Do Judge-Lawyer Relationships Influence Case Outcomes?

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Abstract

We examine whether law school alumni relationships between the lawyers and judges affect case outcomes. We show that in the context of medical malpractice lawsuits in Florida, the plaintiff lawyer sharing the same law school as the judge increases the chances of recovery by 2%. Furthermore, the effect is confined to younger lawyers who see a 4% increase in the likelihood of recovery from having been to the same law school as the judge, and is absent in older lawyers. We interpret our results as evidence that lawyers gain school-specific human capital from their law schools which helps in their interactions with judges that graduated from the same school, and that this school-specific human capital become less important further on in the lawyers' careers.

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1 Introduction

Do law school alumni relationships between lawyers and judges influence case outcomes? In an empirical analysis of the Florida medical malpractice lawsuits, we show that getting assigned a judge that went to the same law school as the plaintiff lawyer increases the likelihood of recovery by the plaintiffs. Furthermore, we find that most of this benefits accrues to younger lawyers, which we interpret as evidence that the differential case outcomes are the result of school-specific human capital, such as communication skills or networking, that are gained in law schools.

Our empirical setting is medical malpractice cases in Florida. Medical malpractice lawsuits are high stakes cases filed when plaintiffs (typically an injured party and their families) believe that their physician and/or their medical facility has not followed the standard of care and committed a medical error leading to personal injury, excessive medical costs, as well as losses from lost wages. Plaintiffs are typically represented by an attorney on contingency, with the lawyer taking between 33% and 40% of the amount recovered from the defendants.[1] Therefore, there is a strong incentive for plaintiff lawyers to recover damages from the defendants, possibly by leveraging their alumni relationships. We assemble a new dataset on medical malpractice lawsuits filed in Florida by matching claims data from Florida's Office of Insurance Regulation on case outcomes to county-level court records.

The process of filing medical malpractice lawsuits is as follows. First, plaintiffs retain an attorney and engages in pre-filing settlement negotiations settlement negotiations with the defense side which can consist of physicians, healthcare facilities, and their insurers. Because no judge is assigned at this stage, we do not study pre-filing settlement, and all of our sample is conditional on a case being filed. After a case is filed, a judge is assigned from the Circuit Civil division. Then, discovery and post-filing settlement negotiations begin, a process that can take years before the case goes to trial. Most cases settle, although less than 8% (as shown in Table 1) does end up in trial. The judge is involved throughout this process by ruling on discovery motions and conducting the trial. This process is illustrated in our Appendix Figure A1.

The medical malpractice setting has several advantages as a place to test the impact of lawyer judge alumni relationships on case outcomes. First, in medical malpractice disputes both the plaintiffs and defendants utilize private attorneys and judges are randomly assigned after the case is filed. In particular, administrative rules require that the medical malpractice cases be randomly assigned to the civil judges within the circuit, which we test in Section 3, giving us an exogenous source of variation for the effect of relationships. This is in contrast

[1] https://www.floridainjuryattorneyblawg.com/attorneys-fees-in-florida-wron/

to criminal cases in which the judge often appoints attorneys after the case has started, for which there is likely not a random matching of judges and lawyers. Second, plaintiffs in medical malpractice cases tend to prefer to hire a single lawyer rather than teams of lawyers, making the identification of relationships relatively straightforward.[2] Third, the plaintiff lawyer have to work on drafting a claim and filing a lawsuit for the medical malpractice cases before a judge can be assigned, so it would be costly for the plaintiff side to switch attorneys based on the outcome of the judge assignment process, making it more likely that alumni relationships are randomly assigned.[3]

We find that, in our medical malpractice setting, plaintiff lawyers who went to the same law school as the judge were 2% more likely to be able to recover damages from defendants. This effect is primarily driven by younger lawyers, whose likelihood of recovery goes up by 4% when assigned a judge that went to the same law school as them, whereas it is close to zero for older lawyers. This suggests the existence of an advantage given by the law school which weakens over time as the lawyer gains experience on their own.

Our study contributes to the literature on role of experience in lawyer career development. Early studies from Leibowitz and Tollison (1978) and Rosen (1992) finds that lawyer earning increases as they accumulate experience, peaking at about 30 years. Furthermore, McIntyre and Simkovic (2017) finds that the level of unemployment at law school graduation predicts lawyers' earnings during the start of their careers, but the effect weaken once the lawyers gain experience and there is only modest impact on lifetime earnings. We find that lawyer experience determines the role that alumni relationships play: law school alumni relationships are important during the start of the lawyer's careers but become less important as they gain experience.

