3]

The lack of a difference in average outcomes and assessed fines across judges with different political affiliations, however, does not preclude the possibility that political affiliation matters. If Democrat-appointed judges impose harsher penalties on some cases because of certain predispositions but Republican-appointed judges impose harsher penalties for a different subset of cases because of different predispositions, we might not observe any difference in average outcomes. To test for this possibility, we now move to estimating our main difference-in-differences specification given in Equation (1).

4.2 Type of crime, political affiliation, and decisions of guilt

To assess whether judicial political affiliation matters for cases as a function of their potential for partisanship, we begin by testing for a change in the proportion of outcomes. In particular, we assess whether being assigned a Democrat-appointed judge is associated

[13] The 2,737 observations reported in Columns 1-6 is lower than the 2,795 observations reported in Tables 1-4 because the Stata *reghdfe* command we use drops singleton observations by default. Singleton observations refers to cases where there is only one observation for a given fixed effect (e.g., a jurisdiction only appears once in the sample). These observations, which do not contribute to the estimated coefficients because they belong to groups with no within-group variation to exploit, are excluded by the *reghdfe* command so as to report more conservatively-estimated cluster-robust standard errors. The dropping of singletons is also why the number of observations in Table 5, Column 7 (1,885) is smaller than the number of observations with non-zero fines reported in Table 3 (1,925).

with a change in the likelihood of a trial conviction, acquittal, dismissal, etc. when the case involves crimes more likely to be viewed as important by Democrats.

Estimating Equation (1), we continue to find no evidence that judicial political affiliation is associated with the proportion of different case outcomes. This is shown in Table 6. For crimes with different values of *DemocratTilt*, being assigned a judge that was appointed by a Democrat president has no differential association with whether the case is likely to result in a plea deal, dismissal, acquittal, trial conviction, etc. Besides lacking statistical significance, the point estimates are economically small; for a one unit change in *DemocratTilt*, the proportional shift in each case outcome is between 0.1 and 1.6 percentage points. Combined with our earlier findings in Table 5, these findings suggest the political-affiliation-based predispositions, if they exist, have no significant impact on the likelihood of a corporation being found guilty, reaching a plea deal, etc.[14]

These non-findings might reflect the limited influence of judges on decisions of guilt. While judges make important decisions on jury selection and admission of evidence that might influence the outcome of a criminal trial, many of these choices must follow existing legal precedents. Moreover, unless the company requests a bench trial, the ultimate decision of whether a firm is found guilty is not made by the judge but is instead made by a jury of individuals, and a firm's choice to accept an offered plea deal or DP/NP agreement will depend on whether this jury of individuals is likely to convict.

4.3 Type of crime, political affiliation, and monetary damages

Where judges can be more influential is in the severity of penalties imposed for firms that are found guilty of the underlying charges. In the federal criminal cases we analyze, it is the judge, not the jury, that determines the penalty following a guilty verdict.[15] Moreover, in plea deals, which account for about 80 percent of our cases outcomes, federal judges retain final authority over sentencing. In federal courts, most criminal plea deals are "open pleas," where the defendant agrees to plead guilty to a list of crimes, and the judge then sets the penalty. Even in negotiated plea deals that include a recommended sentence from the prosecutor, the judge is not bound by the recommendation and can

[14]The number of observations in Table 6 (2,560) is lower than that of Table 5, Columns 1-6 (2,737) because the inclusion of judge fixed effects increases the number of singleton observations that are dropped by the Stata *reghdfe* estimation command.

[15]See www.uscourts.gov/about-federal-courts/types-cases/criminal-cases.

reject the plea deal.[16] And while there are federal sentencing guidelines that judges use when setting the penalty, there is considerable judicial discretion in this decision.

Judges, however, have no direct say on penalties imposed as part of a DP/NP agreements. These are agreements between the prosecutor and the company that occur outside the courtroom. So, a judge's potential influence on monetary fines paid for these type of agreements are likely to be less. Therefore, in our subsequent tests that analyze the impact of judicial political affiliations on monetary damages, our baseline test excludes cases that result in DP/NP agreements. But, as we will show, our findings are robust (though, smaller in magnitude) when including DP/NP agreements in the estimation.

To analyze the potential impact of judicial political affiliation on fines, we restrict the sample to cases with a non-zero fine and use *Ln(Fine)* as our dependent variable. This sample restriction ensures that our coefficients reflect the association between judicial political affiliation and the amount of monetary damages conditional on there being a fine. These intensive margin estimates are reported in Table 7.

Consistent with judges exercising more influence over the amount of monetary damages assessed and with political judicial appointments being important, we find evidence that the judicial political affiliation is strongly associated with the level of fines imposed as a function of how partisan the underlying crime is likely to be. This is seen in the first column of Table 7, which provides estimates for the sample of cases with a plea deal or trial conviction that have a positive monetary fine. For a one unit change in the *DemocratTilt* of a case, being assigned a Democrat judge is associated with a 189 percent increase in the amount of monetary damage being assessed (Table 7, Column 1).[17]

This finding is robust. Including additional controls for whether the firm is publicly listed, which is positively associated with the assessed fine, or has a criminal history does not effect the estimates (Column 2). In both cases, controls or no controls, the point estimates are statistically significant at the one percent level. The finding also holds when including the cases that end with a DP/NP agreement. This is shown in the last two columns of Table 7, which provide estimates when also including DP/NP cases with a positive fine. The point estimate on $Democrat_j \times DemocratTilt_k$ remains positive and statistically significant, but consistent with judges having less influence on the monetary damages assessed in these cases, the point estimates become smaller, indicating a 112

[16] See www.law.cornell.edu/wex/plea_bargain.

[17] The increase in fines of 1.060 log points corresponds to an increase of $\exp(1.060) - 1 = 189$ percent. We use this method throughout the paper to interpret estimates from the *Ln(Fine)* regressions.

percent difference in fines for Democrat and Republican judges (Columns 3-4).[18]

The importance of political affiliation does not appear limited to a small subset of judges. To illustrate this, we estimate our main specification 1,000 different times after dropping a random 10% of judges. The distribution of resulting p-values for the coefficient on $Democrat_j \times DemocratTilt_k$ are plotted in Appendix Figure A.1. In all cases, we continue to find a statistically significant coefficient on the interaction between *Democrat* and *DemocratTilt* with the highest p-value being 0.041. The same is true when we instead drop 20% of judges. The highest p-value is 0.072. See Appendix Figure A.1.

The association between political affiliation, crime-types, and monetary damages is also not driven by a subset of particularly large fines. This is shown in Appendix Table A.5, where we repeat estimations of Table 7, but either exclude the largest 1% of fines each year (columns 1-4) or the largest 5% of fines each year (columns 5-8) from the sample. The point estimates remain largely unchanged. This is also true if we instead drop the largest 1% or 5% of fines across the entire sample (rather than by year).

We also find suggestive evidence that judicial political affiliation is associated with the likelihood of a monetary penalty. While our earlier findings in Table 6 show that judicial political affiliation is not associated with the likelihood of outcomes that typically incur a fine (i.e., plea deal, trial acquittal, and NP/DP agreements), it is weakly associated with the likelihood of a fine. This is shown in Appendix Table A.6, where we find that for a one unit change in the *DemocratTilt* of a case, being assigned a Democrat judge is associated with about a six percentage point increase in the likelihood of a fine. The point estimates, however, are only statistically significant at the ten percent level.[19]

A limitation of the above specification is that it does not allow us to see what underlying variation is driving the coefficient on $Democrat \times DemocratTilt$. For example, do Democrat judges both impose larger fines for cases with a positive *DemocratTilt* (i.e., labor and environmental cases) and smaller fines for cases with a negative *DemocratTilt* (i.e., immigration cases), or are the findings only being driven by one of these two crime

[18] Consistent with judges having less ability to influence the penalty imposed in cases that end with a NP/DP agreement, we also fail to find a statistically significant association between $Democrat_j \times DemocratTilt_k$ when restricting the sample to those cases. See Appendix Table A.4.

[19] The potential impact of judicial political affiliation on the extensive margin for fines also means that our findings with respect to the intensive margin of fines could be, in part, influenced by a shift in the composition of cases with a fine; see Angrist and Pischke (2009), pp. 64-66 for more details.

types? To more clearly examine this question, we estimate

$$\begin{aligned} Outcome_{i,j,k,l,t} =& \delta_1 Democrat_j \times Environment\&Labor_k \\ & + \delta_2 Democrat_j \times Immigration_k \\ & + Judge_j + Crime_k + Year_t + \nu_{i,j,k,l,t} \end{aligned} \tag{3}$$

where $Environment\&Labor_{i,j,k,l,t}$ is an indicator for case involving crimes related to the environment or workplace safety and *Immigration* is an indicator for crimes involving the hiring of illegal immigrants. As before, we continue to include judge, crime, and year fixed effects. These estimates from this regression are provided in Table 8.

