Corruption and Property Rights: Evidence from Russian Commercial Courts

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Abstract

Corruption is often rampant within state bureaucracies and judicial systems, yet we know little about its micro-level consequences on policymaking and the provision of public goods. In this paper, we investigate how corruption shapes property rights protection in one prominent autocracy: Russia. First, we use income and asset disclosures to construct novel individual-level measures of corruption for 366 commercial court judges working in and around Moscow. Then, drawing on data from more than 400,000 court cases heard between 2011-2018, we leverage random assignment of cases to judges to show that corrupt judges are much more likely to find in favor of private firms in their disputes with government agencies. Not only are these decisions of lower judicial quality, but they tend to favor disreputable firms. In contrast to existing work that emphasize the importance of political pressure on Russian court cases, we show that judicial corruption enables firms to capture the state, depriving it of financial resources and undermining the rule of law.

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What are the governance costs of corruption? Even if pursuing their private interest guides their time in office, corrupt public officials still must legislate, implement policy and provide public goods. Perhaps surprisingly, we know little about the aggregate consequences of corruption within the state apparatus, particularly how the drive for personal gain affects the specific decisions officials make about distributional outcomes. Work in economics, for example, has calculated the welfare and efficiency losses of misappropriating budget funds from education and infrastructure (Ferraz, Finan, and Moreira, 2012; Olken, 2007). But in many political settings, corrupt officials thrive not from their access to government coffers, but from their authority in relations with citizens and businesses. When and how do opportunities for self-enrichment affect governance and the rule of law?

This paper introduces several new datasets on officialdom in Russia to investigate the relationship between corruption and public officials' performance. Answering this question raises several thorny empirical challenges, perhaps partially explaining the minimal progress in the literature so far. What we know about the political and economic costs of corruption often cannot account for the fact that not only is corruption very difficult to measure, but it is also endogenous to other antecedents of governance quality (Olken and Pande, 2012). Individuals inclined towards self-enrichment often self-select into the public sector, and into particular specific agencies, institutions, and roles (Banerjee, Baul, and Rosenblat, 2015; Gans-Morse, 2022; Hanna and Wang, 2017). This can undermine the task of cleanly measuring how different types of public officials perform their jobs (Best, Hjort, and Szakonyi, 2017). This paper introduces a new approach to tackling both problems. We first generate novel measures of corruption at the individual level and then exploit a robust identification strategy to overcome endogeneity related to measuring individual effects on policy outcomes.

Our data comes from the Russian system of commercial courts (*arbitrazhnye sudy*). No matter the institutional setting, commercial and trading disputes are a staple of doing business. Disputes vary widely, ranging from suppliers failing to fulfill contractual obligations to aggressive competitors orchestrating hostile corporate raids and rapacious bureaucrats burdening firms with regulatory demands. In many countries, governments have invested heavily in commercial courts as a mechanism for resolving such disputes, adjudicating property claims, enforcing contracts, and more generally facilitating economic transactions (Pistor, 1996). Acting as neutral third-parties, commercial courts hear cases involving disputes between commercial enterprises, disputes between companies and government agencies, and bankruptcy cases (Hendley, 1998).[1] In Russia, firms have

[1]Criminal cases and civil cases involving individual litigants in Russia are heard in the courts of general

increasingly turned to litigation to resolve their problems, rather than relying on criminal protection rackets or other forms of private enforcement methods that had been widespread the 1990s (Gans-Morse, 2017). By the mid-2010s, some commentators had even gone as far as to laud Russia's commercial court system as among "the very best of the post-Soviet legal system" (Pomeranz and Rojansky, 2014). Though corruption and political capture continue to pose challenges, the commercial courts are among the most important political institutions backing investment and the broader business environment (Frye, 2017).

To study the commercial courts' operations, we first use public income and asset declarations paired with both public and leaked automobile databases to derive corruption red flags for individual judges. Since 2008, the Russian government has required nearly all elected and appointed public officials, including commercial court judges, to annually report all income, real estate and transportation assets for themselves, their spouses and dependent children earned over the previous year. We collect, parse, and standardize these disclosures for all 366 commercial court judges in Moscow city and its surrounding province, Moscow Oblast. Then exploiting a newly created database of nearly three million luxury car annual ownership records and valuations, we develop an individual-level measure of corruption based on judges' hidden assets (the luxury cars they fail to report) and hidden earnings (the cars they do report but should not be able to afford based on their income, an approach that builds on Braguinsky, Mityakov, and Liscovich 2014). Overall, 42 (11.5%) of the judges in the dataset either hid assets or earnings, and consequently were flagged as potentially more corrupt than their peers. More corrupt judges are more likely to be male, but otherwise resemble their less corrupt peers along all other demographic characteristics on which we have data.

We next leverage the institutional features of the Russian commercial court system, a unique setting in which government officials are in essence randomly assigned to make policy decisions. This design allows us to study the effect of individual traits (such as corruption) on case outcomes. We collect complete data on roughly 2 million cases adjudicated by these judges in Moscow and the Moscow oblast from 2011-2018; of these, roughly 430,000 involve disputes between companies and the state. Building off the extensive literature studying similar processes in US court systems, our identification strategy exploits the conditional random assignment of cases to judges to investigate whether specific judge characteristics affect which and how decisions are handed down. We develop a simple theoretical framework to derive predictions about how cases heard by corrupt judges may turn out differently than those heard by judges less motivated by

jurisdiction (*sudy obshchej yurisdiktsii*).

personal profit.

Our results show that corrupt judges are more likely than their less corrupt peers to find in favor of private firms in disputes with government agencies. We argue that this bias towards private firms suggests corrupt judges solicit and entertain side payments. Not only do such judges appear willing to rule against government entities if the sum offered by private litigants is sufficiently attractive, but state actors, who may at times wield political pressure but are unlikely to offer bribes, may find themselves at a disadvantage in the courtrooms of judges whose decisions are for sale. This bias is particularly pronounced among high-stakes cases where significant sums or important rulings are being decided, indicating that the non-negligible cost of bribes forces firms to use them strategically on a selective basis. Next, we see that corrupt judges' rulings are more likely to be issued with delayed, appealed by the losing side, but only weak evidence that they are overturned by higher level courts.

Finally, we explore the normative implications of this type of corruption. On one hand, firms may be using corrupt judges to push back against a predatory state trying to extract rents through unjustified fines, regulations, and lawsuits. On the other, disreputable firms may be exploiting the court system to avoid abiding by the law, meaning that corrupt judges' decisions in favor of such firms serve to undermine the rule of law. Using new data on firm reputation, we find evidence for the latter explanation. Corrupt judges are much more likely to find in favor of firms that are registered at 'mass addresses', appear on a list of dishonest suppliers, or have disqualified directors. Corruption allows shady firms to win rulings against the state, and often times to extract rents. Importantly, because decisions are not being overturned by higher-level appelate courts, these disreputable firms are able to purchase "final" verdicts in their favor from corrupt judges.

This paper is among the first to directly connect personal corruption motives with the administration of property rights. By opening the black box of a critically important economic institution, we show how individual judges seeking bribes can undermine key building blocks of market capitalism, such as contract enforcement and tax collection. We extend micro-level research on corruption among bankers (Weill, 2011), bureaucrats (Weaver, 2021; Bertrand et al., 2007), CEOs (Mironov, 2015), and elected officials (Eggers and Hainmueller, 2009; Fisman, Schulz, and Vig, 2014) to include work on the judicial branch, which has not received the same degree of scholarly attention. Importantly our findings contrast with popular accounts of judicial corruption in Russia that posit the importance of 'telephone justice', whereby higher-level officials pressure judges, including those working in commercial courts, to pass certain rulings (Ledeneva, 2008; Lambert-Mogiliansky, Sonin, and Zhuravskaya, 2007). While we do not deny that telephone justice plays some role in the Russian judiciary, particularly in high-profile cases, our results show that corrupt judges in fact more frequently rule against the government, suggesting that the vertical political hierarchy is not so strong as to prevent private actors from influencing the judicial system for their own ends. Judges may be pursuing profit and personal ambitions without direction from above, and seeing financial windfalls accrue to their families from catering to private companies that make the most attractive offers.

This paper also extends previous work about how commercial court quality in Russia affects firm performance (Lambert-Mogiliansky, Sonin, and Zhuravskaya, 2007; Shvets, 2013), as our findings draw attention to corruption's distortionary effects on the state's ability to enforce the law. By helping firms win disputes against the government, corrupt judges may be contributing to the market consolidation and firm inequality that has produced a significant drag on economic growth in Russia (Di Bella, Dynnikova, and Slavov, 2019). Russian commercial court judges who issue rulings in exchanges for bribes also may be privileging the property rights of a subset of firms with a high level of resources and/or a low level of ethical inhibitions, undermining the judiciary's ability to contribute to fair and equitable development (Chemin, 2009).

1 Theoretical Framework

Unpacking how corruption affects about judges' decision making first requires tracing how illicit money enters the judicial system. We assume that the primary mechanism through which corruption operates is through bribes paid by litigants to the judge in charge of their case. Commercial court judges extract rents from their office not from siphoning off funds from state budgets (Liu and Mikesell, 2014) or taking personal ownership stakes in companies (Szakonyi, 2020), but by accepting, and often times extorting, money in exchange for passing preferential decisions.

A review of journalistic accounts of corruption in the Russian commercial court systems corroborates this assumption. One experienced lawyer likened the corruption to an efficient market, with an average bribe paid of 25,000 Euros.[2] But depending on the case, sums can reach into the millions of dollars. Intermediaries – often judges' relatives and close friends – facilitate the payments, helping litigants make an offer, usually as a percentage of the amount of the claim, to the judge in exchange for the desired ruling. Judges rarely demand specific sums, but instead can entertain several offers and enter into an agreement (sometimes informal, sometimes in writing) through the intermediary with the chosen litigant.[3] Burger (2004) cites conversations with Russian attorneys about

[2] Ivan Remeslo, "Korruptsiya v sudax: Vzglyad praktikuyushego yurista," *Ekho Moskvy* (July 19, 2014).

[3] Litigants can also approach judges with unsolicited bribes, even if they are unsure about whether a

judges analyzing the merits of a case beforehand and then seeking payments from the litigant who would benefit from the proper decision being made. In other cases, judges actually meet in person with all litigants and operate on the principle of 'whoever brings the most money will win the case.'[4] A single bribe in an important case can equal or exceed the official annual income of a judge.

These media accounts align with the small number of anecdotes we have from criminal cases against commercial court judges brought by law enforcement officials. A commercial court judge in Sverdlodsk Oblast was sent to seven and a half years in prison for accepting 14 million rubles ($350,000) in bribes through his son to help commercial firms win cases.[5] Another case from Moscow Oblast accused two judges of helping fake companies win large VAT refunds from the government; the case was ultimately overturned by a higher appellate court's decision.[6] Moscow commercial court Judge Irina Baranova fled to the United States after being accused of accepting over 100 thousand Euros in exchange for helping a firm orchestrate a hostile takeover (raid) of a valuable building in the center of Moscow.[7] However, only a small percentage of corruption is ever uncovered by law enforcement officials.

We treat the corruption in the adjudication process as conforming most closely to an auction. Corrupt judges first solicit and then review bids submitted in the form of bribes by litigants. Rulings are issued in favor of the highest bidder; if only one litigant offers a bribe, then by default they earn preference. We hypothesize that there are several empirical implications from the argument that corrupt judges are more receptive to the litigants most willing and able to offer substantial bribes in exchange for favorable rulings. Although our data does not allow us to observe the size of bribes offered, we can observe characteristics of the litigants and infer their ability to pay through their registration records. That said, in most cases that pit one firm against another, assessing willingness to pay bribes is nearly impossible. While it is tempting to treat firm size or revenue as a proxy for capacity to offer bribes, there may be cases where losing a dispute poses more of an existential threat to the litigant with fewer resources, leading smaller firms to outbid larger adversaries.

judge generally entertains such offers. We found no instances of honest judges reporting litigants to the authorities for making such an advance, suggesting there is little cost for this type of probing.

[4]Quote from a letter sent by Chairperson of the Council of Judges Yuri Sidorenko to the Russian Federal Security Service (FSB) documenting corruption in the Moscow Oblast commercial court system. Reported in Regnum (May 3, 2012).

[5]Aleksandr Lukmanov, "Sledovateli nashli dokazatsva v dele o vzyatke sudi Arbitrazhnogo suda Sverdlovskoy oblasti," *Ura.Ru* (August 28, 2019).

[6]"Uvolen sudya, prinimavshiy resheniye v polzu nalogoplatelshikov," *Klerk.ru* (November 28, 2016).

[7]Vladimir Polataev, "Sudya pod arestom," *Rossiiskaya gazeta*, (May 30, 2018).

However, commercial courts are also the venue where disputes between firms and the state are resolved. For example, in Russia firms often sue the government for tax refunds or to challenge determinations of their tax liability, while the government sues firms for unpaid tax bills and contributions to pension and social funds. If money does talk, we should expect that corrupt judges will be more receptive to the interests of private litigants in their disputes with government entities. Although state officials may be able to place other types of pressure on judges to tip the scales of justice, few have such vested interests that they would be able or willing to offer large monetary sums to offset the bribes proposed by private litigants. Corrupt judges may also be particularly hesitant to accept monetary overtures from state officials, due either to wariness of law enforcement sting operations or to a broader perception that illegal activity by another state actor runs a higher risk of attracting law enforcement's attention. Therefore, we expect corrupt judges to exhibit differential decision-making patterns in public-private disputes.

Hypothesis 1. *In cases involving firms and government agencies, corrupt judges will ceteris paribus be more likely to find in favor of firms.*

Next, we expect that corrupt judges will return lower quality decisions that do not hold up well under scrutiny. One perceived strength of the Russian commercial court system is its divided hierarchy: Appellate courts are functionally (and often times) geographically distinct from the courts of first instance. We accordingly examine whether verdicts are appealed, as a sign that the losing party felt the initial decision had been undeservedly handed down and the opinions of more qualified judges needed to be considered. Among those that are appealed, we then examine whether they are upheld in appellate courts. Such reversal rates have long been used as indicators of judicial performance in empirical legal scholarship focused on the US judicial system (see, e.g., Choi, Gulati, and Posner, 2012; Halberstam, 2016; Posner, 2000; Vakilifathi and Kousser, 2020), and more recently have been fruitfully employed to measure judicial quality in studies of court systems in Eastern Europe and post-Soviet Russia (Avdasheva, Golovanova, and Sidorova, 2022; Dimitrova-Grajzl et al., 2012, 2016; Lambert-Mogiliansky, Sonin, and Zhuravskaya, 2007; Shvets, 2013; Spáč, Šimalčík, and Šípoš, 2018).

Appellate court judges typically are more qualified, more experienced, and, ultimately, more likely to issue a legally 'correct' ruling (i.e., a decision more in line with the merits of the case) (Lambert-Mogiliansky, Sonin, and Zhuravskaya, 2007; Shvets, 2013). Additionally, all cases in Russia's commercial appellate courts are heard by a panel of three judges, which both bolsters the quality of decision-making and makes it significantly more difficult for corrupt litigants to 'buy' a decision (Burger, 2004, 2). We therefore might expect corrupt judges' rulings to be more frequently appealed and more frequently overturned by higher level courts.

Hypothesis 2. *Cases assigned to corrupt judges will ceteris paribus be more likely to be appealed and then overturned.*

The framework presented here holds that companies view corrupt judges as an instrument for defending their interests within the judicial system. Companies with substantial sums of money on the line will be more willing to risk the legal consequences of getting caught, and also pursue cases aggressively from initiation to final resolution. In the analysis below we accordingly focus primarily on high-stakes cases where it makes financial sense for a firm to pay bribes; petty cases with small claims or insignificant stakes are not worth breaking the law over. But in larger cases, corrupt judges offer their services for a hefty price, thus skewing the justice system towards those who have the capacity, motivation, and willingness to make illicit investments.