In addition, our paper adds to the literature on the interaction between law schools and labor market outcomes. In particular, Sander and Bambauer (2012) finds that law students' performance in law school impacts legal careers, and Oyer and Schaefer (2019) finds that the eliteness of law schools matter for careers. McIntyre and Simkovic (2018) finds that law schools are more valuable for minorities. We add to this literature by illustrating a specific mechanism through which law schools add value: by making younger lawyers more effective when faced with a judge that graduated from the same law school as them.

Finally, we provide one more case study where judicial decisions can be affected by factors other than the case itself. For example, Glaeser and Sacerdote (2003), Argys and Mocan

[2]In 81% of the cases in our data, the entire plaintiff side was represented by a single attorney throughout their entire case, with the rest typically consisting of attorneys representing other plaintiffs on the same side of the case.

[3]In particular, to switch attorneys the plaintiff would have to compensate their existing attorney for work done at a high hourly rate, which few plaintiffs would be willing to do.

(2004), Abrams, Bertrand, and Mullainathan (2012), and Alesina and La Ferrara (2014) finds that the race and demographics of the parties matter in judicial decisions. Furtehrmore, Chen, Moskowitz, and Shue (2016), Danziger, Levav, and Avnaim-Pesso (2011), Eren and Mocan (2018) finds that the recent experiences of judges in terms of their decisions in other recent cases, proximity to food breaks, and even outcomes of sports games affect their decision making. Finally, Shayo and Zussman (2011) finds evidence from in-group bias from judges in Israel that becomes stronger after military action. Our study contributes to this literature by looking at how alumni relationships between lawyers and judges affect case outcomes.

The rest of this paper is organized as follows. Section 2 describes the theory that motivates our empirical analysis. Section 3 presents the data we collected for our study. Section 4 presents the empirical results. Section 5 concludes.

2 Theory

Why does the relationship between a judge and an attorney influence case outcomes? We posit two hypotheses: (1) in-group bias from a preference for lawyers from the same school and (2) school-specific human capital which allows lawyers to be more persuasive in front of judges they shared a law school with. We first describe the role of judges in determining the final ruling and how lawyers may affect judges. Then we compare two hypotheses and their predictions in the legal setting. Finally we link the theory with empirical tests.

Lawyers and judges interact after judges are assigned, and judges play an important role in the outcomes of cases no matter whether the litigants go to trial or not. For example, judges may rule on motions to dismiss or motions for discovery, the outcomes of which would change the bargaining power held by the plaintiffs and defendants when they negotiate settlements. Judges also consider the admissibility of the witness, especially when the validity of experts is challenged (Daubert challenge) and a hearing is conducted before the judge. During trial, when attorneys raise objections, judge's ruling determines whether the evidence will be considered when deciding the verdict of the case. If juries are involved, judges' attitudes also matter as they provide jury instructions to help them understand how jury's role and how laws apply to the specific case.

During their interactions with the judge, lawyers can influence judges' perception of the case, which in turn affects case outcomes. How persuasive an lawyer is can be thought of as the confluence of two types of factors. One on hand, attorneys and judges have different identities based on social categories, such as school, gender, and race. Researchers found that people tend to hold "higher opinions of members of their own group" (Akerlof and Kranton, 2000) or are more altruistic toward an in-group member (Chen and Li, 2009). Therefore, judges may favor lawyers who went to the same law school with them due to in-group bias. On the other hand, lawyers may learn to become persuasive towards particular kinds of judges over time. During law school, lawyers may have learned to better communicate with judges who graduated from the same law school.[4] As they start working in the industry, they may also learn from interactions with judges. How to more effectively exhibit evidence before judges and under the pressure of the opponents' challenges can only be improved after numerous real courtroom presentations. As a result, as lawyers gain more experience, the increase in the productivity would compensate for the differences in school learning.

Since the in-group bias should hold regardless of an attorney's experience but learning occurs both at school and throughout a lawyer's career, these two hypotheses differ in whether their predictions vary by lawyers' experience. Therefore, in Section 4, we explore whether the impact of being judges' alumni differs across younger and older lawyers and find evidence in support of the learning hypothesis rather than judges being consistently biased towards graduates of their own law school.