Relative to cases with a *DemocratTilt* value of zero (i.e., cases involving crimes with no obvious partisan tilt), environmental- and labor-related cases that are assigned to Democrat-appointed judges are assessed larger fines, while the opposite is true for immigration cases. Fines imposed in environmental and labor cases are 136 percent larger when assigned to a Democrat-appointed judge rather than a Republican-appointed judge (Table 8, Column 1). Fines imposed in immigration cases, however, are 92 percent smaller when assigned to a Democrat-appointed judge rather than a Republican-appointed judge (Column 1).[20] The results are robust to adding firm-level controls (Column 2) and, as expected, weaker when including fines imposed in cases with DP/NP agreements, where judges do not have final say on the imposed penalty (Columns 3-4).

4.4 Election cycles, partisanship, and political affiliation

If the observed difference in monetary penalties are driven by a judicial political bias associated with the political affiliation of the nominating president, then we might expect these differences in fines to become amplified during time periods where political partisanship is particularly high. Such periods likely include the months immediately prior to when a national presidential or congressional election occurs.

To test for this possibility, we modify our difference-in-differences regression to include additional interactions for whether the case is concluded during the four months prior to a national election (see Kaviani et al., 2019). Specifically, we estimate a triple difference specification that compares fines assessed in cases with (1) a Democrat- versus

[20]Because judges are either Democrat- or Republican-appointed, the point estimates indicate the opposite pattern holds for Republican judges. Fines imposed in environmental and labor cases are smaller when assigned to a Republican-appointed judge, while fines for immigration cases are larger.

Republican-appointed judge, (2) a high- versus low-level of *DemocratTilt*, and (3) in the four months prior to a national election versus not. Specifically, we estimate

$$\begin{aligned} Outcome_{i,j,k,l,m} =& \beta_1 Democrat_j \times Election_m + \beta_2 DemocratTilt_k \times Election_m \\ &+ \beta_3 Democrat_j \times DemocratTilt_k \\ &+ \beta_4 Democrat_j \times DemocratTilt_k \times Election_m \\ &+ Judge_j + Crime_k + Month_m + \epsilon_{i,j,k,l,m}, \end{aligned} \tag{4}$$

where $Election_m$ is an indicator for the four months prior to a national presidential or congressional election (i.e., the months of July through October in years that end in an even number), and $Month_m$ are month-year fixed effects. Because *Election* is measured on a monthly basis, we use month-year fixed effects in this specification to ensure that our estimates are obtained by comparing cases that conclude in the same month.

To complete the triple difference estimation, we also include controls for $Democrat \times Election$ and $DemocratTilt \times Election$, which allow for the possibility that the average outcomes for Democrat-appointed judges or cases with different levels of *DemocratTilt* differ in these months. The controls for *Election*, *Democrat*, and *DemocratTilt* are not included as they are co-linear with the included judge, crime, and month-year fixed effects. The estimates of this regression are provided in Table 9.

The difference in fines imposed in cases more likely to be associated with partisan views is larger during the months preceding a national election. This is seen in the positive point estimates on the triple interaction for $Democrat \times DemocratTilt \times Election$ in Table 9. In an average month, cases assigned to a Democrat-appointed judge exhibit fines that are 197 percent larger for a one unit increase in *DemocratTilt*, but for cases where judgement is rendered in the four months prior to a national election, this difference increases by an additional 483 percent (Table 9, Column 1). The results are similar, but weaker in magnitude when we include NP/DP agreements in the sample (Column 2). We find no evidence of a difference in the average fine assessed by Democrat-appointed judges in the months prior to an election (see coefficients on $Democrat \times Election$) or in the average fine assessed for crimes with different levels of *DemocratTilt* in the months prior to an election (see coefficients on $DemocratTilt \times Election$).

These findings are particularly striking given the inclusion of judge fixed effects. By including judge fixed effects, the importance of election cycles is estimated using only judges that impose fines in both months before a national election and all other months, indicating that judges are imposing fines that vary both with the national election cycle and the partisan tilt of the underlying crime. The time-varying estimates also indicate that the differential fines observed in Table 7 are not driven by fixed, judge-level ideological differences associated with the political party of the nominating president.

As an additional test of whether the importance of judicial political affiliation increases during time periods of greater partisanship, we next divide our sample using two measures of political polarization from Gallup's PEW Research Center. Specifically, we divide the sample between months reported by Gallup as having a larger than average difference in partisan beliefs regarding the health of the economy and years where there is an above average difference in the partisan approval rating of the sitting president.[21] Periods where there are greater differences in partisan views of the economy and in the sitting president's approval rating are viewed as time periods with higher political polarization. These subsample findings are reported in Table 10.

We again find evidence that judicial political affiliation is more important for the level of monetary damages assessed during time periods of greater political partisanship. The coefficient on $Democrat \times DemocratTilt$ is positive and statistically significant only when the gap in partisan beliefs regarding the health of the economy is above average (Table 10, Column 2) and when there is a greater difference in the partisan approval rating of the sitting president (Column 4). Interestingly, we find little evidence that judges' political affiliations are associated with the outcomes of corporate prosecutions during time periods with less political polarization (Columns 1 and 3).

4.5 The potential importance of judicial career motives

Career motives is another possible explanation for why the political party of the nominating president might matter for judicial outcomes. Judges that wish to be promoted to a higher court could seek to signal their ideological compatibility through their judicial decisions (Savchak et al., 2006). For example, if Democrat presidents tend to view labor and environmental violations as important, a Democrat-appointed judge that seeks to be nominated for a higher court might levy larger fines on companies engaged in such crimes to attract the attention of the nominating president. If true, this career motive might be

[21] Historical data for these two variables were obtained directly from PEW, and graphic depictions of the two data series are made available at www.pewresearch.org/fact-tank/2018/08/01/trumps-approval-ratings-so-far-are-unusually-stable-and-deeply-partisan/ and www.people-press.org/2019/01/18/trump-begins-third-year-with-low-job-approval-and-doubts-about-his-honesty/.

particularly strong when a vacancy exists on a higher court to which the district judge seeks an appointment.

To analyze this possibility, we test for heterogeneity depending on whether the case is concluded during a period where a vacancy exists on a higher court that oversees the jurisdiction of the presiding district-level judge. Specifically, we estimate

$$\begin{aligned} Outcome_{i,j,k,l,m} =& \theta_1 Democrat_j + \theta_2 Vacancy_{l,m} \\ &+ \theta_3 Democrat_j \times Vacancy_{l,m} \\ &+ \theta_4 DemocratTilt_k \times Vacancy_{l,m} \\ &+ \theta_5 Democrat_j \times DemocratTilt_k \\ &+ \theta_6 Democrat_j \times DemocratTilt_k \times Vacancy_{l,m} \\ &+ Crime_k + Jurisdiction_l + Month_m + \epsilon_{i,j,k,l,m}, \end{aligned} \tag{5}$$

where $Vacancy_{l,m}$ is an indicator for there being a judicial vacancy on a higher court for jurisdiction l in month m. Because there are not many judges in our sample that rule on corporate criminal cases both when there is a higher-court vacancy for their jurisdiction and when there is no vacancy, our baseline triple-difference specification excludes judge fixed effects and instead includes jurisdiction fixed effects. In doing so, the coefficients of this equation will be estimated using cross-sectional variation rather than within-judge variation as in earlier specifications. Nevertheless, we also later report estimates from a specification that includes judge fixed effects. The exclusion of judge fixed effects is also why we add back the control for *Democrat*. The control for $DemocratTilt_k$, however, is still not included as it remains co-linear with the crime fixed effects.

We define *Vacancy* as a month where there is a vacancy on either (1) the Court of Appeals that oversees the judge's jurisdiction, (2) the Federal Circuit Court in DC, or (3) the Court of International Trade. We use geographic-based appellate court vacancies as judges nominated for these courts are often judges from a district court in the appellate court's jurisdiction (e.g., see Savchak et al. (2006)).[22] In total, there are 12 geographic-based appellate courts that oversee the 94 geographic-based district courts (the level of our analysis). We also include vacancies on the Federal Circuit Court in DC and Court of International Trade as these are courts with national jurisdiction over certain cases that

[22] Using data from 1946 to 1995, Savchak et al. (2006) find that 43.6% of appellate court federal judges were elevated from a district court, and in all cases, this elevation occurred from a district court within the jurisdiction of the appellate court that judge sat on.

could also be viewed as a promotion for district court judges. Our subsequent findings, however, are robust to excluding vacancies on these two latter courts and instead only using vacancies on the geographic-based appellate courts.