2 Data and Measurement

To some, Russia's judicial system may seem an unlikely candidate for accurately measuring the impact of corrupt behavior on governance, particularly as related to the judicial system. Yet Russia enacted transparency measures in the 2000s that made commercial court decisions publicly available to a degree rarely found even in Europe or North America. Complete data on roughly twelve million commercial and bankruptcy cases filed from 2011 to 2018 is stored on a publicly accessible website KAD (kad.arbitr.ru).[8] Not only can the litigants to each case be identified and matched to external datasets, but the courts provide detailed information on the judges assigned, hearings held, and every document, decision, and enforcement throughout the entire litigation process, from filing to final appeal.[9]

We focus in this paper only on cases heard in the two commercial courts of the first instance representing the city of Moscow and the Moscow Oblast. First, only in these two regions do we have access to more detailed information on judge background and

[8] We restrict our end date to 2018 so as to ensure that complete data on all cases had been entered at the time of scraping in early 2021. Since some cases can last over two years, for consistency we only use those that began in 2018.

[9] Russia's commercial court system is hierarchically structured, with 84 first instance courts located in each of Russian's regions, 21 appellate courts, 10 cassation courts, and then two higher courts located within the Supreme Court (Bocharov and Titaev, 2018). Case rise up the ladder on appeal, though scholars have noted the different levels of courts are functionally independent from one another.

personal wealth.[10] Second, as we have argued above, we expect the observable patterns emerging from corrupt judge bias to be strongest in business-state disputes. By focusing on the federal center, we capture a large portion of the cases between firms and the federal government; by also including Moscow Oblast, we can expand our coverage of regional and municipal government actors beyond the city of Moscow, improving our generalizability to other parts of Russia.

Because Moscow and its surrounding region account for such a disproportionate part of Russia's economy, we are still left with roughly 12% of our original sample, or 1,953,796 cases heard by 366 judges. All our analysis is done at the case level; each observation is a case filed at one of these two first instance courts. To ensure we can draw a direct line from individual officials to case outcomes, we restrict analysis to cases overseen by a single judge for whom we have basic biographic and income data. This excludes mainly the small number of cases where judges were substituted in over the course of proceedings as well as those who submitted limited documentation.

We then take several steps to narrow the data further to fit our precise research aims. First, we are most interested in the effect of corruption on the 432,725 'administrative' disputes between firms and the government, where we expect government threats to firms' property rights protection to be most severe. Therefore, our main analysis excludes all civil (i.e., firm versus firm) and bankruptcy cases. Table A3 lists the most common types of administrative disputes heard by judges in our data.

Our theoretical interest in relations between firms and government also requires we ensure that these two sets of actors are distinguishable as opposing litigants in the judicial process. For example, in some cases, firms may bring litigation in conjunction with certain government entities against other government entities. To more cleanly separate the two sets of actors, we focus on cases that see firms and government in opposition to one another with no other types of actors included as litigants to the case. In other words, we focus our analysis on cases where firms sue the government or vice-versa. This leaves us with 328,876 administrative cases.[11] Figure A4 shows graphically how we construct this analysis sample from the universe of cases, while Appendix Section A1 provides more background on each step.

[10] Biographies for Moscow-based judges are more likely to be available as are the databases we use to track assets.

[11] We analyze disputes between government actors and fully state-owned enterprises, individual entrepreneurs, and other actors in Appendix Table A7.

2.1 *Background on Commercial Court Judges*

Commercial court judges take office after passing a stringent application process.[12] Candidates for judgeships must be 25 years of age, hold a university law degree, and possess at least five years of legal experience. Applicants must first pass a judicial exam and submit a series of documents to the regional judicial qualifying board (*kvalifikatsionnye kollegii sudej*). More recent reforms required documents including certificates of income and assets for the applicant as well as his or her spouse, parents, and adult children, as discussed in more detail below. At monthly meetings, judicial qualifying boards then evaluate and nominate their preferred candidates.[13]

As in many countries with civil law traditions, the Russian judicial system largely resembles a "career judiciary." Legal professionals aspiring to the bench frequently work within the court apparatus as a judge's assistant or a court clerk. Most judges spend their entire careers within the judicial apparatus, seeking promotions within their court or to higher courts. This stands in contrast to the "recognition judiciary" model characteristic of Anglo-American common law systems, in which judges are appointed or elected at later phases in their career, usually based on their accomplishments as a practicing lawyer or legal academic (Georgakopoulos, 2000). Accordingly, judges in Russia often rise to the bench at a relatively young age. In our sample of judges from the Moscow City and Moscow Oblast commercial courts, the average judge was appointed at the age of 36, with some judges receiving appointments as early as age 26.[14]

Although judges in the 1990s came to the judiciary from relatively diverse backgrounds, with approximately one in three having worked as private sector legal professionals or as legal academics (Solomon and Foglesong, 2000, 97-98), the clear majority of applicants since the mid-2000s have worked exclusively or primarily within the court apparatus or, to a lesser degree, in the prosecutor's office. Not only are applicants with experience outside of state institutions increasingly rare, but Dzmitryieva (2021, 148) finds that judicial qualifying boards are less likely to nominate such candidates. Our data from the Moscow sample reflect these broader trends. Around 77 percent of judges about whom we have data worked in the court apparatus before appointment to the bench. Approximately 12 percent came to the bench after working as prosecutors, lawyers in government agencies, or serving in the military. Less than 6 percent had private sector experience as a commer-

[12] Russia's 1993 Constitution establishes the prerequisites for judicial appointees, with further details provided by two federal laws, the Law 'On the Judicial System' and the Law 'On the Status of Judges in the Russian Federation.'

[13] For details of the selection process, see Volkov et al. (2015, 107-114) and Dzmitryieva (2021, 136-137).

[14] Five judges in the sample joined the bench while still 25 years of age or younger, but all of these were appointed during Soviet times.

cial or defense lawyer; another 5 percent worked as legal researchers or professors before becoming judges.

Following the Soviet Union's collapse, the judicial system was underfunded, judges poorly paid, and the profession's prestige low, but since the early 2000s, the Russian government has significantly improved funding for the judiciary (Solomon and Foglesong 2000, ch. 5; Volkov et al. 2015, 32-36). The commercial courts in particular are considered relatively prestigious, even for administrative staff (Bocharov and Titaev, 2018, 129-132). Bocharov and Titaev (2018, 135) estimate that an average commercial court judge earns approximately 25,000 USD annually.[15]

Relevant to our analyses below, judges' salaries and perks are high enough that bribes have to be of a reasonably large magnitude to warrant the risk of engaging in corruption, and the size of a bribe that might tempt judges exceeds the sums of money at stake in many court cases. At the same time, the fact that judgeships in Russia's civil law system resemble in many ways a typical civil service position, with few individuals leaving lucrative private sector careers to take up the post, facilitates our development of corruption indicators based on anomalies in income and assets that exceed expectations of what an honest judge should be able to accumulate.

2.2 Measuring Corruption

Our first empirical challenge relates to identifying judges with a higher likelihood of engaging in corruption. Obviously this is not a straightforward task, as corruption is illegal. Even though prosecutions of corruption in Russia are pursued only selectively (Popova and Post, 2018; Rochlitz, Kazun, and Yakovlev, 2020), commercial court judges, as occupants of a relatively prestigious office that bestows an upper-middle class salary and generous benefits, have strong incentives to avoid any appearance of misusing their office for personal gain. Recognizing that there are many ways judges can conceal any illicit earnings, our empirical strategy uses a combination of indicators to flag judges who show signs of engaging in more corruption than their peers.

We build our composite measure of corruption using publicly available income and asset disclosures that judges file annually. By April 1 each year, all judges must submit an

[15]Salaries for judges in Russia are determined by statutory law according to a complex formula that takes into account the type of court a judge works in (e.g., commercial courts versus courts of general jurisdiction); the level of the court (e.g., first instance versus appellate courts); the court's geographic location; judges' rank on a 10-level scale of "classes" that reflects years served, legal knowledge demonstrated, and position within the judicial hierarchy; and additional awards and distinctions such as post-graduate degrees in law and knowledge of foreign languages. See Ekaterina Borzenkova, "Tsena sudyi: skolko poluchayut rossiiskie sudyi" [The price of a judge: How much Russian judges earn], *Pravo.ru* (March 1, 2019).

eight-page form containing information on their incomes, expenditures, bank accounts, stocks, real estate, and transportation assets for themselves, their spouses and dependent children. Most of this data is kept confidential from the general public and analyzed by a judicial oversight department tasked with monitoring corruption. However, data on income, real estate and transportation are released publicly on court websites; Appendix Section A3 shows examples of these electronic forms in both Russian and English. We collected and standardized the raw disclosures for all 366 commercial court judges that heard cases in Moscow and Moscow Oblast from 2011-2018. These disclosures data have aided major journalistic investigations as well as triggered criminal prosecutions into corrupt Russian officials at all levels of government (Szakonyi, 2020). In response, corrupt judges may strategically disclose or hide certain information on their forms to forestall scrutiny into their behavior in office.

Our measurement strategy creates two red flags for corruption using these disclosures data, drawing on previous work by Szakonyi (2024). Fearing outside scrutiny by media and law enforcement, corrupt judges may choose not to disclose the extent of their wealth. Validating whether judges are telling the truth requires comparing income and assets reported in the publicly accessible disclosures to those reported to other official registries, such as real estate cadastres or automobile registers. The approach of cross-referencing financial disclosures with credible external sources has become a critical anti-corruption tool for uncovering anomalies and potential graft worldwide, even by Russian oversight agencies.[16] Previous academic work has adopted similar forensic approaches, for example, to measure tax evasion (Fisman and Wei, 2004).

Of the three types of income and assets listed on Russian disclosures (income, real estate and cars), only external registries on car ownership are available at scale to researchers.[17] Using publicly available sources, including the Russian Union of Auto Insurers and leaked data from Russia's Main Directorate for Traffic Safety (GIBDD), we were able to construct an annual panel dataset of the ownership of 2,742,113 luxury cars records from 2011-2019.[18] We focus on luxury cars for both substantive and logistical rea-

[16]In most countries, individuals must register different forms of property with the government for taxation and licensing purposes. In Russia, oversight agencies can request official access to these databases in order to verify the contents of disclosure forms. Nina Astafyeva, "Kak prokuratura proveryaet dokhody gosudarstvennykh sluzhashikh," *Online812* (February 8, 2011).

[17]In the early 2000s, data from the Russian Pension Fund provided insight into the official salaries of most Muscovites, but no leaked data has emerged since 2005 (Szakonyi, 2019). Individual real estate records once were available from the Russian land registry can be purchased at a cost of $3 each, but following Russia's 2022 all-out invasion of Ukraine, access to the cadastre has been completely shut down.

[18]We selected 19 luxury brands based on an list issued annually and used by the Russian Ministry of Industry and Trade to levy an additional tax on vehicles costing more than 3 million rubles. The brands are Aston Martin, Audi, Bentley, BMW, Cadillac, Ferrari, Genesis, Hummer, Infiniti, Jaguar, Lamborghini,

sons. First, officials who fail to disclose expensive cars are more likely to have earned greater amounts of illicit income in their position. Second, building such a dataset for all brands of cars would have been prohibitively expensive, costing more than $1 million; this budget constraint forced us to look at instances of only the most expensive cars being hidden. The full process of acquiring and processing this data is described in Appendix Section A2.

Our first red flag denotes whether a commercial court judge failed to disclose any luxury car in their annual public disclosure. Of the 366 judges in our dataset, 17 judges (4.6%) owned luxury cars that neither they themselves nor their immediate family members disclosed. Table A1 lists the make, model and manufacture year for the cars that went undeclared in judges' disclosures. We interpret these omissions as an intentional and strong signal that judges are earning illicit income that they are trying to hide from oversight commissions (and which would be uncovered if questions were asked about the cars they actually drive).

Our second red flag recognizes that cars are more visible to journalists and authorities than other types of assets (as evidenced by data availability). As a result, some corrupt judges may be accurately reporting all vehicles they drive, yet still be figuratively (or literally) hiding cash derived from bribes in their mattress, which is harder to detect. Economists working with leaked datasets from the early 2000s developed a set of forensic tools to exploit this discrepancy and measure the extent of informal or hidden income in the Russian economy. More specifically, Braguinsky and Mityakov (2015) create a measure of hidden earnings by comparing individuals' officially reported earnings to the market values of the cars recorded in automobile registries. Similarly, judges who drive expensive cars yet report modest earnings in their disclosures may be attempting to hide illicit sources of income from authorities.[19]

We assign the market value to each car reported in a judge's disclosure at the time it was disclosed using prices from 'for-sale' listings on Russia's largest automobile marketplace (`http://www.auto.ru`) in 2021 and then applying a simple depreciation rate to estimate its past value. The methodology is described in full detail in Appendix Section A2.2, but for the sake of a concrete illustrative example, consider the 2012 Honda Civic that appeared in a judge's disclosure in 2015. The average price for this model in 2021

Land Rover, Lexus, Lincoln, Maybach, Mazerati, Mercedes, Porsche, Rolls Royce, and Volvo. For more information on the tax, see Ekaterina Drobinina, "Is Russia's new luxury car tax necessary?" *Russia Beyond the Headlines* (January 27, 2014).

[19] This approach again draws on several high profile investigations. For example, in 2018, a team of investigators led by activist Alexey Navalny published a report on State Duma Deputy Leonid Slutsky that raised questions about the market value of his family's car collection (two Bentleys and a Mercedes-Benz) versus his official annual income (roughly $30,000).[20]

was 827,500 rubles, or roughly $12,000.[21] Backing out the depreciation rate to 2015, we find its value in that year to be roughly 1,507,803 rubles, or roughly $21,500, a reasonable price for a three-year old Honda Civic in Moscow for that time. We calculate our hidden earnings ratio for each judge by summing all estimated car values for each judge and his or her family and dividing by the total income declared in each year (across all family members).[22] Higher hidden earnings ratio are more suggestive of corruption.

To ease integration with our first (binary) red flag concerning undeclared cars, we code all judges as being more corrupt if they had an average hidden earnings ratio of above two while in office.[23] This means that during their time in office, judges drove cars that collectively were worth twice as much than their entire family's salary for that year. Even with access to car loans, this red flag suggests some judges are living far beyond their official means and potentially earning undeclared income. A slightly higher number of judges (25, or 6.9%) meet this criteria; because of the relative ease that car registration data can be verified, we suspect more corrupt judges choose to underreport their income rather than hide cars. In Appendix Table A9, we show our main results are robust to using the continuous ratio and using a lower threshold of 1 to denote corrupt judges.[24]

Our main corruption index then takes a 1 if either (a) a judge failed to disclose a car or (b) had a hidden earnings ratio of above 2 during their time in office; and 0 otherwise. In all, 42, or 11.5%, of our judges met either of these criteria.[25] Figure 1 plots the percentage of judges displaying either of the red flags for each year of the sample. We see remarkable consistency over time, suggesting that the percentage of most corrupt judges across the two courts does not change markedly.

Table 1 presents summary statistics using this binary indicator for more corrupt versus less corrupt judges using a variety of hand-coded demographic, educational, and pro-

[21] We convert ruble amounts to dollars in all cases using average annual exchange rates and present all monetary values in the paper in dollar terms.

[22] We aggregate all data to the entire family for each year, given the ample evidence in Russia about corrupt earnings accruing to or being hidden away by relatives of officials (Szakonyi, 2019). We cannot calculate hidden earnings ratios for judges that do not report any cars on their disclosures, hence the need to adopt the first strategy for red-flagging corruption.

[23] Although the hidden earnings ratio is a continuous measure, for ease of analysis we dichotomize it in order to combine it with the first red flag and identify all judges who exhibit any signs of having engaged in corruption (i.e., by adopting various evasion strategies).

[24] **?** analyzes hidden earnings among State Duma deputies, a considerably wealthier population of officials that includes celebrities, billionaire businesspeople, and athletes among others. Given higher income rates, he flags deputies as being corrupt for whether they drove cars worth at least their annual income, which totalled over $100,000 a year on average. Commercial court judges earn far less (on average roughly $50,000 a year); thus we use a higher ratio of 2 in the main analysis to denote corruption. Appendix Table A9 shows robustness checks using the lower ratio of 1 for 116 judges (31%) of the sample that clear that bar.

[25] Eight judges met both criteria. Our result are robust to using an additive measure instead of a composite one.

Figure 1: Corruption Measure over Time

Note: This figure plots the percentage of judges that either had undeclared cars or had an hidden earnings ratio of above 2 during their time in office.

fessional data. We coded the official biographies where available for commercial court judges on the two courts' websites. For the 40% of judges who had missing or incomplete biographies, we collected open-source biographical data from the internet. Table 2 regresses our binary measure of corruption at the individual judge level on these demographic, educational, and professional indicators.