3 Data

We use malpractice claims data from the Florida Office of Insurance Regulation (FLOIR) for case outcomes from 1990-2018. This data contains detailed information on case characteristics and outcomes, including the amount paid by the defendant to the plaintiff, the severity of the claim, patient demographics such as their age and gender, and the county the case was filed along with the court case number. This data has been used in Sieg (2000) and Watanabe (2006). For our purposes, an important limitation of the claims data is that it does not contain information about the lawyers or judges associated with each case.

To supplement the claims data, we collected civil court records from 21 counties and matched it to the FLOIR data. These court records contain information about the lawyers involved in the case and the judge that was assigned to it, and can be requested from the Clerk of the Court in each county. A map of the counties from which we collected data is shown in Appendix Figure A2. In particular, we cover the most of the population centers of Florida, including the cities of Miami, Tampa, St. Petersburg, and Orlando. Together, the counties represent 76% of all claims in our FLOIR dataset. The remaining counties either did not respond to our request for data or were unable to provide their court records in usable electronic form.

We match the FLOIR data to the by the court case number, the filing year, and name

[4] For example, students may learn how to talk with alumni by going to networking events, e.g. https://law.stanford.edu/careers/getting-the-job/networking/.

of the defendant. We needed to use the filing year and defendant because the court case number in FLOIR is sometimes abbreviated and matches multiple claims in the civil court records.[5] To get a match, we require exact matching on either the full court case number (subject to abbreviation) or the defendant last name plus the last four digits of the court case number and no more than 2 digit difference in the Levinstein distance in the remaining court case numbers. Manual inspection reveals that this criteria typically leads to correct matches. When there are multiple matches, we break ties using defendant last name and filing year, in that order, and keep only unique matches that remain. We show our match rate by county in Appendix Table A1. Our unique match rate is fairly high at 82% on average, which compares favorably to the literature matching court records to administrative records which are typically 60-80%.[6]

We collect a third set of data on lawyer and judge education. For lawyers, we requested data on all active lawyers in Florida from the Florida Bar, which has information on lawyer bar numbers, law school, law school graduation year, and date of admission to the bar. We then matched the lawyer information to court records using their full names. Some lawyers in our FLOIR-court records matched sample were inactive (primarily because they were retired or deceased), and for them we scraped the Florida Bar website which contains information on those lawyers. We take the first plaintiff lawyer listed on the court records as the plaintiff lawyer associated with the case, which is typically the sole plaintiff lawyer listed in the court records. The unique match rate for these lawyers is 91%. For judges, we obtained education from the Florida Bar though a similar matching algorithm process, but also supplemented them with manual searching for any missing information from publicly available biographies.

We present some summary statistics on cases and outcomes in Table 1. Overall, 80.5% of the malpractice cases filed resulted in some amount of recovery for the plaintiffs, which is our main outcome variable. This varies by severity (for which "emotion only" is associated with the least likelihood of recovery at 47.6% and "permanent grave" is associated with the greatest at 89.9%) and by the experience of the plaintiff lawyer associated with the case (for which a less experienced lawyer recovers 78% and a more experienced lawyer recovers 84%).

[5] When matching by court case number we use the Python weighted-levinstein 0.2.1 package with deletion costs set to zero in order to deal with abbreviations.

[6] See e.g. Dobbie, Goldin, and Yang (2018) and Travis, Western, and Redburn (2014).

Table 1: Summary statistics on cases and outcomes

	(1) Percent of Sample	(2) Percent with Recovery
All	100.0	80.5
Patient Sex		
Female Patient	52.8	81.2
Male Patient	47.2	79.8
Case Severity		
Death	28.5	83.1
Permanent grave	4.0	89.9
Permanent major	6.4	86.3
Permanent significant	10.9	83.0
Permanent minor	17.3	80.3
Temporary major	9.7	81.9
Temporary minor	16.7	78.1
Temporary slight	3.4	67.7
Emotion only	3.1	47.6
Patient Age		
0 to 30	17.9	82.0
30 to 60	48.1	79.9
over 60	34.0	80.7
Plaintiff Lawyer Experience		
1 case	23.1	78.4
2 to 4 cases	24.4	81.9
5 to 12 cases	24.9	82.9
more than 12 cases	27.7	83.7
Settlement decision		
Settled	92.3	82.2
Trial	7.8	60.6
N	14164	14164

Note: this table shows the summary statistics on the patient, case and lawyer characteristics as well as the case outcomes in our sample. Column (1) of this table shows the characteristics and outcomes as a percentage of the sample, in units of percentage points. Column (2) of this table refers to the percent of cases with a given characteristic (e.g. Female Patient = 1) that ended up in recovery, again in units of percentage points.