To determine when vacancies exist on these higher courts, we use the biographies of judges provided on the United States Courts' website. This data provides us with the full career path of each judge, including their appointments and terminations at each position, and the exact date of these events. Hence, we are able to identify when vacancies open up by focusing on judges whose careers were terminated at any of the three courts mentioned above and then tracking when a new judge was added to that particular court to determine when the vacancy was officially filled. In total, 123 vacancies occur during our sample period, of which, almost three-fourths of them (92) are because the existing judge died. A histogram documenting the reason for these vacancies is provided in Figure 2, and the estimates of Equation (5) are provided in Table 11.

Consistent with a possible career motive, we find evidence that the observed differences in monetary penalties is larger when there exists a vacancy on a higher court. For a one unit change in the *DemocratTilt* of a case during periods where there does not exist a higher-court vacancy, being assigned a Democrat-appointed judge is associated with a 63 percent increase in the amount of monetary damages being assessed (Table 11, Column 1). But, during periods with a higher-court vacancy, being assigned a Democrat-appointed judge is associated with an additional 295 percent increase in the amount of monetary damages for a one unit increase in *DemocratTilt*. We find similar results when including NP and DP prosecutions (Column 2). We find no evidence of a difference in the average fine assessed by Democrat-appointed judges during vacancies (see coefficients on $Democrat \times Vacancy$) or in the average fine assessed for crimes with different levels of *DemocratTilt* during vacancies (see coefficients on $DemocratTilt \times Vacancy$).

The point estimates are similar when we instead include judge fixed effects. Estimates of Equation (5) that replace the jurisdiction fixed effects with judge fixed effects are provided in Appendix Table A.7. The point estimates for the triple interaction are quantitatively similar to those reported in Table 11, but no longer statistically significant. The increased standard errors, however, likely reflect the relatively small number of judges that decide cases during both vacancy and non-vacancy periods.

4.6 Robustness tests and alternative explanations

While the assignment of a judge to a particular case is random, a potential concern with our identification strategy is that a judge's political affiliation can be correlated with other characteristics of the judge. For example, Democrat judges might be more likely to be younger or female. If true, and if these other characteristics drive differential judicial predispositions for cases involving immigration-, environmental-, and labor-related crimes, then it is possible that some of our above findings are being driven by differences in other judge-level characteristics rather than political affiliation.

To test for this possibility, we augment our main estimation in Equation (1) to include controls for judicial characteristics and their interaction with *DemocratTilt*. We do this for four judge-level characteristics: gender, race, experience, and age. If the observed differences in monetary damages across crimes and political affiliation is being driven by these other judge-level characteristics, then the estimate for $Democrat \times DemocratTilt$ would not be robust to the inclusion of these additional controls. For example, if our earlier findings are being driven by Democrat-appointed judges tending to have more experience, and judges with more experience tending to come down harsher on cases involving environmental- and labor-related crimes, then the inclusion of $Experience \times DemocratTilt$ would control for this possibility. These tests are reported in Table 12.

Our findings do not appear driven by a potential association between being a Democrat-appointed judge and other judge-level characteristics. Allowing for male judges to impose different fines as a function of *DemocratTilt* does not affect our main findings (Table 12, Column 1), nor does allowing for different outcomes as a function of a judge's race (Column 2). We also find that including the additional interactions for a judge's experience, as measured by the number of years since their initial appointment, and age do not affect our estimate for $Democrat \times DemocratTilt$ (Columns 3-4). Even when including all of these additional controls at once, we continue to find that cases assigned to a Democrat-appointed judge, on average, exhibit a monetary fine that is about 198 percent larger for a one unit increase in the *DemocratTilt* of the underlying crime (Column 5).

The increased importance of political affiliation when a national election is approaching (Table 9), political partisanship is greater (Table 10), or there exists a vacancy on a higher court (Table 11) also suggest that our findings are not driven by other types of judicial predispositions. In particular, it is unclear why other types of judicial predispositions (e.g., those related to race, gender, age, experience, etc.) would exhibit larger differences in outcomes as a function of *DemocratTilt* in highly partisan time periods or when a vacancy appears on a higher court for a judge's jurisdiction.

Federal prosecutors choosing to file certain types of criminal cases in jurisdictions where they anticipate a more favorable judge is an additional mechanism by which judicial political affiliations might matter. For example, if prosecutors tend to file cases involving the most egregious immigration violations in districts with more Republican-appointed judges because they anticipate such judges are likely to impose larger fines, then our findings could partly be driven by this selection of where prosecutors file cases. While such forum shopping by prosecutors, if true, would still reflect an effect of political affiliation on corporate prosecutions, the mechanism would be different.

Our findings, however, do not appear to be driven by such forum shopping. Excluding cases that were filed in a district where 90 percent or more of the judges were appointed by a president of a particular party does not affect our main findings. This is shown Columns 1-2 of Appendix Table A.8. Likewise, excluding cases that were filed in jurisdictions where 75 percent or more of the judges were appointed by a particular political party also does not meaningfully change the estimates (Columns 3-4). These findings suggest that a different distribution of cases filed in jurisdictions dominated by one political party is an unlikely channel for our findings and is instead consistent with evidence that the first federal prosecutor's office to file a case tends to retain jurisdiction, even if other offices are potentially interested in pursuing the matter (see Chemerinsky, 2018).[23]

Our choice of clustering also does not affect our conclusions. In our main analysis, we double cluster our standard errors at the judge and crime levels. But, clustering at other levels (or not clustering at all) does not significantly affect our standard errors. This is shown in Appendix Table A.9, where we repeat the estimation of Table 7, Column 2 with alternative forms of clustering. Only clustering at the level of judge (Appendix Table A.9, Column 1) or crime (Column 2) does not meaningfully change the standard errors

[23]Another potential mechanism by which political affiliation might matter is through a shift in the composition of cases that end with a NP/DP agreement. If firms and prosecutors are aware of differences in the importance of political affiliation, then their willingness to strike an out-of-court agreement that is not subject to the judge's approval could shift once a judge of a particular political party is assigned to the case. For example, companies accused of an immigration crime that are assigned a Republican judge might be more willing to accept a NP/DP agreement that includes monetary damages rather than attempt to be acquitted of the charges at trial. While we find no evidence that the combination of political affiliation and crime type is associated with a shift in the overall proportion of cases that result in a NP/DP agreements or trials (see Table 6), we cannot rule out the possibility of a shift in the type of immigration-, environment-, or labor-related cases that conclude with a NP/DP agreement or trial. Such a shift in composition, if true, would still be an effect of political affiliation.

relative to the double clustering used in Column 2 of Table 7. The same is true if we just use heteroskedastic robust standard errors (Column 3).

Our findings are also robust to excluding cases where we are unable to to fully identify the jurisdiction of the case. This is shown in Column 4 of Appendix Table A.9. And, double clustering by judge and jurisdiction (instead of by judge and crime) in this smaller sample also does not alter our findings (Column 5).

Our findings are also robust to various other specification changes. For example, the main findings for monetary fines are robust to dropping judge fixed effects and instead controlling for the available judicial characteristics (race, gender, age, and experience). This is shown in Appendix Table A.10. We continue to find larger fines being assessed in cases assigned to Democrat judges for each unit increase in a crime's *DemocratTilt*, though the coefficients are economically smaller when we do not include judge fixed effects. The findings are also robust to excluding cases from the five non-geographic jurisdictions, "US Antitrust," "US Criminal," "US Tax," "US Environmental," and "US National Security," where the assignment process of judges is less clear. This is shown in Appendix Table A.11, which repeats the estimation of Table 7 on this smaller sample.

5 Discussion of Potential Economic Implications

Our findings suggest that presidential elections matter for the outcomes of corporate prosecutions, and hence, the enforcement of existing business regulations and laws. Because the political party that holds the presidency can meaningfully shift the proportion of judges appointed by a political party, the penalty firms can expect to incur for violating different regulations can vary considerably as a function of which political party currently holds and has held the presidency in the recent past. If these expected fines factor into firms' investment and hiring choices, then these potential shifts could in turn affect the aggregate economy. In this section, we perform a simple back-of-the-envelope calculation to estimate how much the monetary damages firms can expect to be assessed for different crimes shifted because of the 2016 presidential election outcome.