Table 1 indicates that the key difference between more and less corrupt judges is gender: Female judges are less likely to be flagged as corrupt using our measure. This accords with a wealth of recent research finding gender to be an important determinant of levels of bureaucratic corruption (Dollar, Fisman, and Gatti, 2001; Decarolis et al., 2021).[26]

[26] We control for gender in all models, as well as interact the corruption measure with judge gender in Appendix Table A8. Overall we see no differences in behavior between more corrupt judges that are men versus women, though more corrupt female judges having their cases appealed at a slightly lower rate.

However, the gender indicator, as well as all other predictors, fail to reach statistical significance in the multivariate models, suggesting that more corrupt judges look quite similar on observables to their less corrupt counterparts. More corrupt judges went to similar universities,[27] have the same amount of experience serving on the court, and are equally likely to have won awards while in office.

As a validity check, we had a research assistant comb the internet for all information about judges in these two first instance courts who have faced official investigations or prosecutions over corruption. We were able to identify 10 such instances. In Table 2, the point estimates on this anecdotal measure of corruption are positive though noisily estimated. The small number of judges publicly connected to corrupt acts are about 6-7% more likely to be labelled more corrupt using our measure. We extend our corrupt index to include these judges found to be corrupt by law enforcement and show robustness checks in Appendix Table A9.

TABLE 1: COMPARING MORE AND LESS CORRUPT JUDGES

Judge Type:	More Corrupt	Less Corrupt
(1) Number of Judges	42	324
(2) Female (%)	0.595	0.701
(3) Age (mean)	42.976	43.708
(4) Oblast Court (%)	0.262	0.333
(5) Years of Experience on Court (mean)	7.976	8.123
(6) University Rank, 1-5 scale (mean)	3.742	3.903
(7) Won Award (%)	0.548	0.562
(8) Leadership Position In Court (%)	0.214	0.171
(9) Anecdotal Evidence of Corruption (%)	0.048	0.025
(10) Family Total Disclosed Income (mean, mil. rubles)	2.329	2.732
(11) Family Total Real Estate Assets (mean)	1.756	1.903

Note: This table shows summary statistics for demographic measures at the judge level for more corrupt versus less corrupt judges. Corrupt judges are defined as having either undeclared cars or a hidden earnings ratios above 2 while in office.

2.3 *Case Outcomes*

Our primary outcome variable comes from the first instance ruling for each case. This is the first decision handed down by a judge in the case, and if no appeal is subsequently filed, it becomes final and enforced by the court. We use a simply coding key to collapse the roughly 100 raw text rulings into the seven unique values in Table 3. When operationalizing below, we code plaintiffs as winning in cases with full or partial wins, and plaintiffs losing in cases with full or partial losses, as well as when the court ended proceedings or refused to hear the case. Figure 2 plots this outcome variable — Private Firm

[27] We measure the quality of university education using a five-point variable with top Moscow and international universities taking values of 1 and institutions located in small regions or former Soviet republics taking values of 5.

TABLE 2: CORRELATES OF CORRUPTION

	Judge Corruption Measure		
	(1)	(2)	(3)
Constant	0.233	0.338	0.515
	(0.306)	(0.331)	(0.521)
Judge is Female	-0.053	-0.046	-0.067
	(0.041)	(0.040)	(0.055)
Judge Age (log)	-0.018	-0.053	-0.064
	(0.083)	(0.093)	(0.151)
Moscow Oblast Court	-0.035	-0.032	-0.033
	(0.035)	(0.035)	(0.050)
Years of Experience on Court (log)		0.008	0.015
		(0.024)	(0.049)
Anecdotal Evidence of Corruption		0.066	0.057
		(0.126)	(0.132)
Judge University Rank			-0.010
			(0.021)
Won Award			-0.077
			(0.073)
Leadership Position In Court			0.009
			(0.059)
Judge Mean Family Assets			-0.007
			(0.018)
R^2	0.009	0.009	0.023
Observations	361	354	224

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ This table shows the correlates of the hidden earnings ratio using data collected at the judge level. Standard errors are clustered on judge.

Wins — over time as a percentage of all cases, and also as a percentage of cases where the government was the plaintiff or the private firm was the plaintiff. We see that private firms won between approximately 25% and 50% of cases depending on the year. In most years, this victory rate does not vary markedly depending on which actor initiated the case.

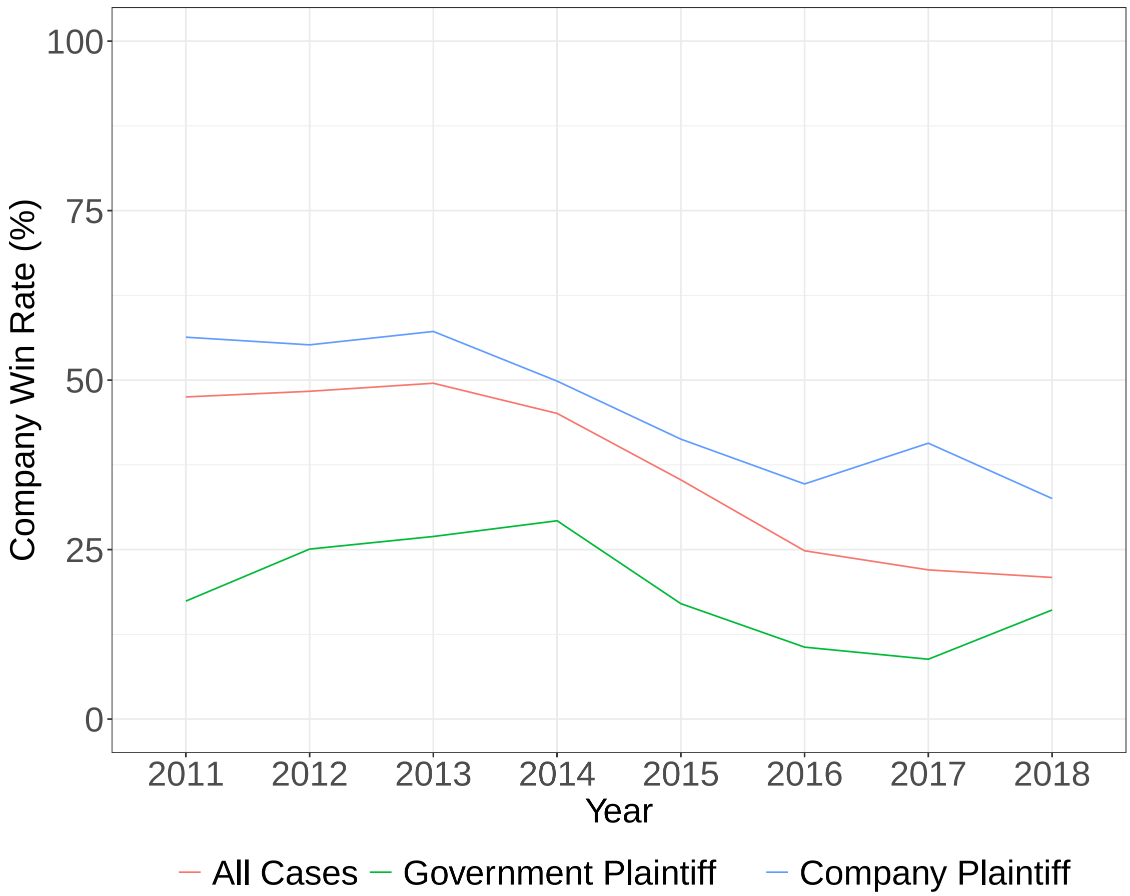
Our next set of outcomes concern case quality, including whether the initial decision was appealed and whether it was then reversed upon reveal. As noted above, empirical legal scholars frequently employ this indicator as a measure of judicial quality. While the outcome of any given appellate hearing might turn on idiosyncratic factors, systematically higher reversal rates for certain judges relative to their peers indicates that more experienced, higher qualified appellate judges consistently find fault with their rulings. Though it is in fact the case that commercial appellate courts in Russia are widely perceived to be less corrupt (Burger, 2004, 2), it is worth noting that the validity of reversal rates as an indicator of judicial quality does not rely on assumptions about higher levels of integrity among appellate judges. Rather, the requirement that all appeals be heard by three-judge panels creates an institutional impediment to bribery, for corrupt litigants seeking to sway rulings face the logistical challenge and additional expenses of having to bribe at least two of three justices (Hendley, 2003, 395). Overall, reversals are rare. Between 2011 and 2018, only 7% to 12% of appealed cases, or between 1% and 3% of the all cases in the sample, were overturned annually.

TABLE 3: CASE OUTCOMES IN ADMINISTRATIVE CASES

Outcome	Number	%
Court ends proceedings	39,269	8.9
Court refused to hear	20,957	4.8
Plaintiff loses	99,144	22.5
Plaintiff loses partially	495	0.1
Plaintiff wins	253,452	57.5
Plaintiff wins partially	9,379	2.1
Settled out of court	7	0
Total Cases	422,703	

Next, we want to focus our analysis on cases with stakes that are sufficiently significant for litigants to consider bribing judges. Government entities in Russia such as the pension fund file thousands of petty cases against firms that fail to pay taxes, dues, or contributions, and frequently these cases involve trivial claims as low as $10. Logic dictates that bribery in such cases is highly unlikely. To capture claim sums at stake, we first rely on the monetary claim information provided by the KAD database. But because this information is missing for the nearly half of the administrative cases, we scraped the final verdict document for each case to fill in the amount of money being contested (size of fine,

FIGURE 2: PRIVATE FIRM VICTORY RATE



Note: This figure plots the percentage of non-petty administrative cases between firms and the government where the private firm won. The green line indicates cases where the government entity was plaintiff, while the red line indicates where the firm was the plaintiff.

tax payment, contract in dispute, etc.). This procedure produced claim sum estimates for 88% of the cases in our administrative sample (up from roughly 47% from the portal). We also create an alternative indicator of high-stakes cases (whether there was a threat of the firm's operations being shut down or its bank accounts frozen) and find our results are robust to subsetting to that sample in Appendix Table A9.[28] For all cases, we transform this ruble amount to US dollars using average annual exchange rates. As discussed above, we also drop all tiny cases (such as those pension-related claims) under $100 as their use of the commercial court system differs significantly from the type of disputes where a bribe

[28] There are certain categories of cases that do not directly involve a monetary claim (e.g., whether a firm will receive a license or permit). Our indicators of shutdowns and frozen accounts partially account for such cases, but future versions of this paper will address the issue more fully.

could conceivably be proffered.

A final step in preparing our data for analysis pertains to classifying cases based on the types of litigants and bringing in external information on their financials. The raw data from the Russian commercial court system includes full coverage on the name and legal address for all 255,458 plaintiffs, defendants, third parties, and related parties involved in the Moscow and Moscow Oblast cases. However, unique tax identification numbers are given for only 45% of this total. To fill in this missingness, we first standardize firm names and geolocate addresses, and then match on both fields with the full Russian firm registry available from the Russian Tax Service. These cleaning and matching procedures improve our coverage of tax numbers to 79% of all litigants.[29]

Using these identifiers, we merge in firm registration data from the Russian Tax Service; these data include a variety of indicators and classifications that allow us to code entity type. For those actors without a tax identification number, we use regular expressions to assign entity type based on the legal name. We thus assign litigants to one of five categories: private firm, government entity, state-owned enterprise or individual entrepreneur. We also use OKFS codes, which denote firms' ownership structures in accordance with Russia's Civil Code, to determine whether companies had any state or foreign ownership.

3 Identification Strategy

To examine the effect on case outcomes of a case being heard by a corrupt commercial court judge, we exploit randomness in the assignment of cases to judges. This identification strategy has a rich history in empirical legal research. In the US context, scholars have used random case assignment to analyze racial disparities in sentencing (Abrams, Bertrand, and Mullainathan, 2012), judges' political affiliation (Cohen and Yang, 2019), pretrial detention (Dobbie, Goldin, and Yang, 2018), the money bail system (Gupta, Hansman, and Frenchman, 2016), and the effects of consumer and corporate bankruptcy rulings (Bernstein, Colonnelli, and Iverson, 2019; Dobbie, Goldsmith-Pinkham, and Yang, 2017). Similar research designs have been employed in India (Ash et al., 2022), Israel (Eisenberg, Fisher, and Rosen-Zvi, 2012; Gazal-Ayal and Sulitzeanu-Kenan, 2010; Grossman et al., 2016), and Kenya (Choi, Harris, and Shen-Bayh, 2022), often to examine how judges' or defendants' ethnicity and other ascriptive characteristics affect judicial outcomes. To our knowledge, our study is the first to apply such an empirical strategy to analyze the effects of corruption or other illicit activity within judiciaries.

[29] More detail on this procedure can be found in Appendix Section A1.

However, this widespread use of judge random assignment has recently faced scrutiny for ignoring common 'de-randomizing events' related to non-compliance with official assignment policies, the need to match cases to judges with appropriate expertise, variation in judges' workloads, and other factors (Thorley, 2020). Here we examine case assignment in the Russian commercial courts in detail and address each of these potential concerns.

3.1 Case Assignment in Russia

The system for assigning cases to judges functions slightly differently in each first instance court in Russia. The Moscow and Moscow Oblast courts were among the first to adopt an electronic case assignment system to facilitate random assignment, a step taken in 2007. As of 2012, three-quarters of the first instance commercial courts were using some form of randomized case assignment.[30]

First, court judicial staff assign an incoming case to a specific category, based on its content and type of dispute. In our data, we see 184 distinct categories. Then an automated system assigns the case to a judge with the appropriate specialization,[31] based on their education and experience (Vladimir, 2009). This assignment is mostly random, but also takes into account the complexity of the case and available judges' current and planned workload.[32] Bankruptcy and intellectual property cases are considered the most complex, the former of which we excluded from our analysis in order to focus exclusively on disputes between firms and the state. The assignment system also takes into account each judge's administrative duties and availability, including whether they are sick or on vacation at the time of the filing. If a judge is recused from the case or is unable to work for an extended period of time, then the automated system is used to pick the replacement judge. The introduction of electronic assignment systems significantly reduced court chairpersons' ability to influence which judges hear which cases.

Assessments of the random assignment system in general are mostly positive. Bocharov and Titaev (2018) argue that the random assignment has prevented litigants from manipulating the system to their advantage, noting that the "implementation of the electronic system of justice in Arbitrazh courts has made it much more difficult to steer the case towards the 'preferred' judge' (Bocharov and Titaev, 2018, 134). But no system is perfect,

[30]Dmitriy Kazmin and Kseniya Boletskaya, "Kak poluchit otvod neugodnogo sudya," *Vedomosti* (April 13, 2012); "VAS sobiraetsya do kontsa goda polnostyu otluchit rukovoditelej sudov ot raspredeleniya del," *Pravo.ru* (August 2, 2013).

[31]Judges in each court are divided into panels, or *sostavy*, specializing in administrative, civil, or bankruptcy cases, or sometimes in more specific case categories.

[32]Moskovskaya gorodskaya kollegiya advokatov, "Formirovanie sostava Arbitrazhnogo suda," (October 17, 2018).

and anecdotal evidence exists of plaintiffs creatively filing cases to bypass the automated system and get their case assigned to specific judges. Such plaintiffs have employed various tactics. Prominent approaches include filing multiple identical cases but only paying the court fees for the one that lands with the preferred judge, or similarly, making intentional mistakes in multiple filings and then correcting the mistakes only for the filing that lands with their judge of choice. Not all of this maneuvering is a sign of corruption. Plaintiffs also may seek to ensure or steer clear of assignment to particular judges based on their past record in similar cases.

To the extent possible, we use the richness of our data to assess whether cases assigned to treatment (i.e., more corrupt judges) look broadly similar to those assigned to the control group (i.e., less corrupt judges). We group our confounders based on three categories, given our reading of the criteria employed by the electronic assignment system. All are measured at the case-level. First, to measure *specialization*, for each judge, we numerically ranked case categories by the number of cases they adjudicated over the entire sample period and created a binary indicator 'Judge Top 5 Category' for whether a specific case fell into one of the top five categories for that assigned judge. On average, each judge hears cases across 20 distinct categories. In Appendix Section A6, we show that the variety of case categories (as denoted by a HHI-inspired specialization index) a judge hears is dependent on their experience. The vast majority of judges work across many specializations.[33] Next, we code whether the case is administrative or civil in nature since assignment to judges includes both sets of disputes.