The key identifying assumption we use is that judges are randomly assigned to cases, such that the interaction of the judge and plaintiff lawyer going to the same law school is uncorrelated with case characteristics once we condition on judge and lawyer specific characteristics. Administrative records and our conversations with clerks of the court revealed that judges were randomly assigned to cases in our setting. We also test this assumption in our data by running an OLS regression of whether the judge and lawyer went to the same school ("Same School") on observable case characteristics, conditioning on the same set of fixed effects (on year, county, judge, and plaintiff lawyer experience) that we use in our empirical analysis. The results are shown in Column (1) of Table 2. As the regression shows, there is little correlation between the “Same School” variable and observable case characteristics, with a F-stat of 1.34 corresponding to a p-value of 0.193 that all coefficients on the case characteristics are zero. By contrast, running the same regression on whether the case resulted in a recovery by the plaintiff which we do in column (2) of Table 2 shows that the observable case characteristics are highly correlated with the probability of recovery, with a F-stat of 25.86 and a p-value of 0.000. The lack of correlation between our “Same School” variable and the observable case outcomes suggests that our identifying assumption of random assignment in judges is likely correct.

Table 2: Randomization Test

	(1) Same School	(2) Recovery
Female Patient	-0.00433	0.0205***
	(0.00595)	(0.00685)
Case Severity		
Permanent grave	-0.00596	0.0672***
	(0.0156)	(0.0181)
Permanent major	0.0176	0.0232
	(0.0128)	(0.0147)
Permanent significant	-0.0150	-0.00439
	(0.0104)	(0.0120)
Permanent minor	0.00335	-0.0293***
	(0.00902)	(0.0104)
Temporary major	-0.0100	-0.0135
	(0.0109)	(0.0126)
Temporary minor	0.0132	-0.0365***
	(0.00916)	(0.0106)
Temporary slight	-0.0299*	-0.139***
	(0.0174)	(0.0196)
Emotion only	0.00296	-0.294***
	(0.0184)	(0.0211)
Patient Age		
30 to 60	-0.00317	-0.0125
	(0.00810)	(0.00937)
over 60	-0.00733	-0.0190*
	(0.00865)	(0.0100)
Year FE	Yes	Yes
County FEs	Yes	Yes
Judge FEs	Yes	Yes
Plaintiff Lawyer Experience	Yes	Yes
Observations	11717	12724

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Column (1) of this table shows the results from our test randomization where we regress case characteristics on whether the plaintiff attorney and judge went to the same school, controlling for year, county, and judge FEs. Only one coefficient is significant at the 10% level. By contrast, Column (2) of this table shows that recovery highly correlated with observable case characteristics. The omitted group for case severity is "Dealth", and the omitted group for patient age is "0 to 30."

4 Empirical Results

As mentioned in section 2, both in-group bias and learning can explain the effect of the relationship between lawyers and judges on case outcomes. In this section, we test the two hypotheses, using law schools to define social groups and examining the importance of school affiliation among younger versus older lawyers. We first document the baseline effect of a plaintiff lawyer and a judge being alumni on case outcomes. This effect only shows up among younger lawyers, consistent with the hypothesis of group specific communication devices and learning at school. The main result holds in several robustness checks and is not driven by a particular group of judges.

Specifically, we estimate the following linear probability model to predict case outcomes:

$$y_{ist} = \alpha Q_i + \beta X_i + \delta Z_i + \eta_s + \nu_t + \epsilon_{ist} \tag{1}$$

where the subscripts i, s, t indicate case, county, and year, respectively. y_{ist} is a dummy variable encoding the recovery in the case. In a separate set of regressions, we also consider y_{ist} as whether the litigants settled out of court. Q_i represent the relationship between the plaintiff lawyer and the judge, and we are interested in estimating β, which measures the impacts of having a relationship on the case outcome. Z_i is a vector of covariates such as patient age, patient sex, and case severity. We include county fixed effects η_s and filing year fixed effects ν_t. We assume that error terms ϵ_{ist} are uncorrelated with the relationship variables Q_i, as the randomization test shows that judge-lawyer relationships are randomly assigned conditional on case characteristics.

