An Event Study of Patent Verdicts and Judicial Leakage

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Abstract

We investigate whether judicial decisions are leaked or stolen prior to their public release. Utilizing an event study methodology, we test for leaked information by analyzing the effect of patent infringement verdicts on the stock prices of the firms involved before and after the public release of the verdict. We find evidence that at least some of the decisions are leaked prior to their public release.

Keywords: event study, abnormal returns, judge, patent infringement, stock prices, leakage, jury, insider trading

JEL Codes: G14, K41

1 Introduction

Judges and juries are to deliver fair and impartial decisions. Furthermore, as stated in Administrative Office of the US Courts (2015), p. 6, "Jurors must not talk about the case with others not on the jury ... The jury's verdict must be based on nothing else but the evidence and law presented to them in court." Under Cannon 3 of the Code of Conduct of United States (US) Judges (Judicial Conference (2014)), "A judge should not make public comment on the merits of a matter pending or impending in any court. A judge should require similar restraint by court personnel subject to the judge's direction and control." In cases involving publicly traded companies, the decisions can have a material impact on the company and its stock price. As a result, judges and juries hold valuable nonpublic information prior to the release of the verdict. While illegal for multiple reasons, it is possible such private information could be used to profit, and by extension, affect a judge's or jury's decision. For example, a judge could not only sell, or trade on, material nonpublic information, but could choose a verdict to maximize stock price volatility and generate higher profits. In order to maintain both the integrity and legitimacy of the judicial system, it is essential that judges and juries do not act on, or sell, material nonpublic information.

In this paper, we conduct a stock price event study using patent litigations to determine whether the United States' judicial system is leaking judicial verdicts prior to their public release. Our test is a first step in determining whether such information affects judges' or juries' decisions. It is a first step because the information may not be sold. In particular, the information could be stolen from the judicial computer networks, and even if it is being sold, may not affect the impartiality of the verdict. That being said, our results are capable of finding leaked information and insider trading.

The patent cases we use were selected from the dataset Patstats, a publicly available online litigations database. From the dataset, we collect only publicly traded litigants from high valued infringement cases because low valued outcomes are indistinguishable from non-material cases. Specifically, if a decision is unexpectedly low, then we are unable to know whether it could have been a high valued case. As a result, we attempt to maximize our power by choosing high valued cases. Given the cases, we pull the decision dates from "Docket Navigator" for jury decisions, and the public archives of the United States Court of Appeals for the Federal Circuit for appeals decisions. Given the decision dates, we use stock price data from Yahoo Finance to run the event study.

Following the methodology discussed in the event study survey MacKinlay (1997), we pair the adjusted returns of each firm with the overall market returns as measured by the S&P 500 index in order to estimate the predicted returns in the days leading up to, and after, each decision. We then find the abnormal returns for each observation by calculating the difference between the predicted returns and the actual returns over the event window. Lastly, we sum across the abnormal returns in the event window in order to calculate the cumulative abnormal returns for each decision. The significance of these pre-decision cumulative abnormal returns can then be analyzed to find information

leakage within the judicial system.

We find evidence of abnormal returns, or the release of nonpublic information, prior to the public release of the verdict at the individual decision level. In particular, we find p-values of 0.0001 for nearly 10% of our observations, i.e., decisions. In jury trials, this information is less useful as jury trials are publicly viewable and can be tracked by informed investors up to the date of the verdict. To resolve this issue, we also conduct an event study on judical patent decisions from the United States Court of Appeals for the Federal Circuit. Since the appeals process at the Federal Circuit is composed of at most a brief fifteen to sixty minute question and answer session, followed by a nonpublic judicial deliberation period, there is no publicly available information from the appeals process that can be priced in immediately prior to the public release of the decision.

Besides the abnormal returns at the individual decision level, we also calculate the cummulative average return across the jury and judge decisions, respectively. We fail to reject the sum to be statistically different from zero. In general, this method can be enlightening due to insignificance at the individual event date level. However, we find large test statistics. As a result, the cumulative returns across decisions is puzzling. However, we speculate that we have run into this issue because the effects of each decision average out. Specifically, we don't have a good proxy for the expected outcome of the decision as is the case in most event studies such as surprise earnings releases. Earnings announcement studies use analysts predictions to separate announcements into positive and negative ones. Once separated, they analyze the results. To remedy this issue, we sum across all the decisions using both the absolute value and squared values of the individual cumulative abnormal returns. The new methods yield all positive values for the individual cumulative abnormal returns. As a result, the coefficients cannot average each other out. Using our alternative approach, we again find evidence of judicial leakage at a p-value of roughly 5% depending upon the type of decision and method of analysis.