To measure *case complexity*, we assume that a greater number of litigants connected to the case will result in a more complicated, resource-intensive judicial process. For example, the number of hearings ultimately held in a case is strongly correlated with the number of plaintiffs, defendants, and other parties that are on the initial filing.[34] We include counts of each type of litigant in our balance assessment. As an additional check, we include separate indicators for whether either the plaintiffs or defendants were government agencies, as well as the number of plaintiffs and defendants from government institutions at either the federal or the regional/municipal level.[35] We also examine an indicator for firms with shady reputations, described in Section 4.2, to test whether certain types of firms are able to game the assignment system to steer their cases to corrupt

[33]Appendix Section A6 also calculates how many judges work within each specific category. A small number of categories that have a limited number of cases usually see one or two judges assigned. But for the most part, there are multiple judges that can be assigned to each category.

[34]Appendix Table A6 shows these results.

[35]We combine the latter two because of the difficulty of identifying different types of institutions in Moscow city.

judges. While we expect that cases involving larger amounts of money will be more complex, not all cases involve monetary claims, as discussed above. We therefore include an indicator for whether there was a specific claim sum specified, or if a different non-monetary outcome was pursued by the plaintiff. Finally, we include our two measures of distinguishing petty from higher-stakes cases, based on whether the case was decided via a summary judgment or court order and whether the case was appealed.

To measure *judge workload*, we calculate the number of cases a judge was assigned during the month prior to the case being initially filed. We also code an indicator for the cumulative number of cases the judge had heard up until the case was initiated. Unfortunately, we do not have data on several other cofounders potentially of interest. For example, we cannot know easily if a case was withdrawn, e.g., whether a plaintiff was pursuing one of the maneuvers to file multiple cases and withdraw those not assigned to their preferred judge. Moreover, we do not have data on judges' vacation schedules or availability.

Since each first instance court processes incoming cases for its own judges, we run separate balance tests for the Moscow City and Moscow Oblast courts. Table A4 present the balance tests across cases heard by judges flagged as more or less corrupt. We show standardized differences in means, set a threshold of 0.1, and indicate whether any of the differences surpass that threshold. We also show variance ratios and set a threshold of 2, noting that variance ratios close to 1 indicate equal variances in both groups, and thus group balance (Austin, 2009). The results show strong balance across the confounders. Almost all groups are balanced across a standardized magnitude of the group difference, which for large datasets is nearly always a better indicator of balance than significance tests (Stuart, Lee, and Leacy, 2013). We also regress assignment to a corrupt judge on all of these cases characteristics together in Table A5 and conduct Wald tests for whether they collectively predict assignment. Across all specifications, the F-tests fail to reject the null hypothesis, providing further evidence of random assignment.

Despite strong evidence in favor of random case assignment in our camps, the analyses below nevertheless control for factors known to potentially undermine that randomized assignment. Such a conditional random assignment approach acknowledges that the month the case was initiated and judges' specializations, as indicated by the panels (*sostavy*) on which they serve, are important determinants of case assignment. In addition to including fixed effects for these characteristics, we also control for various measures of workload and case complexity in our OLS models. We cluster standard errors on both judge and case category.

4 Empirical Results

We present empirical results testing our first hypothesis – that firms are more likely to win disputes with the government – in Table 4. We begin with an analysis of all administrative cases that pit companies against government entities (Column 1). Here we see no effect from our measure of corruption on whether private firms win their disputes with the government. Overall, corrupt judges do not seem to bias cases in any direction.

However, in Column 2, we interact our binary measure of judge corruption with the measure of the monetary claim at stake in each case (in USD logged). We see that in very small cases, corrupt judges are actually more likely to side with the government during disputes. But in higher-stakes cases, more corrupt judges are significantly more likely to find in favor of companies, in line with our contention that in lower-stakes cases firms are unlikely to offer bribes large enough to induce judges to risk engaging in illegal activity.

Figure 3 shows that these effects are large in magnitude by displaying the interaction effect for the model specified in Column 2 of Table 4. The y-axis shows how the point estimates on the Judge Corruption Measure change based on different values for case size (shown on the x-axis); the shaded region represents 95% confidence intervals. Effects first become statistically distinguishable from 0 for cases with monetary claims of approximately \$1 million. For cases of this size, judges are roughly 4 percentage points more likely to side with private firms, which accords with our expectations that bribes are not worth taking for smaller sums. The magnitude of the effect increases as claim sum values rise. Cases with \$10 million at stake see private firms win at rates of roughly 6 percentage points higher than those heard by less corrupt judges, a significant increase from the baseline win rate of roughly 50 percent.[36] Concerned about the economic costs of losing in these higher-stakes cases, firms are potentially willing to offer bribes to the judges in exchange for favorable rulings; judges, recognizing the value firms place on prevailing, may also be more likely to solicit bribes.

The final two columns of Table 4 use that \$1 million threshold shown in Figure 3 to focus on just large cases; Column 3 subsets to below that figure while Column 4 subsets to above. The results are instructive. While corrupt judges show little to no bias for small cases, they are roughly 9% more likely to favor private firms in these larger cases. These

[36] When considering effect sizes, it should be kept in mind that our analyses do not produce estimates of the average effect of a firm paying a bribe, but rather the average effect of a case being assigned to judges who sometimes engage in corruption relatively to judges who do so less often. Most of the judges in our sample hear several thousand cases per year, and even the most corrupt judges likely engage in bribe transactions only in a relatively small number of these. Accordingly, the effect size is averaged out across a small set of cases influenced by bribery and a larger set of cases in which bribery played no direct role, even though they are heard by corrupt judges.

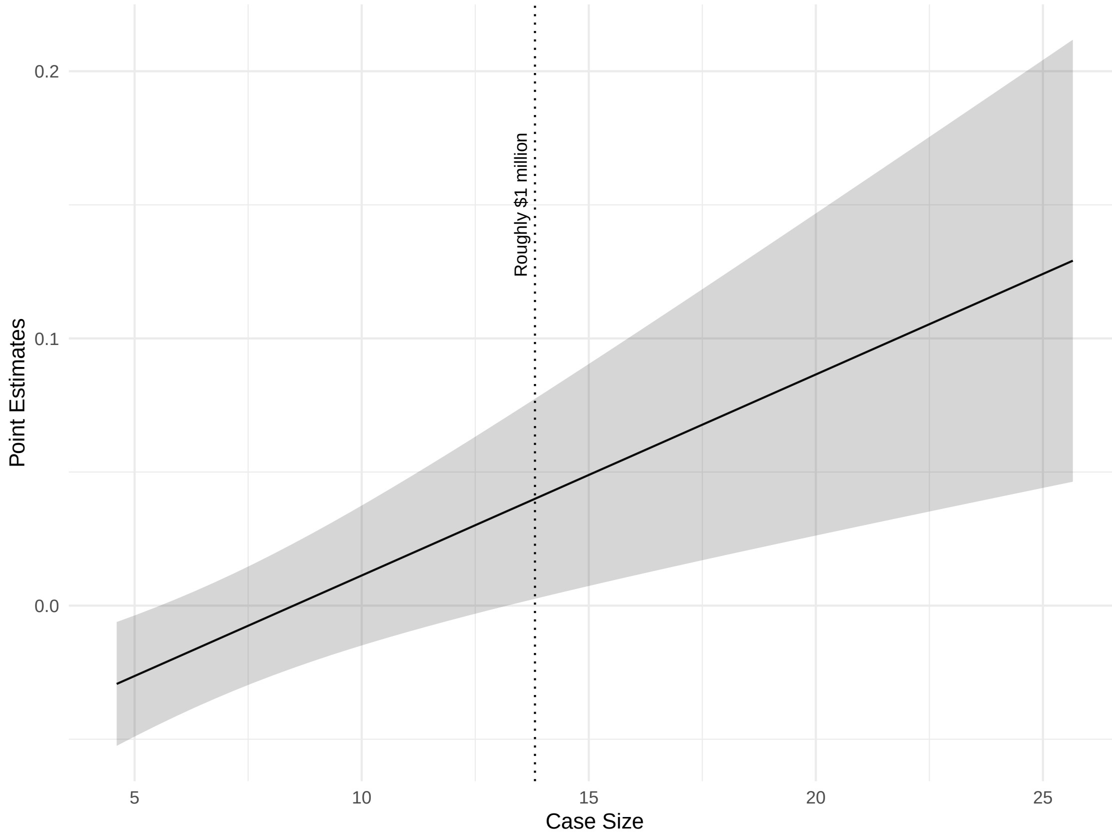
results are robust to adjusting for a comprehensive set of covariates measuring both judge and case-level characteristics.

TABLE 4: BIAS OF CORRUPT JUDGES TOWARDS COMPANIES

	Private Firm Wins			
	(1)	(2)	(3)	(4)
Judge Corruption Measure	-0.004	-0.060**	-0.005	0.091***
	(0.017)	(0.029)	(0.017)	(0.028)
Judge Corruption Measure × Case Size		0.007**		
		(0.003)		
Judge Mean Family Assets	0.013**	0.012**	0.011*	0.019***
	(0.006)	(0.006)	(0.006)	(0.001)
Judge Age (log)	-0.022*	-0.023*	-0.020	-0.221***
	(0.013)	(0.014)	(0.013)	(0.041)
Judge is Female	-0.012	-0.011	-0.011	0.075***
	(0.015)	(0.015)	(0.015)	(0.023)
Has Spouse	-0.013***	-0.013***	-0.013***	0.017
	(0.004)	(0.004)	(0.005)	(0.026)
Case Size	-0.0005	-0.0010	-0.0004	0.0004
	(0.006)	(0.006)	(0.009)	(0.004)
Judge Top 5 Category	0.028	0.028	0.025	0.009
	(0.019)	(0.019)	(0.018)	(0.032)
Judge Num. Cases (Cumulative)	0.004	0.004	0.004	0.018
	(0.007)	(0.007)	(0.007)	(0.020)
Judge Num. Cases in Previous Month (log)	-0.016	-0.016	-0.011	-0.096***
	(0.014)	(0.013)	(0.011)	(0.027)
Private Firm is Plaintiff	0.200***	0.200***	0.206***	-0.033
	(0.058)	(0.058)	(0.059)	(0.095)
Case Num. Plaintiffs	0.011	0.012	0.012	0.023**
	(0.017)	(0.017)	(0.019)	(0.009)
Case Num. Respondents	-0.042	-0.042	-0.047*	0.004
	(0.027)	(0.027)	(0.027)	(0.012)
Case Num. Other Parties	-0.020	-0.020	-0.023	-0.007*
	(0.017)	(0.017)	(0.018)	(0.004)
R^2	0.219	0.219	0.223	0.207
Observations	109,797	109,797	105,874	3,923
Sample	All	All	<$1mil	>$1mil
Judge Group (Court) fixed effects	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether companies win administrative cases against government institutions. The first two columns the full sample of cases of over $100. Columns 3 and 4 divide the sample based on whether the amount contested was above or below $1 million. Standard errors are clustered at the judge and case category levels.

FIGURE 3: EFFECTS OF ASSIGNMENT TO CORRUPT JUDGES BY CLAIM SIZE



Note: This figure plots the marginal effects of case assignment to a corrupt judge on private firms' win rates as case size (measured in logged USD) increases. Estimates are based on the model specified in Column 2, Table 4, which interacts the Judge Corruption Measure with the Case Size Variable. The shaded area represents 95% confidence intervals.

4.1 Appellate Outcomes

Next, in Table 5 we test our second hypothesis that rulings by corrupt judges are more likely to be appealed, and when appealed, overturned by higher-level courts. Analyzing all cases in Column 1, we see a negative effect of corrupt judges on appeal rates in cases where a corrupt judge has been assigned to the case. But the interaction term with case size is positive and statistically significant at the 90% level. This suggests that, at least for high-stakes cases, losing parties appear more likely to question corrupt judges' rulings, arguably either because the decisions such judges issue are on average of noticeably lower quality or because litigants are aware of these judges' proclivity to accept bribes in exchange for favorable rulings. In Column 2, we see that in cases with over $1 million at stake, appeals are roughly 5 percentage points more likely, though this effect is not precisely estimated. Importantly, private firms are much more likely to appeal cases that they lose if they are heard by a corrupt judge.

In Columns 4-6, we see further, but less precisely estimated, evidence that corrupt judges issue lower quality decisions when examining the rulings of appellate courts. The point estimate of a 1 percentage point increase suggests that these cases heard by more corrupt judges are 11% more likely to be overturned than those heard by less corrupt judges. Given that appellate court rulings are issued by a panel of judges and that appellate court judges are typically more qualified (Shvets, 2013), these results provide evidence that our measure of corruption among first instance judges could map onto a validated indicator of low quality decision-making.

4.2 Mechanisms and Heterogeneity

We next turn to mechanisms, motivated by the question about which types of litigants stand to benefit most from having a corrupt judge hear their case. In Table 6, we examine heterogeneity in our treatment effect. We focus in these analyses only on higher-stakes cases of over $1 million. First, we might expect that partially state-owned companies do not face the same set of incentives to win disputes with the government, and therefore will not go so far as to engage in corruption in order to achieve a favorable outcome. State-owned companies may have other mechanisms to resolve disputes with the government, including engaging the support of political patrons or paying bribes directly to public officials to avoid the need for litigation in the first place. Interacting our indicator of judges' corruption with indicators of partial state ownership, indeed we find evidence that judges are much less likely to side with state-owned firms, as can be seen in Column 1. Per the analysis in Column 2, we find an opposite effect for foreign firms, which perhaps have more at stake from losing an arbitration ruling that could spell larger issues for their business. In future versions of this paper, we hope to investigate this finding more deeply.

The benefits of having a case assigned to a corrupt judge do not appear to depend on a litigant's prior interactions with this judge or the resources at a firm's disposal. As can be seen in Columns 4 and 5, neither firm size (as measured by relative size of revenue)[37] nor having appeared as a litigant in previous cases with the same judge influences the impact of having a case heard by a corrupt judge. These results may suggest some degree

[37] We average revenue data and rank companies into quantiles (0,100) based on where they fall into a distribution of all firms operating in Russia. Litigants with higher ranks on average over 2011-2018 generated more revenue than those with lower ranks. Revenue data is available for 42% of all litigants; many smaller companies fail to file.

TABLE 5: CORRUPT JUDGES AND APPELLATE RULINGS

	Case Appealed			Case Overturned		
	(1)	(2)	(3)	(4)	(5)	(6)
Judge Corruption Measure	-0.025*	0.046	-0.274	0.011	0.009	0.009
	(0.013)	(0.050)	(0.168)	(0.022)	(0.040)	(0.040)
Judge Corruption Measure × Case Size	0.005*			-0.003		
	(0.003)			(0.002)		
Judge Corruption Measure × Private Firm is Plaintiff			0.328**			
			(0.155)			
Case Size	0.021***	0.015***	0.015***	0.0002	-0.004*	-0.004*
	(0.004)	(0.005)	(0.005)	(0.001)	(0.002)	(0.002)
Judge Mean Family Assets	-0.008	-0.011	-0.011	-0.002	0.0002	0.0002
	(0.005)	(0.012)	(0.011)	(0.002)	(0.007)	(0.007)
Judge Age (log)	0.022***	-0.015	-0.015	0.043**	-0.055	-0.055
	(0.007)	(0.072)	(0.072)	(0.018)	(0.051)	(0.051)
Judge is Female	0.0006	-0.004	-0.003	-0.017*	0.013	0.013
	(0.006)	(0.031)	(0.030)	(0.009)	(0.024)	(0.024)
Has Spouse	-0.0002	0.006	0.007	-0.009**	0.021*	0.021*
	(0.002)	(0.017)	(0.017)	(0.004)	(0.012)	(0.012)
Judge Top 5 Category	0.004	-0.009	-0.010	-0.001	-0.003	-0.003
	(0.009)	(0.029)	(0.029)	(0.014)	(0.033)	(0.033)
Judge Num. Cases (Cumulative)	-0.006	0.027*	0.025	-0.013**	0.009	0.009
	(0.004)	(0.016)	(0.016)	(0.005)	(0.011)	(0.011)
Judge Num. Cases in Previous Month (log)	0.003	-0.008	-0.009	0.014***	-0.015	-0.015
	(0.005)	(0.009)	(0.009)	(0.003)	(0.014)	(0.014)
Private Firm is Plaintiff	0.177***	-0.010	-0.027	-0.013	-0.013	-0.013
	(0.014)	(0.085)	(0.081)	(0.024)	(0.153)	(0.153)
Case Num. Plaintiffs	0.308***	0.115***	0.114***	-0.0003	0.008	0.008
	(0.038)	(0.031)	(0.031)	(0.004)	(0.007)	(0.007)
Case Num. Respondents	0.205***	0.108***	0.108***	6.89×10^{-6}	0.014	0.014
	(0.023)	(0.024)	(0.024)	(0.003)	(0.010)	(0.010)
Case Num. Other Parties	0.195***	0.062***	0.062***	-0.005	-0.009	-0.009
	(0.058)	(0.006)	(0.006)	(0.004)	(0.007)	(0.007)
R^2	0.318	0.222	0.223	0.028	0.105	0.105
Observations	111,189	3,981	3,981	30,033	2,581	2,581
Sample	All	>$1mil	>$1mil	All	>$1mil	>$1mil
Judge Group (Court) fixed effects	✓	✓	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether the case is appealed (Columns 1-3), and if so, whether the 1st instance ruling is overturned (Columns 4-6). Columns 2 and 3, as well as Columns 5 and 6, subset to those with monetary claim sums more than $1,000,000. Standard errors are clustered at the judge and case category levels.

of equality of access to corruption: Smaller firms and litigants without long-term relationships with corrupt judges appear equally capable of purchasing favorable rulings.