To begin, we assume that the political party that holds the presidency is able to shift the proportion of judges by 7.5 percentage points in their first term. This number is comparable the 8.2 and 7.0 percentage point swings in the first terms of presidents George W. Bush and Barack Obama, respectively; e.g., see Figure 1. If true, this would suggest that the election of a Republican president in 2016 will cause a 15 percentage point swing in the proportion of judges appointed by a Democrat by the end of 2020. For example, at the end of the Obama presidency in 2016, approximately 52.6% of district court judges had been appointed by a Democrat. Had Hillary Clinton, the Democrat candidate, won the election in 2016, this share might have increased to 60.1% by the end of her first term. Instead, with the election of Donald Trump, the Republican candidate, we might instead expect the share of Democrat-appointed judges to decline to 45.1%.

Next, we use our point estimates from Table 8 to calculate an implied average fine assessed by Democrat- and Republican-appointed judges for crimes with a potential partisan tilt. For example, the estimates in Table 8 suggest that, on average, a Democrat-appointed judge will assess labor- or environment-related fine that is 136 percent larger than that of a Republican-appointed judge. Given that about 53.4% of judges in our sample were appointed by a Democrat and the average fine assessed for such crimes was $4.05 million, that would suggest that, on average, one might expect a Democrat-appointed judge to assess a labor- and environmental- fine of about $5.54 million while a Republican-appointed judge would assess an average fine of about $2.35 million.

Using these numbers, combined with the predicted shift in proportion of judges that are Democrats, one finds that the expected fine for labor- and environmental-related crimes would have been about 12.6% higher at the end of 2020 if Hillary Clinton had instead won the presidential election. When 45.1% of judges are appointed by a Democrat, the expected labor- and environment fine is about $3.79 million, but when 60.1% of judges are appointed by a Democrat, the expected fine increases to about $4.27 million. A similar calculation for immigration crimes suggests the Trump election in 2016 will result in an expected fine for immigration crimes that is 30.9% higher by the end of 2020 than what it would have otherwise been under a Clinton presidency.

6 Conclusion

The increasing lengths by which political parties will go to scuttle the judicial appointments of the opposing party while promoting appointments of their own party suggests that each party increasingly views these lifetime appointments as playing a key role in promoting their policy agenda. For example, in 2016, the Republican-led senate refused to even consider President Obama's judicial nominations, including the nomination of Merrick Garland to the U.S. Supreme Court, while a few years earlier, Senate Majority Leader Harry Reid invoked the 'nuclear' option to overcome Republican objections and push through some of Obama's judicial nominees.[24] These partisan fights over judicial appointments continue to grow despite the insistence of judges that their decisions are not influenced by political predispositions. As Chief Justice John Roberts famously stated in 2016, "[Judges] don't work as Democrats or Republicans."[25]

Our findings show that the identity of the political party making these judicial appointments does matter. In corporate prosecutions, the average fine imposed on companies can vary considerably depending on the political affiliation of the assigned judge and the underlying crime. In particular, cases assigned to Democrat-appointed judges have fines that are, on average, 136 percent larger if the underlying crime involves violating labor or environmental regulations and 92 percent smaller if related to violating immigration laws. The difference in fines imposed across these different types of crime conform to the typical priorities associated with each political party.

These differences in fines across Republican and Democrat judges appear to reflect a political bias rather than fixed ideological differences as they are even larger during time periods of greater partisan polarization. The observed differences are also not driven by other time-invariant judge-level characteristics, like race, age, experience, that might be correlated with a judge's political affiliation. There is also evidence the observed differences increase during periods where there exists a vacancy on a higher court, suggesting a potential career motive among judges when setting monetary damages.

These findings have numerous implications for companies. Judicial rulings can set long-lasting precedents regarding the enforcement of various business regulations, and the penalties imposed by judges for violating existing laws can act as important deterrent that affect the broader economy.[26] To the extent that judicial political affiliations contribute the the amount of penalties companies can expect to incur for violations, a shift in the composition of judges also has the potential to shift companies' priorities. For example, if the recent push to confirm President Trump's nominees results in firms expecting to incur smaller fines for any environmental violations but larger fines for hiring illegal workers, then companies may prioritize abiding by immigration laws rather than environmental

[24]See www.washingtonpost.com/news/the-fix/wp/2018/06/29/democrats-overplayed-their-hand-on-the-nuclear-option-and-here-we-are/ and www.npr.org/2018/06/29/624467256/what-happened-with-merrick-garland-in-2016-and-why-it-matters-now.

[25]See www.nytimes.com/2018/12/23/us/politics/chief-justice-john-roberts-supreme-court.html.

[26]For example, Oregon Senator Jeff Merkley argued in 2012 that the lack of significant penalties imposed on large banks following the 2008 financial crisis was sending a message that some firms are simply "too big to jail." See www.merkley.senate.gov/news/press-releases/merkley-blasts-too-big-to-jail-policy-for-lawbreaking-banks.

regulations, which could influence both the types of workers they hire and the investments they make. This potential impact of judicial political affiliations on the real economy presents an interesting direction for future research.

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Figure 1: Active District-Level Judges By Year and Political Party

This figure plots the percent of active district-level federal judges that were appointed by a Democrat by year from 1970 to 2018. The red solid lines indicate years where a Republican was newly elected president, while the blue dashed lines indicate years where a Democrat was newly elected. The yearly fraction was calculated using the biographies of federal judges, as provided on the US Courts' website.

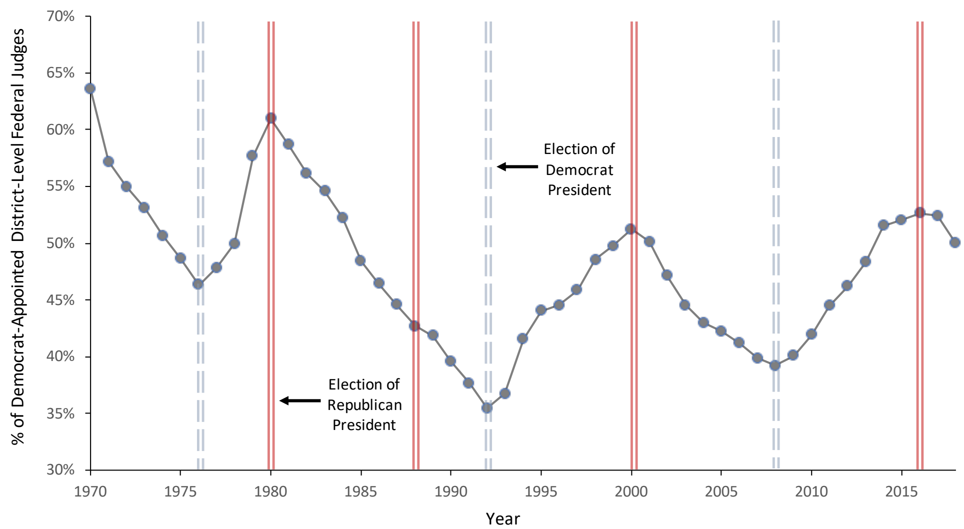


Figure 2: Number of Vacancies and Reason for Termination, 2000-2018

This figure plots the number of vacancies that occur on one of the 12 geographic-based appellate courts, the Federal Circuit Court in DC, and the Court of International Trade during our sample period, 2000 through 2018, by reason for the departing judge's termination.

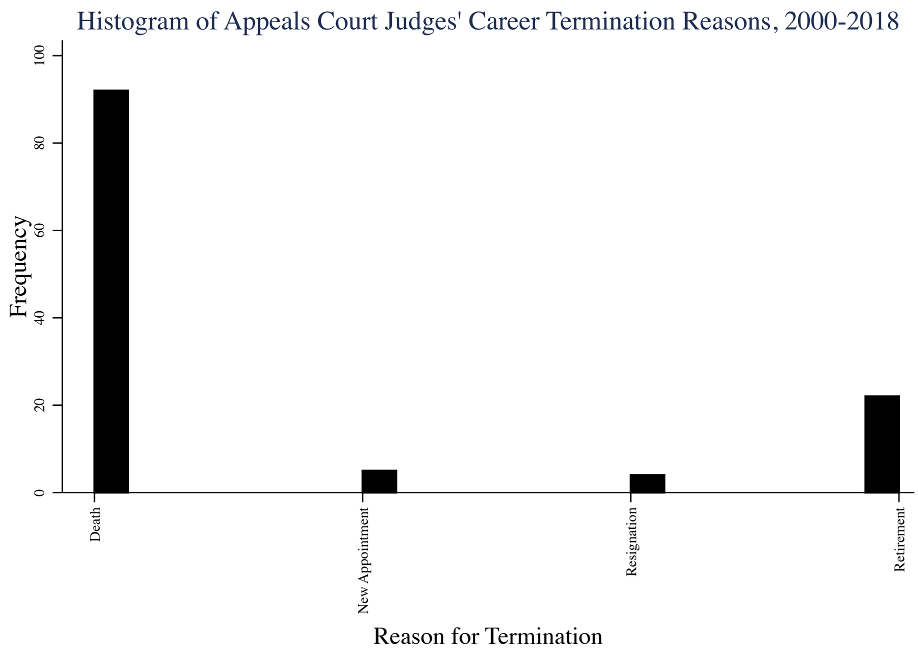


Table 1: Distribution of Crime Types

This table reports the distribution of crime classifications for the sample of cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the case docket. These crime classifications are provided by the Corporate Prosecutions Registry, which is produced jointly by Legal Data Lab at the University of Virginia School of Law and Duke University School of Law. The "Other" primary crime code refers to crimes that are not frequent and therefore do not have their own unique classification in the registry.