Patient sex indicates whether the plaintiff is a male or a female. Since plaintiff may be compensated for their life time wage loss and younger patients have more years left on average, we include patient age fixed effects. We divide patients into three groups according to their ages. In our sample, 18% of patients are below 30 years old at the time of filing the lawsuit, 48% have ages between 30 and 60 years old, and the remaining 34% older than 60. Moreover, as documented in section 3, we expect more severe damages would be more likely to receive any recovery. When insurance companies report the claims to FLOIR, they can choose from 9 severity categories that ranks the injuries or medical problems caused during the medical process.[7] It ranges from the most minor physical ailments to the death of the insured. We control for these different severity groups. Because it is possible that more

[7] The 9 categories are: (1) Emotional Only: fright, no physical damage. (2) Temporary: slight lacerations. (3) Temporary: minor infections, missed fracture, fall in hospital. (4) Temporary: major burns, drug reaction. (5) Permanent: minor – loss of finger, damage to organs. (6) Permanent: significant – deafness, loss of limb, loss of eye. (7) Permanent: grave – paraplegia, blindness, loss of limbs. (8) Permanent: grave – quadriplegia, brain damage. (9) Permanent: death.

experienced lawyers worked on more severe cases, we also control for the number of medical malpractice cases that a plaintiff lawyer has worked on, including the current case. We call this variable "Plaintiff Lawyer Experience" and divide it into four categories according to its quartile. Roughly 23% of the cases are the first case of the plaintiff lawyer. Cases in the second quartile were repesented by lawyers who have worked on 2 to 4 cases. The third quartile have lawyers with 5 to 12 cases, and the last quartile are the most experienced lawyers with more than 12 cases. Other fixed effects including county that the case was filed, filing year, and the individual judge fixed effects.

In Table 3, we compare cases where lead plaintiff lawyers graduated from the same law school as judges did. To match with the specification in equation 1, the outcome variable Q_i is a dummy that equals 1 if the plaintiff side receives positive payment from the defendant, Q_i is a dummy reflecting whether the litigants settled out of court or not. The baseline group is this regression are cases where lawyers and judges went to different law schools and thus "Same School = 0". As shown in columns 1 and 2, having an alumni plaintiff lawyer would increase the probability of the plaintiff getting paid by 2.4 percentage point and the probability of settling out of court by 1.73 percentage point, controlling for case observables and fixed effects. Because cases that settled may have higher payment rate mechanically, as plaintiffs are more likely to go to the court when they are unsatisfied with defendant's offerings, we control for the settlement dummy in Column 3. Although the estimate on the same school variable is less significant, the magnitude does not change much, so what we find in column (1) is not driven by the a sample of cases where settlements break down.

A key difference between the two hypotheses proposed in section 2 is whether the sames school premium fades out as a lawyer becomes older. To test which hypothesis is more consistent with the data, we construct a dummy "Young" that equals 1 when the lawyer in the case filing year is younger than the sample's median lawyer age 50, and equals 0 otherwise. The independent variables include dummy Young and its interaction with the same school dummy that indicates whether the lawyer and the judge are alumni. That is, we are dividing lawyers into two groups by their age, and treat lawyers that go to different law school from the judges as the baseline. The omitted group is older lawyers above the median age of 50 who went to different law schools from the judges. As we can see in Table 4, among young plaintiff lawyers, going to the same law school as the judge would increase the probability of the plaintiff getting paid by 3.96 percentage point and increase the probability of settling out of court by 2.33 percentage point. Controlling for settlement in column (3) does not affect the same school estimate much, although it becomes slightly less significant. In contrast, looking at the group of lawyers older than 50, we do not see statistically significant effects from going to the same school with the judge, as more experience compensates for the social

Table 3: Same School Effect

	(1) Recovery	(2) Settle	(3) Recovery
Same School=1	0.0240**	0.0173**	0.0200*
	(0.0112)	(0.00789)	(0.0110)
Settle			0.227***
			(0.0131)
Constant	0.846***	0.387*	0.759**
	(0.307)	(0.217)	(0.303)
Patient Sex	Yes	Yes	Yes
Age FEs	Yes	Yes	Yes
Severity FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Case Exp FEs	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes
Observations	11745	11745	11745

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: this table documents the baseline effect on case outcomes of plaintiff attorneys and the judge being law school alumni. The omitted group is "Same School=0," or cases where lawyers went to a different law school from the judge. Columns 1 and 2 show that having an alumni plaintiff lawyer increases the probability of the plaintiff getting paid by 2.40 percentage point and of settlement by 1.73 percentage point. All columns control for case characteristics and other fix effects. Column 3 also controls for settlement.

skills acquired at school.