Finally, we address the most potentially consequential implication of corruption in the judiciary: Are corrupt judges helping firms defend their property rights against the aggressive state, or are they allowing unscrupulous firms to avoid repercussions of illicit business practices? The literature on corruption offers plentiful examples of bribery helping otherwise honest firms navigate perilous, extortionary bureaucracies (Méon and Weill, 2010; Dreher and Gassebner, 2013). And as in many other countries, there is considerable evidence that state officials in Russia regularly co-opt judges to target and repress both individuals and firms, especially in criminal cases heard by the courts of general jurisdiction (Hendley, 2009; Schultz, Kozlov, and Libman, 2014).

We examine this issue by analyzing several red flags commonly used to identify disreputable companies operating in the Russian business environment, which allows us to evaluate whether less reputable litigants in our sample are more likely to receive favorable rulings from corrupt judges. Given problems with contracting, counterparty checking services are big business in Russia, and several service providers have developing detailed methodologies to assess firms' reputations and likeliness to engage in unethical business practices.[38] We back out their methodology for flagging suspicious firms by collecting the same publicly available data along three key dimensions: a) whether a firm is registered in a so-called mass address (home to at least 30 other companies)[39], b) whether a firm is included on a federal list of dishonest suppliers of public procurement[40], or c) whether a firm had on its board a director who was later disqualified from operating a business.[41] Roughly 17% of large cases (over $1 million) heard in our sample involved a firm with at least one of these three red flags; we refer to these litigants with the variable 'Private Firm has Reputation Risk'.

Column 5 interacts the presence of a litigant with reputation risk with our indicator for assignment of a case to a corrupt judge to test whether the bias towards these types of firms is greater. First, the point estimate on the constituent term of the firm with reputation risk is negative and statistically significant. Firms with questionable reputations are overall much less likely to prevail in their disputes with the government, prima facie val-

[38]Several leading providers include https://reputation.ru/ and https://spark-interfax.ru/.

[39]Each year the Russian Tax Service issues a list of such mass addresses it deems potentially home to suspicious companies. Work by Mironov (2015) has shown that 'fly-by-night' companies with similar features to be used for income diversion and other illicit activities.

[40]These lists are compiled based on bad execution of public procurement contracts at any levels of government and used to exclude future bidders.

[41]The Federal Tax Service also bans individuals from operating business as an administrative punishment for violating a variety of business-related laws.

Table 6: Corrupt Judges and Heterogeneity in Firm Characteristics

	Private Firm Wins				
	(1)	(2)	(3)	(4)	(5)
Judge Corruption Measure × Private Firm Has State Ownership	-0.147*				
	(0.084)				
Judge Corruption Measure × Private Firm Has Foreign Ownership		0.086**			
		(0.037)			
Judge Corruption Measure × Private Firm Revenue Rank			0.003		
			(0.002)		
Judge Corruption Measure × Private Firm Previous Cases w/ Judge (log)				0.017	
				(0.012)	
Judge Corruption Measure × Private Firm has Reputation Risk					0.074***
					(0.026)
Judge Corruption Measure	0.109***	0.078**	-0.239	0.057	0.082***
	(0.027)	(0.034)	(0.276)	(0.039)	(0.026)
Private Firm Has State Ownership	0.025				
	(0.026)				
Private Firm is Plaintiff	-0.031	-0.038	-0.066	-0.014	-0.027
	(0.095)	(0.095)	(0.113)	(0.095)	(0.097)
Private Firm Has Foreign Ownership		0.027			
		(0.023)			
Private Firm Revenue Rank			0.001**		
			(0.0005)		
Private Firm Previous Cases w/ Judge (log)				-0.005	
				(0.003)	
Private Firm has Reputation Risk					-0.062***
					(0.012)
Judge Mean Family Assets	0.019***	0.019**	0.026***	0.019***	0.019***
	(0.001)	(0.008)	(0.009)	(0.004)	(0.001)
Judge Age (log)	-0.220***	-0.226***	-0.260***	-0.226***	-0.218***
	(0.041)	(0.041)	(0.057)	(0.048)	(0.039)
Judge is Female	0.075***	0.076***	0.065**	0.072**	0.076***
	(0.023)	(0.025)	(0.032)	(0.028)	(0.022)
Has Spouse	0.018	0.018	0.013	0.018	0.019
	(0.026)	(0.029)	(0.035)	(0.030)	(0.026)
Case Size	0.0003	0.0001	-0.003	0.0004	0.0004
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Judge Top 5 Category	0.010	0.008	0.015	0.018	0.008
	(0.032)	(0.032)	(0.045)	(0.029)	(0.031)
Judge Num. Cases (Cumulative)	0.018	0.019	-0.001	0.020	0.018
	(0.020)	(0.021)	(0.021)	(0.022)	(0.021)
Judge Num. Cases in Previous Month (log)	-0.096***	-0.096***	-0.084***	-0.090***	-0.096***
	(0.027)	(0.027)	(0.029)	(0.026)	(0.026)
Case Num. Plaintiffs	0.023**	0.023*	0.018	0.022**	0.025***
	(0.009)	(0.012)	(0.013)	(0.009)	(0.009)
Case Num. Respondents	0.004	0.004	0.002	0.003	0.003
	(0.011)	(0.012)	(0.015)	(0.012)	(0.013)
Case Num. Other Parties	-0.007*	-0.007	-0.004	-0.006	-0.008*
	(0.004)	(0.005)	(0.008)	(0.004)	(0.004)
R^2	0.208	0.208	0.224	0.210	0.209
Observations	3,923	3,923	2,783	3,773	3,923
Judge Group (Court) fixed effects	✓	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether companies win administrative cases against government institutions. The main corruption index is interacted with firm-level measures of state and foreign ownership, size, previous experience in front of the judge and having a shady reputation. All models only include non-petty cases that were appealed. Standard errors are clustered at the judge and case category levels.

idation that the measure is picking up something important about the way they conduct business. But when a corrupt judge hears a case involving with these less reputable firms, their likeliness of prevailing rises significantly and is much higher from those with cleaner business histories. In other words, corrupt judges appear to specifically help shady firms either defend themselves against government regulations or in some cases, extract money from the government in the form of tax refunds or other transfers. Corruption in the judiciary benefits not those fighting against an overbearing system, but rather those firms looking to gain an unjust advantage through bribery.

4.3 Robustness Checks and Extensions

In the Appendix, we run a battery of robustness checks for our main results, starting with Table A9. Columns 1-3 show that the results are robust to more reduced form models that include fewer cofounders. In Column 4, instead of using the Case Size variable to subset cases, we only examine cases where the private firm was at risk for being shutdown or having their tax status frozen. This step helps us account for the fact that not all cases can be assigned a monetary value. Corrupt judges are more likely to side with private firms in these disputes as well. In Columns 5 and 6, we show results disaggregating our composite measure of corruption. We see positively signed coefficients for both the continuous measure of hidden earnings and whether judges had hidden assets (i.e., not declaring their luxury cars). Finally, in Column 7, we show the results are robust to using a measure of corruption of undeclared cars and a ratio of over 1, rather than over 2 as used in the main analysis.

Next, in Table A7, we conduct placebo tests to show that the bias of corrupt judges only extends to those companies that are able to pay bribes. Columns 1 and 2 present the same model specifications as in our main analyses but include only cases between the government and individual entrepreneurs, a class of small business in Russia akin to microenterprises. Entrepreneurs do not receive any favorable treatment from corrupt judges, irrespective of the size of the claim being contested. The same is true for completely state-owned enterprises (SOEs), as shown in Columns 3 and 4. In line with the analysis above of partially state-owned firms above, SOEs do not see higher win rates in their cases heard by corrupt judges, presumably because bribes are either not being offered or are not of the magnitude to sway the judges. Corrupt judges appear to help only private firms in their disputes with the state. In Table A11, we show the results are robust to using different monetary thresholds to subset the analysis, ranging from $1,000 to $5 million. Finally, in Table A12 we find that corrupt judges appear to most often shape cases involving social funds and pensions.

5 Conclusion

Our results indicate that more corrupt judges give preferential treatment to private firms in their high-value disputes with the government. These companies benefit from having a more corrupt judge assigned to their case, yet we see little evidence that the random assignment in use within the Russian system is being undermined by companies trying to work the system to get certain judges to hear their disputes. Although substantial progress has been made to improve the quality of the Russian judiciary, the continued presence of profiteering judges threatens the institution's ability to impartially protect the property rights of all litigants. Corruption allows enterprising firms to exploit the commercial courts in an effort to evade government authorities' attempts to hold them accountable for administrative or other violations.

This type of corruption costs the government dearly. Corrupt judges in our sample were responsible for adjudicating nearly 20,000 administrative cases, with a very conservatively estimated total amount at stake of roughly $5 billion.[42] Even if bribes were used to sway a small percentage of these cases, the damages to state revenues by just a fraction of judges in two of Russia's 84 regions amounts to tens of millions of dollars, if not much more. These payoffs are most often accruing to firms with histories of dishonest or income diverting behavior.

This research points to several areas where steps could be taken to prevent firms from capturing state officials. First, increasing judge salaries might be first step to reduce the temptation of outside money. But the real weaknesses in the system perhaps lies earlier in the processes of selecting, promoting, and disciplining members of the judiciary. Both court chairpersons and non-judicial actors such as representatives of the Presidential Administration and top law enforcement officials influence decisions of the presidential commission that officially confirms judicial qualifying boards' nominations. In recent years the commission has wielded significant power in the judicial appointment process, rejecting as many as one in four nominations (Dzmitryieva, 2021, 134-135). Moving to a meritocratic system free from top-down influence from senior elites might dissuade potential candidates with strong motivations for private gain from seeking judgeships, without jeopardizing the institutions of self-governance that have helped make the Russian commercial court system relatively independent.

Second, we were identify just ten instances of judges being held accountable for corruption by law enforcement authorities. This small number pales in comparison with the

[42]We arrive at this figure by summing the claims for all cases heard by more corrupt judges where a monetary amount was entered or parsed using the dataset, roughly 84% of the sample. We cannot however observe the amounts at stake for the remaining 16% of cases, so this estimate is biased downwards.

more than 40 judges flagged as ‘more corrupt‘ using data on just transportation assets. In addition to potential problems related to the selection of judges, Russia has a clear enforcement problem, where the vast majority of corrupt acts go unpunished. The examples of sitting judges facing consequences are not enough to deter their colleagues from exploiting their positions for financial gain, creating a culture of impunity and encouraging private firms to abuse the system.

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Appendix

A1 Constructing the Case Data

The commercial court dataset comes from the official government repository Kartoteka Arbitrazhnyi Del (KAD), housing at http://kad.arbitr.ru. This website allows users to search for all 34 million (as of September 2022) electronic commercial court cases at the first instance, appellate, cassation, and Supreme Arbitration Court levels. The commercial court system first began using electronic case records in the late 2000s, and by 2011, the vast majority of regional courts were submitting data to the central repository. Therefore to ensure our coverage is comprehensive, we begin our sample collection in 2011. Because some cases can take years to adjudicate (particularly those having been appealed), we chose an end date of December 31, 2018 for cases to be initiated at the first instance level. This ensures that at the time of our data collection in January 2021, we could observe the entire adjudication of each case through any appeals processes.

To collect the case data, we queried the KAD back-end API using a list of unique case identifiers we built from searching the main user interface at http://kad.arbitr.ru. Converting these JSON files into flat structured data left us with information on roughly 13 million cases initiated countrywide during this period. Although our data covered all 84 regional first-instance courts, for this paper we choose to focus on Moscow and Moscow Oblast for the reasons outlined in the main text (availability of background data on judges and the likelihood of business-state disputes to be initiated). In total, there were 1,953,796 cases heard in these two regions; Figure A4 provides a flow chart of the further narrowing down beginning with this sample of cases and using the data below on legal entities.

First, we use data from the API to distinguish civil cases from administrative cases. Civil cases generally involve plaintiffs suing about private sector commercial matters, whereas administrative cases pertain to violations of state administrative law and therefore involve at least one government actor (either as the plaintiff or the defendant). Next, we code up information on litigants to the process by merging in firm-level data from the Russian State Statistics Office, the Federal Tax Service, and the Federal Anti-Monopoly Service using each's tax identification number (INN). To address the issue where these identifiers are missing 55% of litigant-case entries, we first standardize firm names using a set of regular expressions. Next, we use the DaData geolocation service to parse and standardizing addresses, assigning each a unique address id according to the Russian Federation Information Address System (FIAS). Finally, we impute INNs for all companies that share the exact same name and address identifier. This produces a substantial improvement in coverage, as 79% could be assigned a tax number.

We first classify litigants into four categories based on the legal entity designations in their name: companies (LLCs, public companies, etc.), government institutions and agencies, state-owned enterprises, and individual entrepreneurs. Our classification procedure is able to identify the legal entity type for 94% of litigants according based on a randomly selected manual review of 100 entries. We then use the firm-level data to construct measures of firm size (based on average revenue during the period), ownership (based on OKFS, the Russian National Classifier of Ownership Patterns), and reputation (based on whether the firm's address is home to at least 30 other companies, the firm has disqualified directors on its board, or it appeared on the Federal Anti-Monopoly Service's Register of Dishonest Suppliers for having been accused of violating procurement contracts).

A2 Constructing Corruption Measures

This section describes the steps taken to construct the two red flags that jointly identify greater corruption at the judge level in Russia.

A2.1 Red Flag #1: Hidden Assets

We code our first red flag by first building a database of luxury car ownership over the period of 2011-2019. To do this we first acquired a list of all 129 million 17-digit vehicle identification numbers (VIN) registered in Russia during this period. This dataset was compiled by the Russian traffic agency, but was leaked openly online in May 2020 for no cost. Several media outlets confirmed the validity of the data, with the original leaker commenting that it covered roughly 95% of the full official car registration database compiled by the Russian government.[43] However, this leaked dataset does not information on the actual owners of the cars.

Establishing ownership at scale is made possible by querying each VIN though the online database of insurance registrations run by the Russian Union of Auto Insurers. This database was built to enable drivers and government agencies to check the validity of insurance registration (for example in case of accidents or other disputes); the insurance records contain information on the driver and owner of nearly every insured vehicle in

[43] The leak was originally discovered by a IT-security firm director who shared it with Vedomosti journalists. Other journalists confirmed a random sample of rows by contacting car owners. Kinyakina, and Yekatyerina Angyelina Kryechyetova "V otkritom dostoopye okazalas' baza dannih rossiyskih avtovladyel'tsyev" *Vedomosti*, May 14, 2020. Lenta.Ru "Bazoo dannih rossiyskih avtovladyel'tsyev vistavili na prodazhoo v darknyetye" *Lenta.ru*, May 15, 2020.

the country.[44] The publicly facing website therefore allows any person to enter a VIN number and date of interest, and receive partially anonymized information about the name of the owner of the vehicle, the person(s) insured to drive it, the insurance provider, policy number, and location of registration (region).[45] To improve historical coverage, a separate query for each VIN was done on the last day of the calendar year (December 31) for each year from 2011-2019. Running these annual insurance queries for the 129 million unique cars was prohibitively expensive, so we instead focused on the 2,742,113 VIN numbers associated with 19 luxury brands that provide a better signal of corrupt behavior.