Crime Type	Frequency	Percent	Cumulative Percent
Fraud - General	512	18.32	18.32
Environmental	441	15.78	34.10
Antitrust	271	9.70	43.79
Other	197	7.05	50.84
FCPA	151	5.40	56.24
Import / Export	148	5.30	61.54
False Statements	127	4.54	66.08
Immigration	125	4.47	70.55
Fraud - Tax	117	4.19	74.74
Act to Prevent Pollution from Ships	103	3.69	78.43
FDCA / Pharma	95	3.40	81.82
Fraud - Health Care	75	2.68	84.51
Money Laundering	70	2.50	87.01
Food	59	2.11	89.12
Controlled substances / Drugs / Meth ..	56	2.00	91.13
Bank Secrecy Act	51	1.82	92.95
Wildlife	48	1.72	94.67
Kickbacks	29	1.04	95.71
Gambling	27	0.97	96.67
OSHA / Workplace Safety / Mine Safety	24	0.86	97.53
Fraud - Securities	23	0.82	98.35
Bribery	21	0.75	99.11
Obstruction of Justice	17	0.61	99.71
Fraud - Accounting	8	0.29	100.00
Total	2,795	100.00	

Table 2: Distribution of Case Outcomes

This table provides the distribution of outcomes for our sample of corporate prosecutions, which includes cases that concluded between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the case docket. We classify the outcomes reported in the registry into six categories: "Plea" (when a defendant pleads guilty), "DP/NP Agreement" (a negotiated deferred or non-prosecution agreement between the defendant and the government that is imposed and monitored outside the judicial system), "Dismissal" (when the judge dismisses the charges), "Declination" (when the prosecutor declines to pursue the case), "Conviction" (when the company is found guilty by a trial), and "Acquittal" (when the company is acquitted by a trial).

Outcome Type	Frequency	Percent	Cumulative Percent
Plea	2,230	79.79	79.79
DP/NP Agreement	418	14.96	94.74
Dismissal	104	3.72	98.46
Declination	20	0.72	99.18
Conviction	12	0.43	99.61
Acquittal	11	0.39	100.00
Total	2,795	100.00	

Table 3: Summary Statistics on Monetary Damages Assessed

This table reports the mean, median, and standard deviation of fines assessed for our sample, which includes cases that concluded between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the case docket. All reported values, except the number of observations, are in millions of US dollars. The first row reports summary statistics for all cases, including those where no monetary damages were imposed, while the second row reports summary statistics only for the cases with positive monetary damages. Only corporate prosecutions that result in a plea deal, conviction, or NP/DP agreements have fines. The third row reports summary statistics for cases with a fine when also excluding cases that result in a DP/NP agreement, which are administered outside the judicial system and typically not subject to a judge's approval.

	Obs	Mean	Median	Std. Dev
All Cases	2,795	13.98	0.05	86.76
Cases With Fines	1,925	20.30	0.30	103.94
Cases With Fines, Excluding DP/NP Agreements	1,667	17.19	0.20	102.77

Table 4: Distribution of Case Assignments

This table provides summary statistics on the characteristics of cases assigned to judges by political affiliation. The table reports the proportion of cases involving "Immigration," "Environmental," and "Labor" crimes, the percent of defendants that are publicly listed, and the percent of defendants with a criminal history. The crime classifications and firm characteristics are obtained from the Corporate Prosecutions Registry, and the sample is limited corporate prosecutions that occurred between 2000 and 2018 and where we can obtain the judge's name from the case docket. The summary statistics for each variable are reported separately for two samples of corporate prosecutions. The first column reports statistics for cases assigned to Democrat-appointed judges, while the second column reports statistics for cases assigned to Republican-appointed judges. The third column reports the *p*-value from a *t*-test for the difference between cases assigned to Democrat and Republican judges.

	Democrat Judge	Republican Judge	*p*-value of difference
Environmental %	17.292	17.728	0.762
Labor %	0.871	0.844	0.938
Immigration %	3.552	5.525	0.012
Public Firm %	11.394	11.128	0.824
Criminal History %	10.589	10.897	0.793
Observations	1,492	1,303	

Table 5: Political Affiliation and Average Outcomes

This table reports estimates from an analysis of whether a judge's political affiliation, as measured using the political party of the nominating president, is associated with different average prosecution outcomes. Specifically, the table reports the coefficients from a regression of case outcomes onto a judge's political affiliation, case year fixed effects, crime fixed effects, and jurisdiction fixed effects. *Democrat* is an indicator equal to one if the assigned judge was nominated by a Democrat president, as identified from the case docket and the United States Courts' website. The dependent variables are indicators for the case concluding with at plea deal, NP/DP agreement, dismissal, declination, conviction, and acquittal [Columns (1)-(6)], and the log of monetary damages assessed, *Ln(Fine)* [Column (7)]. The sample in Columns (1)-(6) includes all cases found in the Corporate Prosecutions Registry that occurred between 2000 and 2018 and where we can identify the judge's name from the official case docket, while the sample in Column (7) is restricted to those cases with positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Plea*	(2) *NP/DP*	(3) *Dismissal*	(4) *Declination*	(5) *Conviction*	(6) *Acquittal*	(7) *Ln(Fine)*
Democrat	-0.028	-0.002	0.005	-0.003	-0.002	0.000	-0.000
	[0.017]	[0.002]	[0.004]	[0.003]	[0.003]	[0.000]	[0.134]
Observations	2,737	2,737	2,737	2,737	2,737	2,737	1885
Adjusted R^2	0.405	-0.010	0.052	0.165	0.067	0.003	0.461
Case Year FE	YES	YES	YES	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES	YES	YES	YES
Jurisdiction FE	YES	YES	YES	YES	YES	YES	YES

Table 6: Political Affiliation, Partisanship, and Decisions of Guilt

This table examines whether decisions of guilt differ based on the political affiliation of the president that nominated the presiding judge and the partisan nature of the underlying crime using our base-case model in Equation (1). Specifically, the table reports coefficients from a regression of case outcomes onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. The dependent variables are indicators for the case concluding with a plea deal, NP/DP agreement, dismissal, declination, conviction, or acquittal. The sample includes all cases found in the Corporate Prosecutions Registry that occurred between 2000 and 2018 and where we can identify the judge's name from the official case docket. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Plea	*NP/DP*	*Dismissal*	*Declination*	*Conviction*	*Acquittal*
Democrat × *DemocratTilt*	-0.016	-0.000	0.000	0.012	-0.001	0.004
	[0.035]	[0.028]	[0.013]	[0.011]	[0.010]	[0.004]
Observations	2,560	2,560	2,560	2,560	2,560	2,560
Adjusted R^2	0.377	0.361	0.268	0.110	0.058	0.173
Judge FE	YES	YES	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES	YES	YES

Table 7: Political Affiliation, Partisanship, and Monetary Damages

This table examines whether monetary damages differ based on the political affiliation of the president that nominated the presiding judge and the partisan nature of the underlying crime using our base-case model in Equation (1). Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample in columns (1) and (2) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. The sample in columns (3) and (4) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*	(3) *Ln(Fine)*	(4) *Ln(Fine)*
Democrat × DemocratTilt	1.060***	1.047***	0.751***	0.696***
	[0.313]	[0.303]	[0.242]	[0.242]
Public Firm		2.269***		2.450***
		[0.503]		[0.492]
Firm: Criminal History		-0.024		-0.090
		[0.230]		[0.249]
Observations	1,404	1,404	1,692	1,692
Adjusted R^2	0.538	0.572	0.524	0.571
Excluding NP/DPs	YES	YES	NO	NO
Judge FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES

Table 8: Immigration versus Environmental & Labor Crimes

This table examines whether a judge's political affiliation is associated with the level monetary damages assessed for labor, environmental, and immigration crimes using our model in Equation (3). Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat×Environment&Labor*, *Democrat×Immigration*, judge fixed effects, crime fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *Environment&Labor* is an indicator that takes the value of one for cases involving environmental- and labor-related crimes, while *Immigration* is an indicator for cases involving immigration crimes. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. Columns (1) and (2) include all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Columns (3) and (4) expand the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*	(3) *Ln(Fine)*	(4) *Ln(Fine)*
Democrat × Environment&Labor	0.859***	0.866***	0.642**	0.572**
	[0.297]	[0.291]	[0.269]	[0.274]
Democrat × Immigration	-2.495**	-2.340**	-1.405	-1.442*
	[1.050]	[1.059]	[0.969]	[0.817]
Public Firm		2.263***		2.452***
		[0.505]		[0.491]
Firm With Criminal History		-0.025		-0.090
		[0.231]		[0.248]
Observations	1,404	1,404	1,692	1,692
Adjusted R^2	0.539	0.572	0.524	0.571
Excluding NP/DPs	YES	YES	NO	NO
Judge FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES

Table 9: Election Cycles, Partisanship, and Political Affiliation

This table examines whether monetary damages vary based on the national election cycle, the political affiliation of the president that nominated the presiding judge, and the partisan nature of the underlying crime using the model in Equation (4). Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year-month fixed effects, and interactions for whether a case concludes in the four months prior to a national election. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Election* is an indicator that flags cases that conclude in the months of July, August, September, and October in years with a national congressional election or presidential election (i.e., even-numbered years). *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. Column (1) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Column (2) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*
Democrat × Election	-0.429	-0.273
	[0.290]	[0.367]
DemocratTilt × Election	0.274	0.167
	[0.344]	[0.318]
Democrat × DemocratTilt	1.090***	0.646**
	[0.305]	[0.248]
Democrat × DemocratTilt × Election	1.918**	1.697*
	[0.832]	[0.872]
Public Firm	2.391***	2.571***
	[0.446]	[0.406]
Firm With Criminal History	-0.322	-0.118
	[0.217]	[0.246]
Observations	1,365	1,660
Adjusted R^2	0.603	0.604
Excluding NP/DPs	YES	NO
Judge FE	YES	YES
Case Year-Month FE	YES	YES
Crime Type FE	YES	YES

Table 10: Partisan Polarization and Political Affiliations

This table studies whether the importance of judicial political affiliation for monetary penalties varies during periods of higher political polarization by separately estimating Equation (1) in periods with high and low partisan polarization. Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects. We identify the periods of high political polarization using two indicators compiled by the PEW Research Center: (1) partisan difference in beliefs on the health of the economy [Columns 1-2], and (2) partisan difference in the sitting president's approval rating [Columns 3-4]. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The estimation includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Columns 1 and 3 restrict the sample to cases that concluded during periods of below median partisan polarization, while Columns 2 and 4 restrict the sample to cases that concluded during periods during periods of above median partisan polarization. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Partisan Diff. in Beliefs on Econ Health		***Partisan Diff. in President Appr. Rating***	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
	Ln(Fine)	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*
Democrat × *DemocratTilt*	0.010	1.292**	−0.278	1.298**
	[0.469]	[0.516]	[0.548]	[0.486]
Public Firm	2.720***	2.130***	2.586***	2.297***
	[0.687]	[0.387]	[0.698]	[0.423]
Firm With Criminal History	−0.188	0.001	−0.242	0.030
	[0.267]	[0.398]	[0.308]	[0.373]
Observations	753	695	668	784
Adjusted R^2	0.620	0.579	0.628	0.568
Excluding NP/DPs	YES	YES	YES	YES
Judge FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES

Table 11: Court Vacancies, Partisanship, and Political Affiliation

This table examines whether monetary damages vary based on whether there exists a higher-court vacancy at the time the case is decided, the political affiliation of the president that nominated the presiding judge, and the partisan nature of the underlying crime using the model in Equation (5). Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, jurisdiction fixed effects, crime fixed effects, and year-month fixed effects, and interactions for whether a case concludes when there is higher-court vacancy for that jurisdiction, *Vacancy*. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Vacancy* is an indicator that flags cases that conclude during a period where their is a vacancy on on either the Appeals Court for that jurisdiction, the Federal Circuit Court in DC, or the Court of International Trade. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. Column (1) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Column (2) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*
Vacancy	-0.035	-0.079
	[0.484]	[0.440]
Democrat	-0.136	-0.031
	[0.113]	[0.098]
Democrat × *Vacancy*	-0.385	-0.622
	[0.644]	[0.613]
DemocratTilt × *Vacancy*	-0.332	-0.350
	[0.551]	[0.470]
Democrat × *DemocratTilt*	0.490***	0.344**
	[0.169]	[0.153]
Democrat × *DemocratTilt* × *Vacancy*	1.373*	1.734**
	[0.769]	[0.684]
Public Firm	2.674***	2.612***
	[0.443]	[0.547]
Firm With Criminal History	0.188	0.244
	[0.266]	[0.212]
Observations	1,626	1,880
Adjusted R^2	0.518	0.541
Excluding NP/DPs	YES	NO
Jurisdiction FE	YES	YES
Year-Month FE	YES	YES
Crime Type FE	YES	YES

Table 12: Robustness to Controlling for Interactions of *DemocraticTilt* and Judge-Level Characteristics

This table analyzes whether the results are robust to including additional controls for judicial characteristics and their interactions with *DemocraticTilt*. Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat×DemocratTilt*, judge fixed effects, crime fixed effects, case-year fixed effects, and interactions between *DemocratTilt* and judge-level characteristics. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Male* and *White* are indicators for whether the assigned judge is male or white, respectively. *Experience* is the number of years the assigned judge has been on the federal bench, and *Age* is the assigned judge's age. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

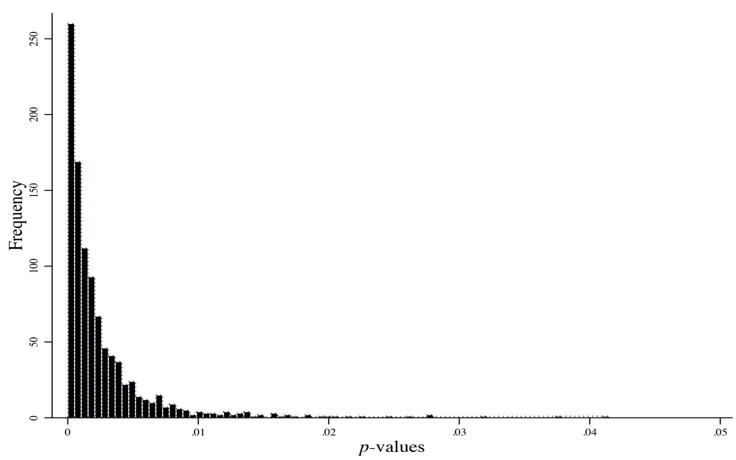
	(1)	(2)	(3)	(4)	(5)
	Ln(Fine)	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*
Democrat × DemocratTilt	1.065***	1.079***	1.035***	1.050***	1.092***
	[0.311]	[0.303]	[0.305]	[0.300]	[0.311]
Male × DemocratTilt	0.184				0.198
	[0.441]				[0.454]
White × DemocratTilt		0.522*			0.509*
		[0.274]			[0.258]
Experience × DemocratTilt			0.241		0.196
			[0.425]		[0.426]
Age × DemocratTilt				0.123	0.133
				[0.315]	[0.323]
Public Firm	2.276***	2.269***	2.273***	2.270***	2.279***
	[0.508]	[0.503]	[0.509]	[0.500]	[0.511]
Firm With Criminal History	-0.017	-0.039	-0.026	-0.027	-0.035
	[0.238]	[0.230]	[0.230]	[0.232]	[0.242]
Observations	1,404	1,404	1,404	1,404	1,404
Adjusted R^2	0.572	0.572	0.572	0.572	0.571
Excluding NP/DPs	YES	YES	YES	YES	YES
Judge FE	YES	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES	YES

Internet Appendix

Figure A.1: Distribution of p-values when Dropping a Random 10% or 20% of Judges

This figure plots this histogram of p-values for the coefficient *Democrat×DemocratTilt* when dropping a random subset of judges from the estimation of Equation (1) that uses *Ln(Fine)* as the dependent variable. Specifically, we repeat the estimation of Table 7, Column 1, but drop either a random 10% of judges from the sample or a random 20% of judges and record the resulting p-value. This is repeated 1,000 times, and the resulting histograms are constructed. The top panel reports the distribution of p-values when dropping 10% of judges, while the bottom panel reports the distribution when dropping 20% of judges. Similar to Table 7, the sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Standard errors were double clustered at the crime and judge levels.