In terms of the literature, MacKinlay (1997) provides a well cited survey of the event study method and its employment. In particular, the method has been used to study the effects of acquisitions and mergers, legal cases, quarterly earnings announcements, and the announcement of various macroeconomic variables. As a conservative estimate, there exists more than 500 event studies. While many legal event studies have been done, our work is the first to examine patent decisions in order to question the impartiality of the judicial system. Specifically, Bessen and Meurer (2008) use an event study to quantify the extra private costs associated with patent litigations. Additionally, Bessen, Meurer, and Ford (2011) examine the economic loss associated with suits filed by nonpracticing entities labeled "patent trolls." While these two works are indeed important, neither test whether information is leaked early. Centering the event window around the suit's filing date rather than the court's decision date, the papers set out simply to discover stock market reactions to public announcements. Marco (2005) also conducts an event study to examine the value of intellectual property rights. While the study does indeed center the event window around the court's decision date, it does so only under the strong assumption that no information will be leaked in the days prior to the decision.

2 Model

2.1 Event and estimation window

Our notation was adopted from MacKinlay (1997)'s highly cited survey of the event study literature. Since our study is centered around the court's decision date, we set our event date, or $t = 0$, to be the day on which the verdict is released to the public. Additionally, since our goal is to calculate a sum of abnormal returns accrued over a given time frame, we use an event window of between two and five days over which we calculate the abnormal returns. We investigate the four separate event windows of

$$\tau_1 = -5 \leq t \leq -1 = \tau_2, \tag{1}$$

$$\tau_1 = -2 \leq t \leq -1 = \tau_2, \tag{2}$$

$$\tau_1 = -2 \leq t \leq 2 = \tau_2, \textit{ and} \tag{3}$$

$$\tau_1 = 0 \leq t \leq 1 = \tau_2. \tag{4}$$

Given our focus on the leakage of private information, the event windows in equation 1 and 2 are the most important to our study.

In order to calculate abnormal returns over the event window, we first estimate the predicted, or normal returns, over the event window. To make this estimation, we use an estimation window of $-60 \leq t < -30$, whereby steady security returns are used to make predictions over the event window. Note that both the event window and estimation window are calculated using trading days rather than calender days.

2.2 Estimating abnormal returns

In order to calculate the abnormal returns, we first use the estimation window to estimate the normal returns over the event window. Specifically, we estimate using ordinary least squares β and α in the equestion

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{5}$$

for each decision date, or observation, "i", where R_{it} represents the one-day returns on security "i" on date "t," and R_{mt} represents the market returns as measured by the S&P 500 on date "t." Let $var(\varepsilon_i) = \sigma^2_{\varepsilon_i}$. To reiterate, this is estimated using data from 60 to 30 trading days prior to the release of the verdict.

Given β and α for each security "i", we calculate an observation's abnormal return as

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt}. \tag{6}$$

In words, AR_{it} calculates how much the stock price deviated on period "t" after controlling for the market. The market

control is standard and follows the Capital Asset Pricing Model. Given standard assumptions about stock market volatility and the effect of the size of the estimation window on the errors of α_i and β_i, the abnormal returns are normally distributed with mean zero and variance $\sigma^2_{\varepsilon_i}$.

2.3 Estimation of the cumulative abnormal return

Once the abnormal returns have been calculated for each of the decisions, we aggregate the abnormal returns across the respective event windows in order to gain information about the overall event. Termed cumulative abnormal returns, we aggregate

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{7}$$

$$\sigma_i^2(\tau_1, \tau_2) = \text{var}(CAR) = (\tau_2 - \tau_1 + 1)\,\sigma^2_{\varepsilon_i} \tag{8}$$

where the time intervals, τ_1 to τ_2, are set to investigate leakage around the event window. We investigate several different windows as note in equations 1-4.

Since we are also interested in the overall effect of these decisions, we use a cross sectional approach to measuring the significance of the cumulative abnormal returns. We first conduct this test using the standard method of calculating the average cumulative abnormal return across all decisions. To make this calculation, we sum all of the coefficients by averaging them into one, labeled $\overline{CAR}$, or

$$\overline{CAR} = \frac{1}{N}\sum_{i=1}^{N}\sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{9}$$

where N is the total number of decisions used. Under the standard model, $\overline{CAR}$ is normally distributed with variance

$$\text{var}\left(\overline{CAR}(\tau_1, \tau_2)\right) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(\tau_1, \tau_2), \tag{10}$$

or

$$\overline{CAR} \sim N\left[0, \text{var}\left(\overline{CAR}(\tau_1, \tau_2)\right)\right]. \tag{11}$$

It is at this point in our model whereby our approach differs from the standard as discussed in MacKinlay (1997). Since our list is composed of both winners and losers, this approach will be somewhat flawed, as our *CAR* coefficients average out. In other words, on average, the market could predict the up and down movement around the window well, i.e., the mean is zero. However, information may still be leaked. In general in event studies, if an announcement could be good or bad, the investigator will group the types into good and bad using analysts predictions. We do not have a similar reference in the case of patent decisions.