To ensure coverage of the Moscow-based judges in our sample, we add to this database leaked data from the Moscow and Moscow Oblast GIBDD[46], a government-run registry of car ownership that has consistently been leaked online and used extensively in economics to track individual wealth, bribe-taking among the traffic police, and propensity to commit traffic violations (Braguinsky, Mityakov, and Liscovich, 2014; Braguinsky and Mityakov, 2015; Mironov, 2015). This data is freely available online and contains over 43 million automobile ownership entries from 2010-2019. Of these, roughy 6% were considered luxury vehicles.

To validate the coverage of this data, we first attemped to locate VIN numbers for all cars that judges declared in their own name. If a large percentage of these cars appeared in the combined insurance and GIBDD, we could be mroe confidence that the coverage of these leaked datasets was strong enough to make claims about the cars that were not uncovered in the disclosures. In all, we were able to assign unique VIN numbers to 75.5% of judges' disclosed cars; this step also allowed us to locate the year of manufacture to better estimate car values in the next step. **?** uses data on foreign car imports into Russia to further validate that the numbers of luxury vehicles in the two datasets together approximates more official statistics.

The use of these leaked databases provides both advantages and disadvantages. On

[44]Stepanov, Dmitriy. 'V Rossii zarabotala infosistyema avtostrahovshshikov, pyeryepisannaya za 2 milliarda ≪s noolya≫' *cnews.ru*, June 29, 2020

[45]For each natural person, the insurance database gives information on the first name, middle name (patronymic), first letter of the last name, and the full birthdate. Encouragingly, the combination of these fields uniquely identifies owners. On average, individuals are associated with on average only 1.43 luxury cars from 2011-2019. Car owners with more than 10 cars make up just 0.07% (2,642) of the over three million individuals in the insurance database. Matching even without the complete last name data is not introducing significant noise into the corruption measure. As an extra check, for any undisclosed cars that appeared in the insurance data, we confirmed that the region the car was insured was either Moscow or Moscow Oblast.

[46]GIBDD translates to the 'General Administration for Traffic Safety' and is the equivalent to the Department of Motor Vehicles in the US.

one hand, the insurance data provides information on both the driver and the owner of the car; in 7.5% of the insurance records, the two are different people. This enables us to locate judges' cars that might be officially registered in the names of relatives or other proxies, but still available for their use. This approach still misses however cars that are registered to companies or legal entities, for which we cannot obtain beneficial ownership information. In addition, our measure of undeclared cars thus only covers cars owned or driven by the judges themselves, since it is impossible to collect name and birth date information for the spouses and dependent children of these judges.

A2.2 Red Flag #2: Hidden Earnings

The second red flag is built by comparing only income and assets reported in the disclosures: a discrepancy between the market value of the car and total reported income may suggest a judge is not fully reporting his or her income because of its illicit origins, e.g. corruption.[47] Several high-profile investigations have caught Russian government officials driving cars that far exceed their disclosed income and made the case the proceeds are derived from corruption.

To calculate this hidden earnings ratio, we first built a dictionary of all make and models for sale in Russia over the past thirty years to identify every car owned by a judge, his or her spouse, or dependent children. Table A2 shows the 15 most popular car brands owned by judges. We then scraped the 'for-sale' listings from the website of Russia's largest automobile marketplace (`http://www.auto.ru`) each month from May to August 2021. The data includes listing price information for roughly 700,000 new and used vehicles for sale in Russia; there are on average 44 cars representing each make-model-year combination (a more popular car, such as a 2012 Honda Civic, saw 92 different listings over these four months).

To back out the value of each car when it appeared in a judge's declaration, we applied the 12% exponential depreciation rate calculated by (Braguinsky, Mityakov, and Liscovich, 2014).[48] Unfortunately, only a small number of judge disclosures include the year of the car owned. Using the leaked datasets described above, we filled in an additional 62% of manufacture years. On average, judges and their families drive cars that

[47] Hiding income could also be part of a tax avoidance strategy: judges may also be underreporting their income to tax authorities and fear that not reporting the same numbers on their anti-corruption disclosures will draw the authorities' attentions.

[48] Using car price data from 2004-2005, (Braguinsky, Mityakov, and Liscovich, 2014) arrive at 12% by regressing listing price on the age of the car and category (luxury, country of origin, etc.). The website auto.ru calculates an average 10.1% depreciation rate using more recent sales data, but though not every make and model combination was included. Future versions of this paper will show results with brand-specific depreciation rates as a robustness check.

Table A1: Luxury Cars Missing from Judge Disclosures

Manufacture Year	Make	Simplified Model	Years Missing from Disclosure
2008	Audi	A4	2012 - 2019
1998	Audi	A6	2018 - 2018
1984	Audi	100	2015 - 2016
2009	BMW	SERIE 5	2016 - 2016
2011	BMW	SERIE 5	2013 - 2013
2014	BMW	SERIE 5	2014 - 2014
2015	BMW	SERIE 5	2015 - 2016
1998	BMW	SERIE 7	2011 - 2011
2008	BMW	M3	2012 - 2012
2015	BMW	X5	2015 - 2016
2015	BMW	X5	2015 - 2018
2016	BMW	X6	2019 - 2020
2007	Infiniti	FX	2011 - 2014
2008	Infiniti	QX70	2012 - 2013
2013	Infiniti	QX70	2014 - 2014
2013	Landrover	RANGE ROVER EVOQUE	2013 - 2017
2016	Landrover	RANGE ROVER SPORT	2017 - 2017
2004	Lexus	GX	2013 - 2013
2005	Lexus	GX	2016 - 2016
2015	Lexus	LX	2015 - 2015
2015	Lexus	LX	2016 - 2016
2016	Lexus	LX	2018 - 2018
2016	Lexus	NX	2016 - 2016
2017	Lexus	NX	2017 - 2020
2001	Lexus	RX	2012 - 2012
2010	Lexus	RX	2016 - 2019
2008	Mercedes	C-KLASSE	2019 - 2019
1995	Mercedes	E-KLASSE	2016 - 2016
2015	Mercedes	GLA-KLASSE	2016 - 2016
2011	Mercedes	GLK-KLASSE	2013 - 2013
2011	Mercedes	M-KLASSE	2012 - 2012
2013	Mercedes	M-KLASSE	2014 - 2014
2008	Volvo	C30	2013 - 2013
2013	Volvo	SERIE FH	2014 - 2014
2015	Volvo	XC60	2015 - 2019
2010	Volvo	XC70	2012 - 2015

Note: This table shows the 36 unique cars that were not declared on the 24 judges' disclosures, yet appeared in the luxury car database built from insurance and ownership records.

TABLE A2: TOP 15 MOST COMMON CAR BRANDS OWNED BY JUDGES

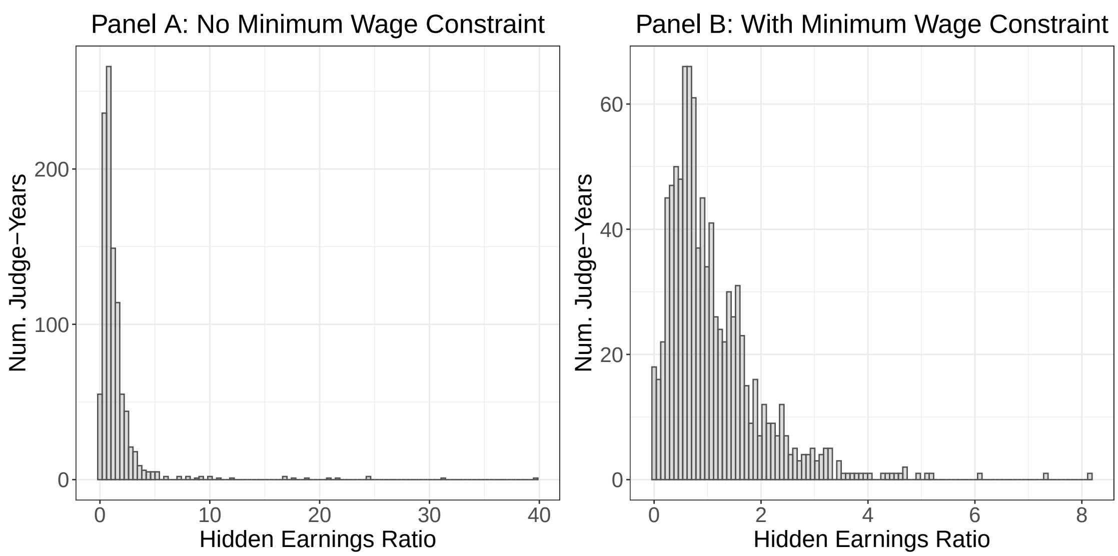
Make	Num. Cars	Mean Price (Rub)	Mean Price (USD)
Toyota	73	2,896,460	44,561
Mercedes-Benz	54	3,486,017	53,631
Nissan	49	1,671,664	25,718
BMW	45	3,523,632	54,210
Volkswagen	45	2,223,927	34,214
Volvo	42	2,989,372	45,990
Honda	33	2,249,134	34,602
Kia	32	1,593,247	24,511
Lexus	29	4,810,111	74,002
Audi	24	3,288,433	50,591
Hyundai	21	1,551,899	23,875
Land Rover	21	3,764,368	57,913
Ford	17	1,012,646	15,579
Mitsubishi	16	1,523,029	23,431
VAZ	14	421,843.8	6,490

Note: This table shows the 15 most common car brands (manufacturers) owned by judges from 2011-2018. Mean price is calculated using the methodology described in (Braguinsky, Mityakov, and Liscovich, 2014), with prices shown in rubles and dollars (at an exchange rate of 65 rubles per dollar).

are two years old when the first time they appear on a disclosure form. For the sake of consistency, for the 24.5% of cases that manufacture year was still missing, we assumed that the car was two years prior to the first year the car appeared on a disclosure. In other words, deputies on average enter into office with cars that are two years old, and any cars they acquire during their time in office were three years old at the time of purchase. This is a conservative assumption for dealing with the missing data problem (it forces downward the total value of cars owned), and future versions of the paper will show robustness checks that allow deputies to own newer cars.

The rightmost columns in Table A2 show the average imputed price in rubles and USD calculated for each brand using this methodology. Luxury vehicles such as Mercedes-Benz, Lexus and Land Rovers are assigned much higher market values, while more mass-market and domestically produced models such as Ford and VAZ are valued much lower. For each judge-family, we sum the total value of all cars reported and divide by total family income. The distribution of hidden earnings over time is shown in Panel A, Table A1. Outlier values are caused by either sudden windfalls in income or reporting errors in the amount of income reported by judges. Therefore, we only calculate hidden earnings ratios for years when the judge reported at least 500,000 rubles in personal income (roughly the minimum wage for commercial court judges in the two regions starting in 2011). This adjustment results a more normally distributed measure, as shown in Panel B, Table A1. Judges that consistently score above 1 (i.e. own cars that collectively are worth more than their income) in every year they disclose income are flagged as more corrupt.

FIGURE A1: DISTRIBUTION OF HIDDEN EARNINGS RATIOS BY JUDGE-YEAR



Note: This figure plots the distribution of hidden earnings by judge-year. Panel A does not require judges to report at least minimum wage income in their disclosure. Panel B applies a 500,000 rubles minimum wage constraint, only calculating ratios for judges that report more than that number.

A3 Example Income and Asset Disclosure

FIGURE A2: ORIGINAL RUSSIAN LANGUAGE

№ п/п	Фамилия и инициалы лица, чьи сведения размещаются	Должность	Объекты недвижимости, находящиеся в собственности				Объекты недвижимости, находящиеся в пользовании			Транспортные средства (вид, марка)	Декларированный годовой доход (руб.)	источниках получения средств, за счет которых совершена сделка (вид приобретенного имущества,
			Вид объекта	Вид собственности	Площадь (кв. м)	Страна расположения	Вид объекта	Площадь (кв. м)	Страна расположения			
1	Абреков Р.Т.	Судья	Квартира	Индивидуальная	61,1	Россия				Автомобиль BMW X3	2 655 918,54	
			Машиноместо	Индивидуальная	12,4	Россия						
	Супруга						Квартира	61,1	Россия		1 945 312,83	
	Несовершеннолетний ребенок						Квартира	61,1	Россия			
	Несовершеннолетний ребенок						Квартира	61,1	Россия			

FIGURE A3: TRANSLATED INTO ENGLISH

Figures/v2023/Dec_English_Judge.png

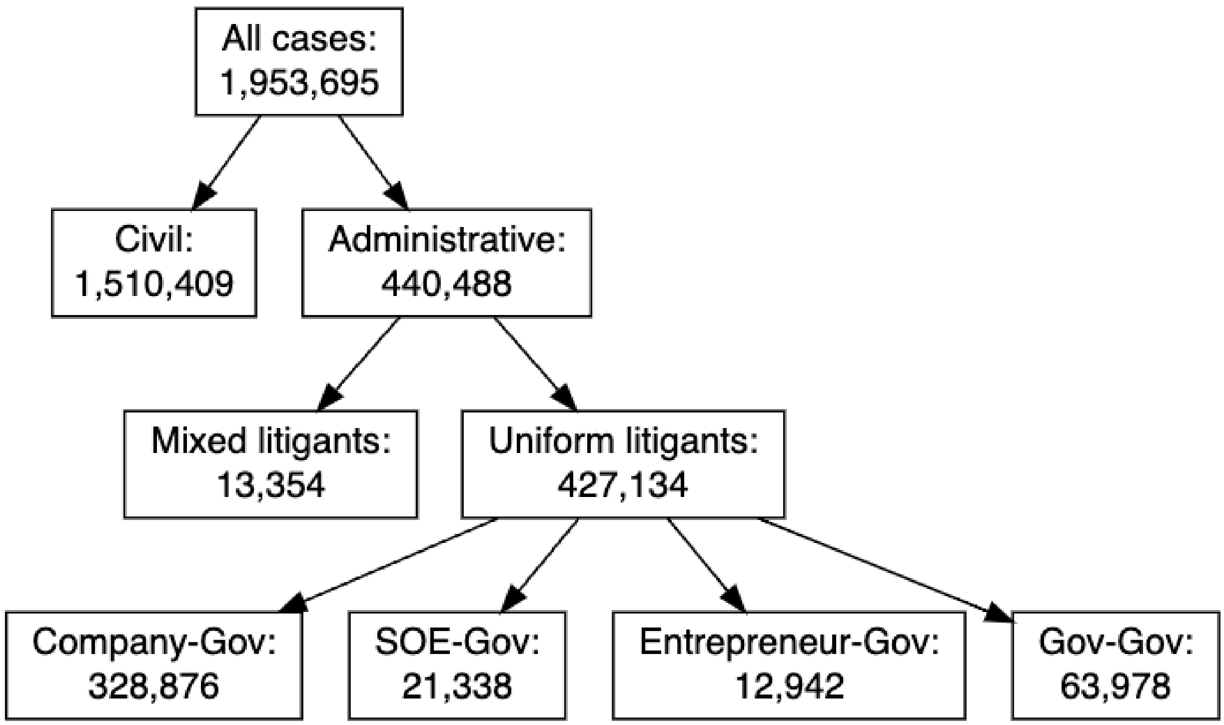
A4 Descriptive Statistics

TABLE A3: TOP 10 TYPES OF ADMINISTRATIVE DISPUTES

Code	Cases	Petty Cases	Non-Petty Cases	Category	Full Description
33.1	161,303	160,168	1,135	Pension contributions	Disputes related to levying mandatory fees and sanctions against companies and individuals requested by the Pension Fund
32.1	79,346	58,552	20,794	Administrative action	Disputes on cases of contesting the decisions of administrative bodies on bringing to administrative action
32.2	33,668	28,269	5,399	Administrative action	Disputes on bringing to administrative action
31.1.2	17,379	13,470	3,909	Bailiffs	Disputes on cases of contestation of substandard legal acts, decisions and actions (inaction) of bailiffs
25.2	15,750	8,753	6,997	Taxes and fees	Disputes on cases of contestation of substandard acts of tax authorities and actions (inaction) of officials
25.3	12,816	12,640	176	Taxes and fees	Disputes on recovery of obligatory payments and penalties on taxes and fees
31.1	12,338	7,548	4,790	Administrative action	Disputes on cases of contest of substandard legal acts, decisions and actions (inaction) of federal state structures
33.2	10,413	10,276	137	Social insurance	Disputes related to levying compulsory payments and sanctions against companies and individuals upon application of the Social Insurance Fund
32.2.2	9,237	8,375	862	Licenses	Disputes related to administrative liability for doing business without state registration or license
31.2	8,321	5,029	3,292	Regional institutions	Disputes on cases of contestation of substandard legal acts, decisions and actions (inaction) of state authorities of subjects of the Russian Federation

This table provides summary statistics about the top 10 types of administrative disputes (by code/statute). The table shows the number of cases overall under each category, then the number of petty versus non-petty cases (based on whether the case was appealed). The Category column summarizes the lengthier Full Description column.