Over the past a few decades, law schools started accepting female students and more women enter the legal profession. Because of this shift in demographics composition, one concern is that the results are driven by a particular group of judges. As robustness checks, Appendix Table A2 shows that the extent of the same school effect does not seem to vary with judge characteristics such as gender and birth cohorts. First, we split the sample into four categories according to judge gender and lawyer age. The baseline group is female judge and lawyers younger than the median age among all lawyers in the sample. For example, j_female_young equals 1 means the judge is female and the plaintiff lawyer is younger than 50 years old at the case filing year. We interact these four dummies with the same school dummy. Therefore, in each category, the baseline group is lawyers who went to a different school from the judge. In all three columns, the estimates on the same school premium are on the border of being significant. Also, the coefficients do not differ significantly across male and female judges, even if we restrict to the sub-sample of young lawyers. Then in columns 3 to 6, we divide our sample according to both judges' and lawyers' age. For example, j_junior_young is comprised of cases where judges with age lower than 50 and plaintiff lawyers younger than 50. The omitted group in the regression table is cases where judges are above the median judge age and lawyers older than median lawyer age in the sample. As before, the effects of lawyers and judges going to the same school are pretty similar across judges born in different cohorts, on both the payment probability and settlement probability.

Finally, we consider whether the same school effect comes from personal connections. Suppose this is true, then lawyers and judges would be more likely to know each other if they were at school at the same time. Therefore, we expect to see stronger effects for lawyers and judges in "overlapping class", i.e. no more than 2 years apart when they graduated from law school. Regressing case outcomes on class differences and their interactions with the same school dummy, Table 5 finds no difference in the same school effect across years.[8] The omitted group here is when lawyers and judges went to different school and are more than 5 years apart in their graduation classes.

5 Conclusion

Our paper shows that by getting assigned a judge that went to the same school as the plaintiff lawyer, the changes of recovery increases by 2% overall and 4% for younger lawyers. Our results point out a source of variation in lawsuit outcomes that is not related to the

[8]The chance of knowing a judge through networking at school should be symmetric in class differences. Therefore, we do not look at younger and older lawyers separately.

Table 4: Young vs. Old Lawyers

	(1) Recovery	(2) Settle	(3) Recovery
Young=1	0.00965	0.0147***	0.00633
	(0.00794)	(0.00561)	(0.00785)
Young=0 × Same School	-0.00894	0.0129	-0.0118
	(0.0165)	(0.0117)	(0.0163)
Young=1 × Same School	0.0396***	0.0233**	0.0344**
	(0.0147)	(0.0103)	(0.0145)
Settle			0.226***
			(0.0133)
Constant	0.843***	0.388*	0.755**
	(0.306)	(0.216)	(0.302)
Patient Sex	Yes	Yes	Yes
Age FEs	Yes	Yes	Yes
Severity FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Case Exp FEs	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes
Observations	11338	11338	11338

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the same school effect accrues to young alumni lawyers. "Young" is a dummy variable that equals 1 when the lawyer in the case filing year is younger than the sample's median lawyer age 50, and equals 0 otherwise. The omitted group is "Young=0," which represents lawyers under the age of 50 and did not graduate from judges' law school. Among young plaintiff lawyers, going to the same law school as the judge increases the probability of the plaintiff getting paid by 3.96 percentage point and of settlement by 2.33 percentage point. All columns control for case characteristics and other fix effects. Column 3 also controls for settlement.

Table 5: Overlapping Class

	(1) Recovery	(2) Settle	(3) Recovery
3 or 4 years apart	0.00987	0.00760	0.00818
	(0.0125)	(0.00879)	(0.0123)
overlapping class	0.00169	0.00459	0.000664
	(0.0114)	(0.00801)	(0.0112)
5 years or more × Same School	0.0231*	0.0180**	0.0191
	(0.0128)	(0.00898)	(0.0126)
3 or 4 years apart × Same School	0.0242	0.0375*	0.0159
	(0.0308)	(0.0216)	(0.0304)
overlapping class × Same School	0.0279	-0.00588	0.0292
	(0.0295)	(0.0208)	(0.0292)
Settle			0.223***
			(0.0132)
Constant	0.847***	0.382*	0.762**
	(0.307)	(0.216)	(0.303)
Plaintiff Lawyer Experience FEs	Yes	Yes	Yes
Patient Sex	Yes	Yes	Yes
Age FEs	Yes	Yes	Yes
Severity FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes
Observations	11634	11634	11634