Distribution When Dropping a Random 10% of Judges



Distribution When Dropping a Random 20% of Judges

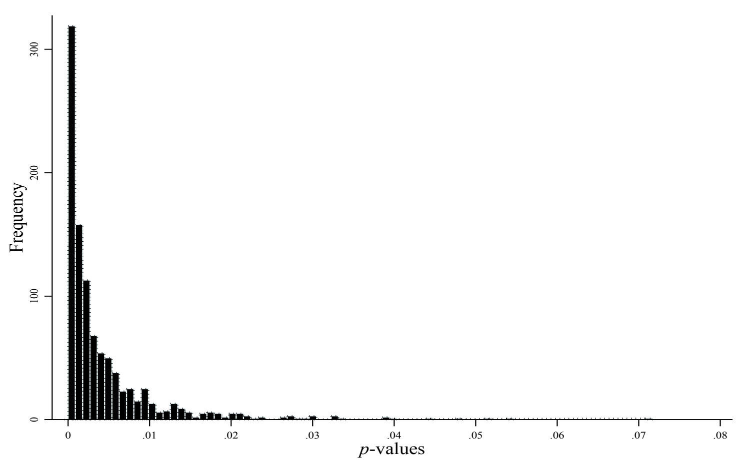


Table A.1: Political Affiliation and Within-Jurisdiction Likelihood of Being Assigned Cases with Particular Crimes

This table regresses indicators for the type of crime onto an indicator for being a Democrat-appointed judge, *Democrat*, and jurisdiction fixed effects, which is the level at which cases are supposedly randomly-assigned to judges. Estimates are reported for the ten most common crimes, including our classification of "Environmental and Labor" crimes. Columns (1)-(10) use indicators for "Fraud – General," "Environmental and Labor (our definition)," "Antitrust," "Other," "FCPA," "Import / Export," "False Statements," "Immigration," "Fraud – Tax," and "FDCA / Pharma," respectively. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the official case docket. Standard errors, clustered at the crime level, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Fraud-Gen.	Env./Labor	Antitrust	Other	FCPA	Imp./Exp.	False St.	Immigration	Fraud-Tax	FDCA/Pharm.
Democrat	0.004	0.011	0.023	-0.013	-0.016*	-0.006	0.007	-0.003	0.001	0.015
	[0.008]	[0.014]	[0.018]	[0.013]	[0.009]	[0.008]	[0.008]	[0.004]	[0.002]	[0.013]
Observations	2739	2739	2739	2739	2739	2739	2739	2739	2739	2739
Adjusted R^2	0.058	0.149	0.486	0.027	0.376	0.035	0.002	0.181	0.606	0.062
Jurisdiction FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A.2: Test of Whether Case Characteristics Predict Political Affiliation

This table reports estimates from a regression of an indicator for whether the presiding judge was appointed by a Democrat onto the partisan tilt of the underlying crime, characteristics of the firm being prosecuted, jurisdiction fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the official case dockets. Standard errors, double clustered at the crime and judge levels, are reported in brackets. The reported p-value is from a joint F-test of the coefficients on *DemocratTilt*, *Public Firm*, and *Firm With Criminal History*.

	(1) *Democrat*
DemocratTilt	0.020
	[0.016]
Public Firm	0.010
	[0.046]
Firm With Criminal History	-0.017
	[0.045]
Observations	2,757
Adjusted R^2	0.122
p-value from F-test	0.59
Case Year FE	YES
Jurisdiction FE	YES

Table A.3: Political Affiliation and Outcomes, Controlling for Judge- and Firm-Level Characteristics

This table repeats the estimation of Equation (2) that is reported in Table 5, but adds additional controls for characteristics of the assigned judge and characteristics of the firm being prosecuted. *Male* and *White* are indicators for whether the assigned judge is male or white, respectively. *Experience* is the number of years the assigned judge has been on the federal bench, and *Age* is the assigned judge's age. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the official case docket. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Plea*	(2) *NP/DP*	(3) *Dismissal*	(4) *Declination*	(5) *Conviction*	(6) *Acquittal*	(7) *Ln(Fine)*
Democrat	-0.031*	-0.001	0.006	-0.003	-0.002	0.000	-0.022
	[0.018]	[0.001]	[0.004]	[0.003]	[0.003]	[0.001]	[0.125]
Male	0.018	0.001	-0.000	0.004	-0.004	0.002	-0.315**
	[0.020]	[0.001]	[0.004]	[0.005]	[0.004]	[0.002]	[0.138]
Age	0.193	-0.003	0.014	0.033	0.013	-0.009	0.623
	[0.125]	[0.004]	[0.023]	[0.032]	[0.010]	[0.010]	[0.455]
White	-0.077***	0.000	0.004	-0.006	-0.000	-0.002	-0.125
	[0.024]	[0.000]	[0.004]	[0.005]	[0.003]	[0.002]	[0.187]
Experience	-0.003	0.000	-0.000	-0.000	-0.000	0.000	0.001
	[0.002]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.007]
Public Firm	-0.246***	-0.000	0.010	-0.004	0.006	-0.002	2.619***
	[0.070]	[0.000]	[0.013]	[0.007]	[0.009]	[0.002]	[0.550]
Firm With Criminal History	0.004	-0.001	0.012	-0.005	0.005	-0.001	0.196
	[0.021]	[0.001]	[0.009]	[0.004]	[0.004]	[0.002]	[0.260]
Observations	2737	2737	2737	2737	2737	2737	1885
Adjusted R^2	0.431	-0.011	0.057	0.166	0.067	0.002	0.517
Case Year FE	YES	YES	YES	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES	YES	YES	YES
Jurisdiction FE	YES	YES	YES	YES	YES	YES	YES

Table A.4: Ln(Fines) Using Only DP and NP Cases

This table examines whether monetary damages can be predicted based on a judge's political affiliation and the partisan nature of the underlying crime using our base-case model in Equation (1). Unlike Table 7, we now limit the sample to those prosecutions that resulted in either a deferred prosecution (DP) or a non-prosecution (NP). The table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a DP or NP deal, and have a positive amount of monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*
Democrat × *DemocratTilt*	-0.847	0.257
	[1.564]	[1.295]
Public Firm		1.962***
		[0.351]
Firm With Criminal History		0.506
		[0.362]
Observations	124	124
Adjusted R^2	0.358	0.417
Judge FE	YES	YES
Case Year FE	YES	YES
Crime Type FE	YES	YES

Table A.5: Robustness To Dropping the Largest Fines Each Year

This table examines the robustness of the findings in Table 7 to excluding the largest fines in a given year. Specifically, the table reports coefficients from a regression of *Ln(Fine)* onto *Democrat*×*DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects, but columns (1)-(4) use a sample that excludes the largest 1% of fines each year while columns (5)-(8) exclude the largest 5% of fines each year. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample in columns (1)-(2) and (5)-(6) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. The sample in columns (3)-(4) and (7)-(8) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Drop Top 1% of Fines Each Year				**Drop Top 5% of Fines Each Year**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(Fine)	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*
Democrat × *DemocratTilt*	0.910***	0.919***	0.642***	0.612**	0.945***	0.953***	0.523**	0.523**
	[0.297]	[0.286]	[0.226]	[0.226]	[0.266]	[0.257]	[0.222]	[0.215]
Public Firm		1.917***		2.249***	1.616***		1.755***	
		[0.479]		[0.486]	[0.555]		[0.506]	
Firm With Criminal History		-0.105		-0.133	-0.138		-0.207	
		[0.216]		[0.247]	[0.195]		[0.206]	
Observations	1,375	1,375	1,660	1,660	1,321	1,321	1,581	1,581
Adjusted R^2	0.531	0.554	0.518	0.558	0.514	0.529	0.516	0.538
Exclude NP/ DP	YES	YES	NO	NO	YES	YES	NO	NO
Judge FE	YES	YES	YES	YES	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES	YES	YES	YES	YES

Table A.6: Political Affiliation, Partisanship, and Likelihood of Fine

This table analyzes whether the likelihood of positive monetary damages differ based on the political affiliation of the president that nominated the presiding judge and the partisan nature of the underlying crime. Specifically, the table repeats the estimation of Equation (1) using an indicator for positive monetary damages as the dependent variable. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The specification include judge, crime, and case-year fixed effects. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, and where we can identify the judge's name from the official case docket. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Non-Zero Fine Dummy*	(2) *Non-Zero Fine Dummy*
Democrat × *DemocraticTilt*	0.059*	0.062*
	[0.032]	[0.032]
Public Firm		-0.069*
		[0.035]
Firm With Criminal History		0.004
		[0.026]
Observations	2,560	2,560
Adjusted R^2	0.242	0.244
Judge FE	YES	YES
Case Year FE	YES	YES
Crime Type FE	YES	YES