FIGURE A4: SAMPLE CONSTRUCTION FLOW CHART: MOSCOW AND MOSCOW OBLAST



Note: This figure shows how we constructed our analysis datasets based on the universe of all commercial court cases heard in Moscow City and Moscow Oblast from 2011-2018. We first restrict to Administrative cases, where a government entity is involved as a litigant (plaintiff, defendant, or both). Next we code litigant type using tax identification numbers and regular expressions based on entity names. Cases with 'Uniform Litigants' involve only uniform litigants (for example, all the plaintiffs are of the same category, all the defendants are of the same category, etc.). Cases with 'Mixed Litigants' involve litigants from different categories on the same side, for example, a firm and an entrepreneur as plaintiffs, the government and a state-owned enterprise as defendants, etc.

A5 Balance Tests

TABLE A4: BALANCE TESTS: MOSCOW CITY, ALL CASES

Case Assigned to:		Less Corrupt Judge		More Corrupt Judge					
	Type	Mean	SD	Mean	SD	Std. Diff	M-Thr	V-Ratio	V-Thr
Specialization									
Judge Top 5 Category	Binary	0.735		0.598		-0.136	Not Bal., >0.1		
Administrative Case	Binary	1.000		1.000		-0.000	Bal., <0.1		
Case Complexity									
Num. Plaintiffs	Contin.	1.051	0.245	1.058	0.254	0.029	Bal., <0.1	1.075	Bal., <2
Num. Respondents	Contin.	1.102	0.390	1.102	0.393	0.002	Bal., <0.1	1.018	Bal., <2
Num. Other Parties	Contin.	0.081	0.333	0.095	0.370	0.037	Bal., <0.1	1.232	Bal., <2
Company is Plaintiff	Binary	0.424		0.457		0.034	Bal., <0.1		
Num. Government Plaintiffs	Contin.	0.591	0.525	0.555	0.523	-0.071	Bal., <0.1	0.990	Bal., <2
Num. Government Respondents	Contin.	0.520	0.709	0.557	0.713	0.052	Bal., <0.1	1.012	Bal., <2
Num. Regional/Municipal Plaintiffs	Contin.	0.027	0.165	0.032	0.180	0.029	Bal., <0.1	1.201	Bal., <2
Num. Regional/Municipal Respondents	Contin.	0.086	0.302	0.108	0.333	0.066	Bal., <0.1	1.214	Bal., <2
Shady Firm	Binary	0.144		0.150		0.007	Bal., <0.1		
KAD + Scraped (log)	Contin.	4.831	3.071	4.984	3.061	0.050	Bal., <0.1	0.993	Bal., <2
Missing: KAD + Scraped (log)	Binary	0.157		0.157		0.000	Bal., <0.1		
Scraped Estimate (log)	Contin.	4.803	3.084	4.980	3.068	0.058	Bal., <0.1	0.990	Bal., <2
Missing: Scraped Estimate (log)	Binary	0.167		0.161		-0.006	Bal., <0.1		
Workload									
Petty (Simplified)	Binary	0.545		0.457		-0.088	Bal., <0.1		
Petty (Not Appealed)	Binary	0.849		0.827		-0.022	Bal., <0.1		
Judge Num. Cases in Previous Month (log)	Contin.	5.229	0.767	4.970	0.616	-0.421	Not Bal., >0.1	0.645	Bal., <2
Judge Num. Cases in Current Year (log)	Contin.	7.570	0.628	7.302	0.574	-0.468	Not Bal., >0.1	0.837	Bal., <2
Total Cases:		838,322		545,291					
Judge Num. Cases (Cumulative)	Contin.	8.436	1.090	7.928	1.082	-0.469	Not Bal., >0.1	0.985	Bal., <2

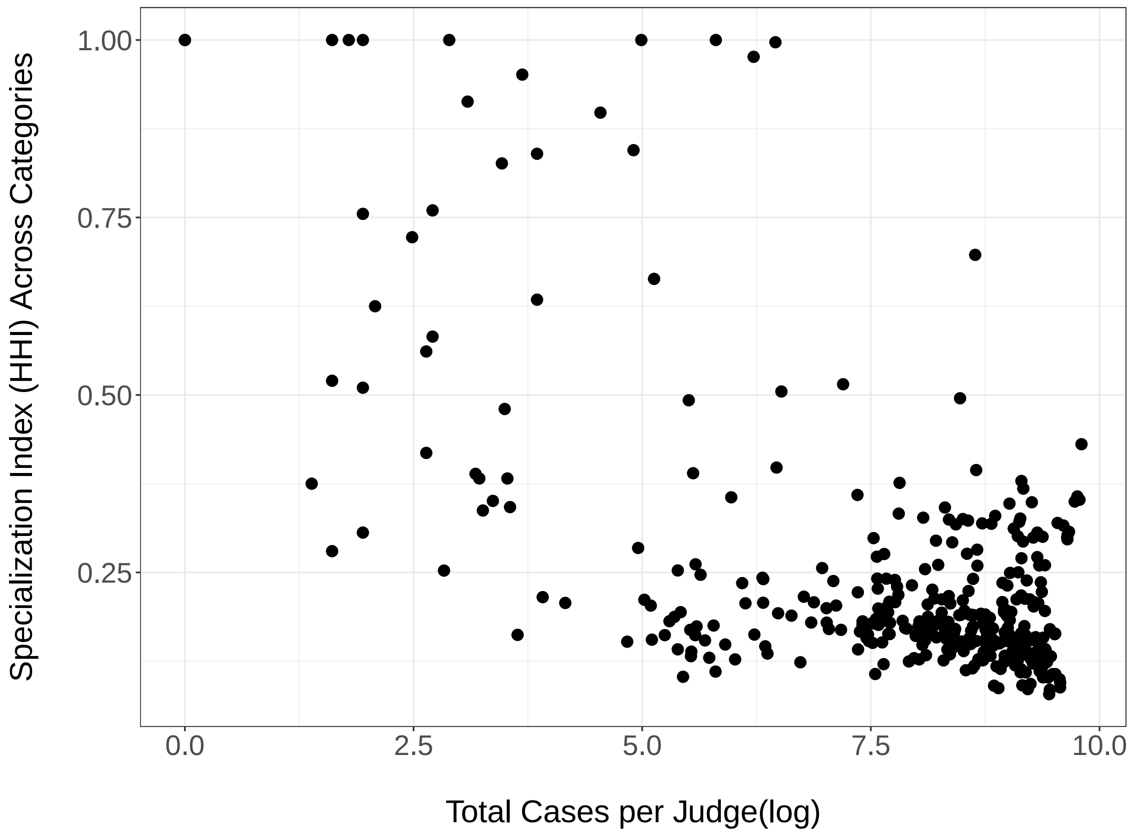
This table shows balance across the treatment group (cases assigned to more corrupt judges) and the control group (cases assigned to the less corrupt judges) for all cases (civil and administrative) in the Moscow City sample. The leftmost columns show raw means and standard deviations for each group. The difference in means is standardized, with any over a means threshold of 0.1 indicating in the 'M-Thr' column. The rightmost columns show the variance ratio with a column flagging if any values exceeded a threshold of 2.

TABLE A5: PREDICTORS OF ASSIGNMENT TO A MORE CORRUPT JUDGE

	Judge Corruption Measure			
	(1)	(2)	(3)	(4)
Constant	0.145**			
	(0.061)			
Judge Top 5 Category	-0.006	0.003	0.004	0.008
	(0.008)	(0.005)	(0.005)	(0.007)
Judge Num. Cases (Cumulative)	0.002	0.0006	-0.005	-0.005
	(0.008)	(0.007)	(0.014)	(0.015)
Judge Num. Cases in Previous Month (log)	-0.011	-0.006	-0.008	-0.006
	(0.012)	(0.012)	(0.012)	(0.017)
Private Firm is Plaintiff	0.002	-0.002	6.82×10^{-5}	0.002
	(0.008)	(0.005)	(0.004)	(0.002)
Case Num. Plaintiffs	0.003	0.0007	0.001	0.003
	(0.004)	(0.003)	(0.003)	(0.003)
Case Num. Respondents	0.002	0.0009	0.002	0.0006
	(0.003)	(0.002)	(0.002)	(0.002)
Case Num. Other Parties	-0.003	-0.002	-0.001	-0.005
	(0.006)	(0.005)	(0.005)	(0.005)
Case Size	0.002	0.0002	0.0006	0.0002
	(0.001)	(0.0007)	(0.0007)	(0.0006)
Administrative	-0.057**	-0.020	-0.023	0.002
	(0.027)	(0.013)	(0.015)	(0.009)
R^2	0.008	0.108	0.110	0.169
Observations	1,834,292	1,834,292	1,834,292	1,834,292
Wald (joint nullity)	1.41	1.21	1.55	0.656
Wald (joint nullity), p-value	0.176	0.285	0.126	0.750
Sample:	All Cases	All Cases	All Cases	All Cases
Judge Group (Court) fixed effects		✓	✓	
Case Start Month fixed effects			✓	
Judge Group (Court) * Case Start Month fixed effects				✓
Category Detailed fixed effects				✓

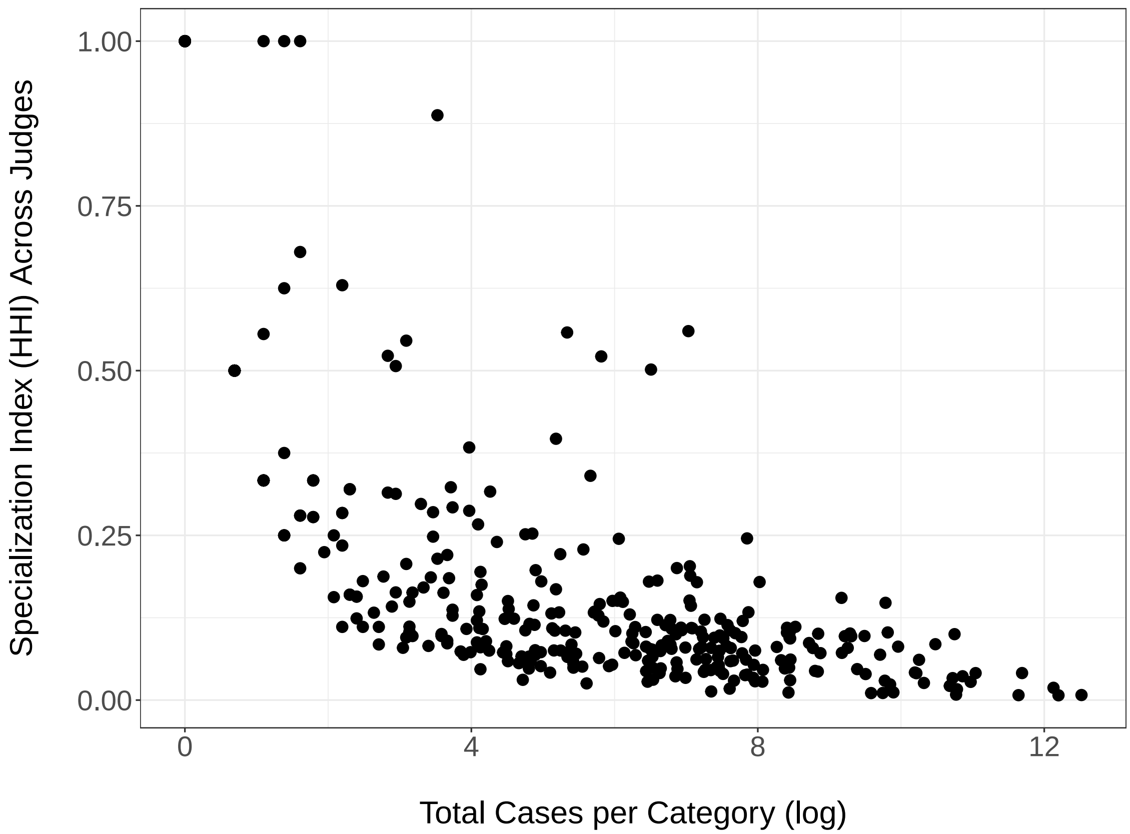
*** p<0.01, ** p<0.05, * p<0.1 This table shows the predictors of a case being assigned to a more corrupt judge. Standard errors are clustered on judge group, the level which cases are randomly assigned.

FIGURE A5: JUDGE SPECIALIZATION ACROSS CATEGORIES



Note: This figure plots a specialization (Herfindahl-Hirschman) index on the y-axis by the number of cases per *judge* on the x-axis. First we counted the number of cases that each judge oversaw in each category. We then calculated a concentration index for each judge across the different categories, with higher values indicating that a judge mainly worked on cases within fewer categories (an index value of 1 means a judge worked only on cases from a single category). Lower values of the index means that judges spread their time across many different case categories. The x-axis plots the number of cases a judge oversaw across all categories.

FIGURE A6: DISTRIBUTION OF JUDGES INTO CATEGORIES



Note: This figure plots a specialization (Herfindahl-Hirschman) index on the y-axis by the number of cases per *category* on the x-axis. First we counted the number of cases that each judge oversaw in each category. We then calculated a concentration index for each category across the different judges, with higher values indicating that a category saw a smaller number of judge assigned to its cases (an index value of 1 means a single judge worked cases from that category). Lower values of the index means that the category saw multiple different judges assigned to it. The x-axis plots the number of cases in each category across all judges.

TABLE A6: NUMBER OF RELATED PARTIES PREDICT CASE COMPLEXITY

	NumFirstInstanceHearings (1)	Num. 1st Ins. Events (log) (2)	Case Length (days, log) (3)
Case Num. Plaintiffs	0.678***	0.235***	0.119***
	(0.067)	(0.015)	(0.008)
Case Num. Respondents	0.526***	0.152***	0.108***
	(0.049)	(0.014)	(0.017)
Case Num. Other Parties	1.03***	0.253***	0.147***
	(0.107)	(0.014)	(0.017)
R^2	0.306	0.353	0.453
Observations	1,953,695	1,953,695	1,953,695
Case Category fixed effects	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓
Moscow Oblast Court fixed effects	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table analyzes the factors predicting the number of hearings a case will ultimately have. All models use OLS and cluster errors on category.