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows that the same school effect is not due to personal connections. The omitted group is when judges and lawyers are 5 years or more apart in law school classes. We define a lawyer and a judge being in "overlapping class" if they graduated from law school with no more than 2 years apart. We regress case outcomes on class differences and their interactions with the same school dummy. We find no difference in the same school effect across years. All columns control for case characteristics and other fix effects. Column 3 also controls for settlement.

merits of the case nor the general quality of the lawyer: we find that the match between lawyer and judge matters. Our results point to a source of variation in case outcomes from having access to the “right” lawyer for the judge, the specific mechanisms of which may be a promising avenue for future research.

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A Additional Figures and Tables

Figure A1: Stages of medical malpractice lawsuit

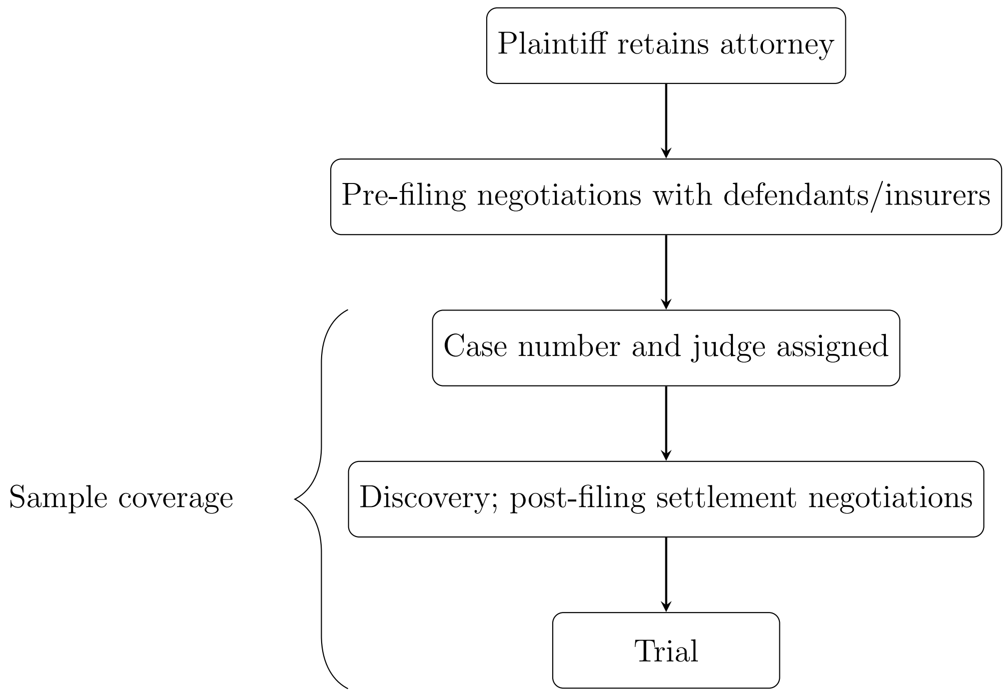

Figure A2: Counties from which we obtained court records

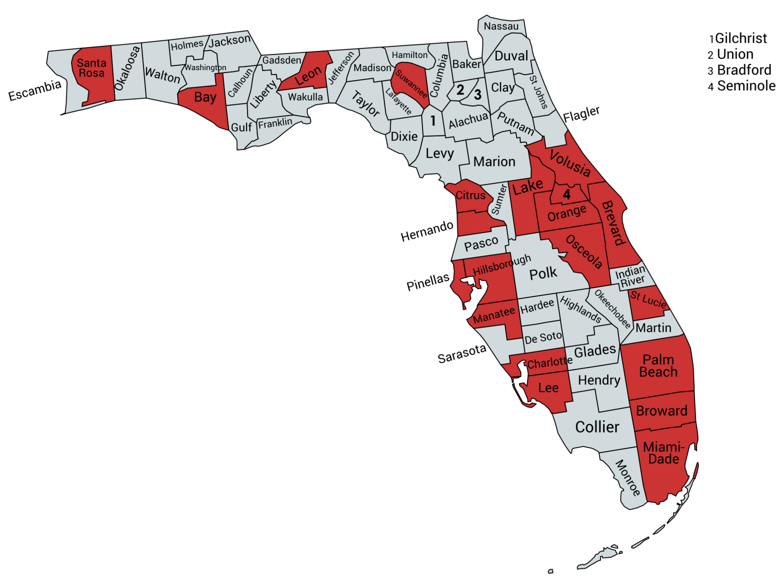

Table A1: FLOIR and county case record match statistics

	(1) FLOIR Claims	(2) Matched Claims	(3) Claim Match Rate
Dade	4745	4170	87.9%
Broward	4556	3425	75.2%
Palm Beach	3529	3110	88.1%
Hillsborough	2669	2215	83.0%
Pinellas	2339	1980	84.7%
Orange	1841	1551	84.2%
Lee	946	831	87.8%
Brevard	833	717	86.1%
Polk	824	195	23.7%
Volusia	772	703	91.1%
St. Lucie	643	540	84.0%
Sarasota	591	436	73.8%
Leon	568	478	84.2%
Lake	461	377	81.8%
Hernando	417	355	85.1%
Manatee	383	329	85.9%
Seminole	381	287	75.3%
Osceola	368	289	78.5%
Charlotte	326	263	80.7%
Bay	245	200	81.6%
Citrus	222	182	82.0%
Santa Rosa	96	83	86.5%
Suwannee	21	14	66.7%
Totals	27776	22730	81.8%

Note: this table shows the match rates from claims to court records by county. Column (1) shows the raw number of claims with a case filed in the Florida Office of Insurance Regulation (FLOIR) database. Column (2) the number of claims we were able to uniquely match based on case number, filing date, and defendant name. Column (3) shows our match rate which was computed by dividing the values in Column (2) by the values in Column (1).