Table A.7: Importance of Court Vacancies when Including Judge Fixed Effects

Similar to Table 11, this table examines whether monetary damages vary based on whether there exists a higher-court vacancy at the time the case is decided, the political affiliation of the president that nominated the presiding judge, and the partisan nature of the underlying crime using the model in Equation (5). Unlike Table 11 and Equation (5), however, we now include judge fixed effects instead of jurisdiction fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Vacancy* is an indicator that flags cases that conclude during a period where their is a vacancy on on either the Appeals Court for that jurisdiction, the Federal Circuit Court in DC, or the Court of International Trade. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. Column (1) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Column (2) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has positive monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)
	Ln(Fine)	*Ln(Fine)*
Vacancy	-0.211	-0.538
	[0.517]	[0.460]
Democrat × *Vacancy*	-0.061	-0.037
	[0.713]	[0.682]
DemocratTilt × *Vacancy*	0.093	0.179
	[1.049]	[0.925]
Democrat × *DemocratTilt*	1.221***	0.658**
	[0.289]	[0.253]
Democrat × *DemocratTilt* × *Vacancy*	1.358	1.955
	[1.339]	[1.183]
Public Firm	2.378***	2.615***
	[0.438]	[0.402]
Firm With Criminal History	-0.219	-0.060
	[0.236]	[0.240]
Observations	1,389	1,689
Adjusted R^2	0.601	0.604
Exclude NP/ DP	YES	NO
Judge FE	YES	YES
Month-Year FE	YES	YES
Crime Type FE	YES	YES

Table A.8: Robustness to Excluding Jurisdictions Dominated by One Political Party

Similar to Table 7, this table examines whether monetary damages differ based on the political affiliation of the president that nominated the presiding judge and the partisan nature of the underlying crime using our base-case model in Equation (1). Unlike Table 7, however, we now exclude prosecutions that occurred in jurisdictions dominated by a one political party in the year in which the case is filed. In particular, Columns 1-2 exclude jurisdictions where 90 percent or more of the judges in the case's jurisdiction were appointed by one political party, while Columns 3-4 exclude cases filed in jurisdictions where 75 percent or more of the judges were appointed by one political party. The table reports coefficients from a regression of *Ln(Fine)* onto *Democrat×DemocratTilt*, judge fixed effects, crime fixed effects, and case-year fixed effects. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president, and equals zero for judges appointed by a Republican president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental- and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or guilty verdict, and have a positive amount of monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Drop Jurisdictions with > 90% Same Party		***Drop Jurisdictions with > 75% Same Party***	
	(1)	(2)	(3)	(4)
	Ln(Fine)	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*
Democrat Judge × DemocratTilt	1.262***	1.311***	1.411***	1.452***
	[0.313]	[0.307]	[0.377]	[0.385]
Public Firm		2.874***		2.754***
		[0.478]		[0.627]
Firm with Criminal History		-0.056		0.032
		[0.202]		[0.263]
Observations	1054	1054	903	903
Adjusted R^2	0.487	0.533	0.500	0.535
Exclude NP/ DP	YES	YES	YES	YES
Judge FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES

Table A.9: Robustness to Alternative Methods of Calculating Standard Errors

This table analyzes whether the choice of how standard errors are calculated matters. Specifically, the table repeats the estimation of Column (2) in Table 7 using different methods to calculate the standard errors. Rather than using double clustering at the crime and judge levels as in Table 7, Column (1) clusters at the judge level, Column (2) clusters at the crime level, Column (3) uses heteroskedastic-robust standard errors with no clustering. Similar to Table 7, the sample for Columns (1)-(3) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. In Columns (4)-(5), we drop observations where we are unable to determine exactly the jurisdiction of the case. Column (4) double clusters at the crime and judge levels, while Column (5) clusters at the jurisdiction and judge levels. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*	(3) *Ln(Fine)*	(4) *Ln(Fine)*	(5) *Ln(Fine)*
Democrat × *DemocraticTilt*	1.047***	1.047***	1.047***	1.254***	1.254***
	[0.322]	[0.272]	[0.302]	[0.286]	[0.405]
Public Firm	2.269***	2.269***	2.269***	1.976***	1.976***
	[0.332]	[0.568]	[0.288]	[0.560]	[0.403]
Firm With Criminal History	-0.024	-0.024	-0.024	-0.242	-0.242
	[0.200]	[0.246]	[0.234]	[0.230]	[0.198]
Observations	1,404	1,404	1,404	1,127	1,127
Adjusted R^2	0.572	0.572	0.573	0.535	0.535
Include Missing Jurisdictions	YES	YES	YES	NO	NO
Exclude NP/ DP	YES	YES	YES	YES	YES
Judge FE	YES	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES	YES
Crime FE	YES	YES	YES	YES	YES
Judge Clusters	YES	NO	NO	YES	YES
Crime-Type Clusters	NO	YES	NO	YES	NO
Jurisdiction Clusters	NO	NO	NO	NO	YES
Robust SE	NO	NO	YES	NO	NO

Table A.10: Robustness to Using Judge-Level Controls Instead of Judge Fixed Effects

This table repeats the analysis of Table 7 replacing judge fixed effects with jurisdiction fixed effects and judge-level controls for political affiliation, age, gender, race, and experience. *Democrat* is a dummy variable that equals one for judges appointed by a Democrat president. *DemocratTilt* is a variable that takes the value of one for cases involving environmental and labor-related crimes, while cases involving immigration crimes are assigned a value of minus one. All other cases are assigned a *DemocratTilt* value of zero. *Male* and *White* are indicators for whether the assigned judge is male or white, respectively. *Experience* is the number of years the assigned judge has been on the federal bench, and *Age* is the assigned judge's age. *Public Firm* is an indicator for the defendant being publicly listed, and *Firm With Criminal History* is an indicator for the defendant having been found guilty of a crime previously. The sample in columns (1)-(2) includes all cases that: occurred between 2000 and 2018, are found in the Corporate Prosecutions Registry, where we can identify the judge's name from the official case docket, result in a plea deal or conviction, and have a positive amount of monetary damages. Columns (3)-(4) expands the sample by also including cases that conclude with a deferred or non-prosecution agreement that has monetary damages. Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1) *Ln(Fine)*	(2) *Ln(Fine)*	(3) *Ln(Fine)*	(4) *Ln(Fine)*
Democrat Judge × DemocratTilt	0.411**	0.365**	0.338*	0.326**
	[0.165]	[0.151]	[0.174]	[0.155]
Male	-0.318**	-0.277*	-0.305*	-0.305**
	[0.126]	[0.136]	[0.154]	[0.128]
White	-0.049	-0.096	-0.060	-0.110
	[0.187]	[0.190]	[0.182]	[0.188]
Democrat	-0.155	-0.133	-0.063	-0.053
	[0.135]	[0.132]	[0.129]	[0.127]
Age	0.440	0.631	0.102	0.434
	[0.587]	[0.555]	[0.498]	[0.507]
Experience	0.002	-0.002	0.010	0.006
	[0.007]	[0.008]	[0.006]	[0.008]
Public Firm		2.785***		2.661***
		[0.393]		[0.542]
Firm With Criminal History		0.220		0.216
		[0.297]		[0.260]
Observations	1,642	1,642	1,898	1,898
Adjusted R^2	0.437	0.493	0.456	0.513
Exclude NP/ DP	YES	YES	NO	NO
Jurisdiction FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime Type FE	YES	YES	YES	YES

Table A.11: Robustness to Excluding "US Antitrust," "US Criminal," "US Tax," "US Environmental," and "US National Security" jurisdictions

This table analyzes the robustness of our findings to excluding cases occurring in non-geographic jurisdictions. Specifically, this table repeats the analysis of Table 7 after excluding cases with a jurisdiction of "US Antitrust," "US Criminal," "US Tax," "US Environmental," or "US National Security". Standard errors, double clustered at the crime and judge levels, are reported in brackets. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Fine)	*Ln(Fine)*	*Ln(Fine)*	*Ln(Fine)*
$Democrat \times DemocraticTilt$	1.137***	1.133***	0.803***	0.773***
	[0.329]	[0.320]	[0.280]	[0.273]
Public Firm		2.743***		2.890***
		[0.418]		[0.363]
Firm With Criminal History		0.007		-0.126
		[0.228]		[0.244]
Observations	1,239	1,239	1,394	1,394
Adjusted R^2	0.489	0.537	0.475	0.540
Exclude NP/ DP	YES	YES	NO	NO
Judge FE	YES	YES	YES	YES
Case Year FE	YES	YES	YES	YES
Crime FE	YES	YES	YES	YES