A7 Robustness Checks

Table A7: Placebo Outcomes: Entrepreneurs and Fully State-Owned Enterprises

	IPWins		SOEWins	
	(1)	(2)	(3)	(4)
Judge Corruption Measure	0.047	-0.389**	0.042	-0.108
	(0.138)	(0.168)	(0.086)	(0.254)
Judge Corruption Measure × Case Size	-0.009		-0.009	
	(0.023)		(0.012)	
Case Size	0.021*	0.022	-0.024*	-0.050
	(0.012)	(0.018)	(0.012)	(0.050)
Judge Mean Family Assets	-0.006	0.117**	0.001	0.033
	(0.012)	(0.044)	(0.003)	(0.023)
Judge Age (log)	-0.150***	-0.443**	0.015	0.695*
	(0.036)	(0.202)	(0.012)	(0.374)
Judge is Female	0.039*	-0.110***	-0.009	-0.292**
	(0.020)	(0.034)	(0.013)	(0.108)
Has Spouse	0.024*	-0.043	0.002	-0.134
	(0.013)	(0.053)	(0.006)	(0.085)
Judge Top 5 Category	0.003	0.013	-0.005	0.056
	(0.019)	(0.112)	(0.016)	(0.185)
Judge Num. Cases (Cumulative)	-0.0003	-0.035	0.003	0.414***
	(0.005)	(0.026)	(0.005)	(0.021)
Judge Num. Cases in Previous Month (log)	0.023**	0.054	-0.011**	-0.206
	(0.011)	(0.051)	(0.005)	(0.284)
Case Num. Plaintiffs	0.070***	0.061**	-0.026	0.167**
	(0.024)	(0.027)	(0.018)	(0.068)
Case Num. Respondents	-0.034**	0.006	-0.054	0.295***
	(0.017)	(0.036)	(0.042)	(0.059)
Case Num. Other Parties	-0.013	0.0005	-0.033*	-0.043
	(0.029)	(0.059)	(0.019)	(0.027)
R^2	0.419	0.493	0.479	0.837
Observations	3,878	598	14,458	151
Sample	All	>$10,000	All	>$1mil
Judge Group (Court) fixed effects	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether individual entrepreneurs (Columns 1-2) and fully state-owned enterprises (Columns 3-4) win administrative cases against government institutions. Standard errors are clustered at the judge and case category levels.

TABLE A8: BIAS OF CORRUPT JUDGES TOWARDS COMPANIES INTERACTED WITH JUDGE GENDER

	Private Firm Wins			
	(1)	(2)	(3)	(4)
Judge Corruption Measure	0.001	-0.027	-0.0010	0.096**
	(0.023)	(0.037)	(0.023)	(0.043)
Judge Corruption Measure × Judge is Female	-0.020	-0.046	-0.018	-0.031
	(0.017)	(0.041)	(0.018)	(0.142)
Judge Corruption Measure × Case Size		0.003		
		(0.003)		
Judge Corruption Measure × Case Size × Judge is Female		0.004		
		(0.005)		
Judge is Female	-0.011	0.027	-0.010	0.077***
	(0.016)	(0.027)	(0.016)	(0.027)
Judge Mean Family Assets	0.012**	0.012**	0.011*	0.019***
	(0.006)	(0.006)	(0.006)	(0.004)
Judge Age (log)	-0.022*	-0.024*	-0.020	-0.223***
	(0.013)	(0.014)	(0.013)	(0.043)
Has Spouse	-0.013***	-0.013***	-0.013***	0.018
	(0.004)	(0.004)	(0.005)	(0.030)
Case Size	-0.0005	0.003	-0.0004	0.0004
	(0.006)	(0.008)	(0.009)	(0.004)
Judge Top 5 Category	0.028	0.027	0.025	0.009
	(0.019)	(0.019)	(0.018)	(0.032)
Judge Num. Cases (Cumulative)	0.003	0.003	0.003	0.017
	(0.007)	(0.007)	(0.007)	(0.022)
Judge Num. Cases in Previous Month (log)	-0.016	-0.016	-0.011	-0.095***
	(0.014)	(0.013)	(0.011)	(0.026)
Private Firm is Plaintiff	0.200***	0.201***	0.206***	-0.033
	(0.058)	(0.058)	(0.059)	(0.095)
Case Num. Plaintiffs	0.011	0.012	0.012	0.023**
	(0.017)	(0.017)	(0.019)	(0.009)
Case Num. Respondents	-0.042	-0.042	-0.047*	0.004
	(0.027)	(0.027)	(0.027)	(0.012)
Case Num. Other Parties	-0.020	-0.020	-0.023	-0.007
	(0.017)	(0.017)	(0.018)	(0.004)
Case Size × Judge is Female		-0.005*		
		(0.003)		
R^2	0.219	0.219	0.223	0.207
Observations	109,797	109,797	105,874	3,923
Sample	All	All	<$1mil	>$1mil
Judge Group (Court) fixed effects	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether companies win administrative cases against government institutions, interacted with judge gender. Standard errors are clustered at the judge and case category levels.

TABLE A9: MAIN RESULTS: ROBUSTNESS CHECKS

	Private Firm Wins						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Judge Corruption Measure	0.104**	0.076***	0.094***	0.029**			
	(0.044)	(0.026)	(0.032)	(0.011)			
Judge Corruption Measure, Ratio >1							0.028***
							(0.010)
Has Undeclared Cars						0.090**	
						(0.041)	
Car Earnings Ratio					0.139***		
					(0.028)		
Judge Mean Family Assets		0.013	0.020***	0.003	0.062***	0.019***	0.021***
		(0.012)	(0.002)	(0.004)	(0.010)	(0.003)	(0.003)
Judge Age (log)		0.188	-0.200***	0.042	-0.084	-0.227***	-0.210***
		(0.180)	(0.030)	(0.027)	(0.074)	(0.045)	(0.041)
Judge is Female		-0.029	0.074***	-0.009	0.005	0.074***	0.046**
		(0.042)	(0.023)	(0.010)	(0.003)	(0.026)	(0.022)
Has Spouse		-0.024	0.014	-0.015***	0.047	0.019	0.011
		(0.040)	(0.023)	(0.006)	(0.029)	(0.029)	(0.029)
Judge Top 5 Category				-0.003	0.008	0.008	0.014
				(0.013)	(0.080)	(0.033)	(0.034)
Judge Num. Cases (Cumulative)				-0.015	-0.080	0.014	0.018
				(0.016)	(0.063)	(0.021)	(0.021)
Judge Num. Cases in Previous Month (log)				-0.017	-0.041	-0.095***	-0.096***
				(0.018)	(0.036)	(0.026)	(0.027)
Private Firm is Plaintiff				0.309***	-0.141	-0.033	-0.036
				(0.064)	(0.167)	(0.095)	(0.095)
Case Num. Plaintiffs				0.002	0.007	0.023**	0.023**
				(0.026)	(0.016)	(0.009)	(0.009)
Case Num. Respondents				0.009	-0.007	0.004	0.004
				(0.034)	(0.018)	(0.012)	(0.012)
Case Num. Other Parties				-0.050*	-0.014***	-0.007*	-0.008*
				(0.029)	(0.004)	(0.004)	(0.004)
Case Size					-0.003	0.0004	8.82×10^{-5}
					(0.007)	(0.004)	(0.004)
R^2	0.002	0.005	0.200	0.381	0.261	0.207	0.207
Observations	3,982	3,923	3,923	5,508	2,034	3,923	3,923
Judge Group (Court) fixed effects			✓	✓	✓	✓	✓
Category Detailed fixed effects			✓	✓	✓	✓	✓
Case Start Month fixed effects			✓	✓	✓	✓	✓

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ This table shows models assessing the main effect of companies winning against government institutions. Columns 1-3 vary the covariates included. Column 4 uses the threat of shutdowns or tax freezes to subset the sample, rather than case size. Columns 5-7 vary the way the corruption measure is calculated. Standard errors are clustered at the judge and case category levels.

TABLE A10: MAIN RESULTS: ROBUSTNESS CHECKS, INTERACTIONS

	Private Firm Wins			
	(1)	(2)	(3)	(4)
Judge Corruption Measure	0.641***	0.096**	0.029	0.641***
	(0.089)	(0.043)	(0.035)	(0.089)
Judge Corruption Measure × Private Firm is Plaintiff	-0.560***			-0.560***
	(0.096)			(0.096)
Judge Corruption Measure × Judge is Female		-0.031		
		(0.142)		
Judge Corruption Measure × Moscow Oblast Court			0.115	
			(0.113)	
Private Firm is Plaintiff	-0.010	-0.033	-0.008	-0.010
	(0.102)	(0.095)	(0.091)	(0.102)
Judge Mean Family Assets	0.019***	0.019***	0.011	0.019***
	(0.001)	(0.004)	(0.010)	(0.001)
Judge Age (log)	-0.222***	-0.223***	-0.121*	-0.222***
	(0.040)	(0.043)	(0.070)	(0.040)
Judge is Female	0.073***	0.077***	0.036	0.073***
	(0.023)	(0.027)	(0.022)	(0.023)
Has Spouse	0.017	0.018	0.004	0.017
	(0.026)	(0.030)	(0.035)	(0.026)
Case Size	0.0005	0.0004	-0.0002	0.0005
	(0.004)	(0.004)	(0.003)	(0.004)
Judge Top 5 Category	0.011	0.009	0.022	0.011
	(0.032)	(0.032)	(0.020)	(0.032)
Judge Num. Cases (Cumulative)	0.021	0.017	0.013	0.021
	(0.019)	(0.022)	(0.020)	(0.019)
Judge Num. Cases in Previous Month (log)	-0.095***	-0.095***	-0.106***	-0.095***
	(0.027)	(0.026)	(0.025)	(0.027)
Case Num. Plaintiffs	0.024**	0.023**	0.020*	0.024**
	(0.010)	(0.009)	(0.010)	(0.010)
Case Num. Respondents	0.004	0.004	0.006	0.004
	(0.012)	(0.012)	(0.012)	(0.012)
Case Num. Other Parties	-0.007*	-0.007	-0.007	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Moscow Oblast Court			0.192***	
			(0.018)	
R^2	0.208	0.207	0.199	0.208
Observations	3,923	3,923	3,923	3,923
Judge Group (Court) fixed effects	✓	✓		✓
Category Detailed fixed effects	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models assessing the main effect of companies winning against government institutions. Each model interacts the main measure of judge corruption with a different case characteristic. Standard errors are clustered at the judge and case category levels.

TABLE A11: MAIN RESULTS: ROBUSTNESS CHECKS, VARYING THRESHOLDS

	Private Firm Wins							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Judge Corruption Measure	-0.004	-0.016	0.007	0.023***	0.041*	0.091***	0.041	0.037
	(0.010)	(0.011)	(0.010)	(0.006)	(0.021)	(0.028)	(0.028)	(0.031)
Judge Mean Family Assets	0.022***	0.031***	0.026***	0.030***	0.013***	0.019***	0.019	0.007
	(0.005)	(0.007)	(0.006)	(0.004)	(0.002)	(0.001)	(0.014)	(0.011)
Judge Age (log)	-0.029	-0.030	-0.068	-0.092	-0.216***	-0.221***	-0.154***	-0.193***
	(0.022)	(0.040)	(0.051)	(0.056)	(0.049)	(0.041)	(0.054)	(0.071)
Judge is Female	-0.034***	-0.038***	-0.024*	-0.004	0.019	0.075***	0.074***	0.058**
	(0.013)	(0.013)	(0.012)	(0.013)	(0.014)	(0.023)	(0.021)	(0.023)
Has Spouse	-0.024***	-0.030**	-0.012	-0.004	0.009	0.017	0.007	0.044
	(0.005)	(0.012)	(0.012)	(0.015)	(0.015)	(0.026)	(0.038)	(0.037)
Case Size	-0.0009	0.003	-0.001	-0.002	-0.0010	0.0004	0.005	0.013***
	(0.005)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Judge Top 5 Category	0.031*	0.025	0.015	0.011	0.008	0.009	0.021	0.003
	(0.016)	(0.024)	(0.026)	(0.029)	(0.033)	(0.032)	(0.050)	(0.042)
Judge Num. Cases (Cumulative)	-0.0005	-0.004	-0.004	-0.003	0.024	0.018	-0.009	0.008
	(0.005)	(0.009)	(0.011)	(0.014)	(0.017)	(0.020)	(0.022)	(0.023)
Judge Num. Cases in Previous Month (log)	-0.047***	-0.071***	-0.065***	-0.078***	-0.095***	-0.096***	-0.079***	-0.099***
	(0.017)	(0.011)	(0.010)	(0.016)	(0.022)	(0.027)	(0.028)	(0.027)
Private Firm is Plaintiff	0.153***	0.007	-0.011	-0.022	0.015	-0.033	-0.157	-0.149
	(0.054)	(0.065)	(0.066)	(0.082)	(0.080)	(0.095)	(0.096)	(0.178)
Case Num. Plaintiffs	-0.005	-0.002	0.015	0.019	0.020**	0.023**	0.015	0.026
	(0.016)	(0.018)	(0.012)	(0.012)	(0.010)	(0.009)	(0.010)	(0.016)
Case Num. Respondents	-0.037	-0.008	0.004	0.006	0.006	0.004	0.006	0.004
	(0.024)	(0.015)	(0.007)	(0.006)	(0.008)	(0.012)	(0.012)	(0.018)
Case Num. Other Parties	-0.015	-0.016	-0.010	-0.005	-0.007	-0.007*	-0.003	-0.003
	(0.013)	(0.010)	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)	(0.005)
R^2	0.159	0.159	0.173	0.175	0.190	0.207	0.236	0.253
Observations	62,134	22,187	15,713	9,908	5,437	3,923	2,380	1,589
Sample	>$1k	>$1k	>$2k	>$100k	>$500k	>$1mil	>$2.5mil	>$5mil
Judge Group (Court) fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models assessing the main effect of companies winning against government institutions, but uses different thresholds to subset the analysis. Standard errors are clustered at the judge and case category levels.

TABLE A12: CORRUPT JUDGES AND HETEROGENEITY IN GOVERNMENT LITIGANTS

	Private Firm Wins				
	(1)	(2)	(3)	(4)	(5)
Judge Corruption Measure	0.061	0.090***	0.091***	0.090***	0.090***
	(0.056)	(0.028)	(0.029)	(0.028)	(0.027)
Judge Corruption Measure × Government: Tax	0.049				
	(0.086)				
Judge Corruption Measure × Government: Social Fund		0.666***			
		(0.138)			
Judge Corruption Measure × Government: Pension Fund				0.187***	
				(0.032)	
Judge Corruption Measure × Government: Regional/Municipal					0.051
					(0.286)
Private Firm is Plaintiff	-0.033	-0.034	-0.031	-0.035	-0.031
	(0.094)	(0.095)	(0.095)	(0.096)	(0.097)
Government: Tax	0.069				
	(0.057)				
Judge Mean Family Assets	0.017***	0.018***	0.020**	0.019*	0.019***
	(0.004)	(0.002)	(0.008)	(0.010)	(0.002)
Judge Age (log)	-0.226***	-0.225***	-0.217***	-0.221***	-0.220***
	(0.045)	(0.040)	(0.041)	(0.044)	(0.041)
Judge is Female	0.079***	0.075***	0.075***	0.075***	0.075***
	(0.025)	(0.022)	(0.025)	(0.025)	(0.021)
Has Spouse	0.022	0.019	0.016	0.018	0.017
	(0.032)	(0.026)	(0.029)	(0.030)	(0.026)
Case Size	0.0006	0.0005	0.0003	0.0004	0.0004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Judge Top 5 Category	0.009	0.011	0.009	0.009	0.010
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)
Judge Num. Cases (Cumulative)	0.018	0.019	0.018	0.018	0.019
	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Judge Num. Cases in Previous Month (log)	-0.094***	-0.096***	-0.095***	-0.096**	-0.096***
	(0.026)	(0.027)	(0.028)	(0.038)	(0.027)
Case Num. Plaintiffs	0.023**	0.023**	0.023*	0.023*	0.023**
	(0.009)	(0.010)	(0.012)	(0.011)	(0.009)
Case Num. Respondents	0.004	0.004	0.004	0.004	0.003
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Case Num. Other Parties	-0.007*	-0.007*	-0.007	-0.007	-0.008*
	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)
Government: Social Fund		-0.386***			
		(0.121)			
Government: Internal Affairs			-0.458***		
			(0.064)		
Government: Pension Fund				-0.063	
				(0.104)	
Government: Regional/Municipal					0.039
					(0.059)
R^2	0.208	0.208	0.208	0.207	0.207
Observations	3,923	3,923	3,923	3,923	3,923
Judge Group (Court) fixed effects	✓	✓	✓	✓	✓
Category Detailed fixed effects	✓	✓	✓	✓	✓
Case Start Month fixed effects	✓	✓	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1 This table shows models predicting whether companies win administrative cases against government institutions. The main corruption index is interacted with indicators for whether the government litigant involved in the case is the social fund, internal affairs, pension fund or a regional/municipal agency. All models only include non-petty cases where an appeal was later filed. Standard errors are clustered at the judge and case category levels.