Table A2: Judge Characteristics

	(1) Recovery	(2) Settle	(3) Recovery		(4) Recovery	(5) Settle	(6) Recovery
j_female_young	0	0	0	j_senior_old	0	0	0
	(.)	(.)	(.)		(.)	(.)	(.)
j_female_old	0.0122	-0.0116	0.0148	j_senior_young	0.0247**	0.0157*	0.0211*
	(0.0155)	(0.0109)	(0.0153)		(0.0114)	(0.00808)	(0.0113)
j_male_young	0.0111	-0.0884	0.0310	j_junior_old	0.0461***	0.0155*	0.0425***
	(0.0989)	(0.0698)	(0.0977)		(0.0131)	(0.00924)	(0.0129)
j_male_old	-0.00591	-0.104	0.0176	j_junior_young	0.0452***	0.0258***	0.0392***
	(0.0989)	(0.0698)	(0.0977)		(0.0129)	(0.00913)	(0.0127)
j_female_young × Same School	0.0562*	0.0265	0.0502*	j_senior_old × Same School	0.0186	0.0297*	0.0117
	(0.0300)	(0.0212)	(0.0296)		(0.0216)	(0.0153)	(0.0213)
j_female_old × Same School	-0.0138	-0.00118	-0.0135	j_senior_young × Same School	0.0419**	0.0289**	0.0352*
	(0.0299)	(0.0211)	(0.0296)		(0.0196)	(0.0139)	(0.0193)
j_male_young × Same School	0.0342**	0.0224*	0.0292*	j_junior_old × Same School	-0.0280	-0.0174	-0.0240
	(0.0168)	(0.0119)	(0.0166)		(0.0260)	(0.0184)	(0.0257)
j_male_old × Same School	-0.00779	0.0190	-0.0121	j_junior_young × Same School	0.0395*	0.0255	0.0336
	(0.0199)	(0.0140)	(0.0196)		(0.0219)	(0.0155)	(0.0216)
Settle			0.226***	Settle			0.232***
			(0.0133)				(0.0140)
Constant	0.847***	0.492**	0.736**	Constant	0.935***	0.315**	0.861***
	(0.322)	(0.227)	(0.318)		(0.220)	(0.156)	(0.217)
Plaintiff Lawyer Experience FEs	Yes	Yes	Yes	Plaintiff Lawyer Experience FEs	Yes	Yes	Yes
Patient Sex	Yes	Yes	Yes	Patient Sex	Yes	Yes	Yes
Age FEs	Yes	Yes	Yes	Age FEs	Yes	Yes	Yes
Severity FEs	Yes	Yes	Yes	Severity FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Year FEs	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	County FEs	Yes	Yes	Yes
Judge FEs	Yes	Yes	Yes	Judge FEs	No	No	No
Observations	11338	11338	11338	Observations	10018	10018	10018

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$