To resolve this issue, we take an alternative approach whereby we first take the absolute value of *CAR* at the individual decision level before summing across all decisions. This process eliminates any canceling of coefficients within the calculation. Label the statistic $|CAR|$, or

$$|CAR| = \sum_{i=1}^{N} \left| \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \right|. \tag{12}$$

For completeness and to enable outliers, we also conduct the above calculation by calculating the squares of the *CAR* coefficients. Label the sum of the squared terms $(CAR)^2$, or

$$(CAR)^2 = \sum_{i=1}^{N} \left(\sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \right)^2. \tag{13}$$

When using these two statistics, we conducted a Monte Carlo simulation of a million random draws using the $\sigma^2_{\varepsilon_i}$ variances for each "i" drawn from a normal distribution. Given the random draws, we are able to precisely estimate the critical values at the 90, 95, and 99 percent significance levels.

3 Data and results

3.1 Data

The data is compiled from multiple publicly accesible online sources. To begin, a list of jury verdicts was pulled from PatStats, an online patent litigation database. This list is composed of the 380 largest patent infringement payouts since 2005, and is sorted by the size of the remedy. For our jury study, we simply located these cases through a program called Docket Navigator, which then allowed us to find the exact date of each decision. After shrinking the list down to contain only publicly traded firms that were ruled to have infringed, we were left with a list of 42 publicly traded firms.

For our appeals study, we searched through the case archives on United States Court of Appeals to locate the original PatStats litigations at the appeals level. After eliminating private firms, along with firms traded on foreign exchanges, we were left with a total of 45 publicly traded firms along with the date of their respective appeals decision. Different from the jury study, we chose to include both the plaintiff and the defendent within the appeals study.

For both event studies, we merged our list of litigants with the adjusted return for each individual firm using the adjusted closing price. The adjusted closing price incorporates corporate actions and distributions. Additionally, all parties were paired with the overall market return for that specific date using the S&P 500 index as the market's return. All stock data was obtained from Yahoo Finance.

3.2 Average return

For a visual inspection of the abnormal returns, we plot the average return calculated across all litigants by type, as a function event time, in Figures 1 and 2. To reiterate, the event time is the difference in trading days from each litigant's respective event, or decision, date $t = 0$.

Figure 1: Jury Average Return over Time

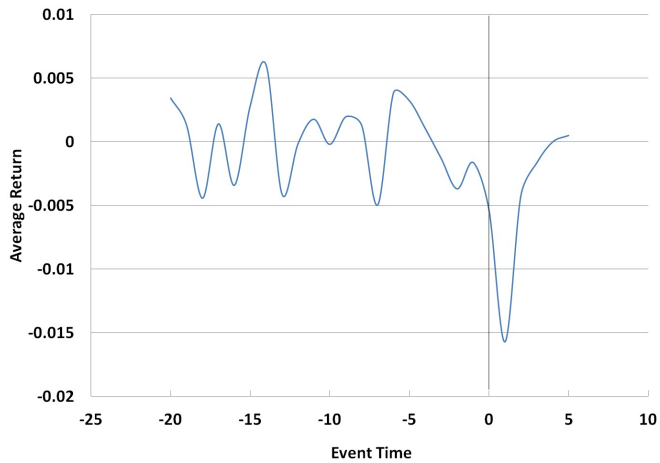
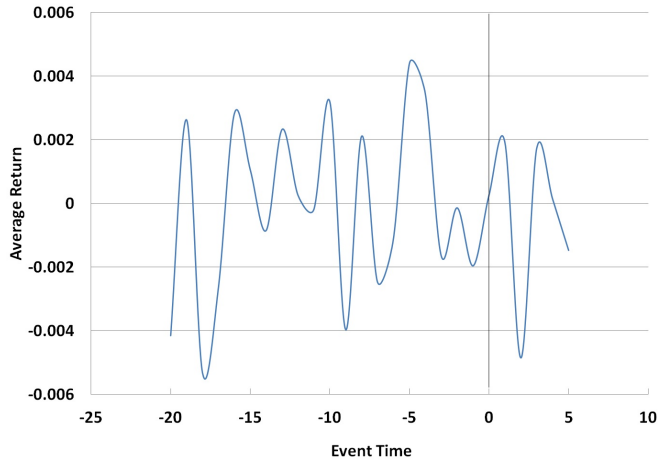


Figure 2: Judicial Average Return over Time



Since the jury data is composed of only infringers, we see a large fall in average return following the decision date in Figure 1. This drop represents the negative reaction of stock prices given the size of the damages. However, given that we have no data relative to the public expectations surrounding the damages, the graph may not be perfect in modeling the market reaction. In some cases, the remedy awarded may have actually been less than expected, causing the prices to rise. Similarly, given that the appeals list is composed of both winning and losing litigants, we see no clear trend in the change in stock returns over time. This could be occurring because the winners and losers are averaging

out.

In order to resolve this issue, we also include the absolute average abormal returns for both the jury and judicial cases. These trends are seen in Figures 3 and 4.

Figure 3: Absolute Average Return over Time

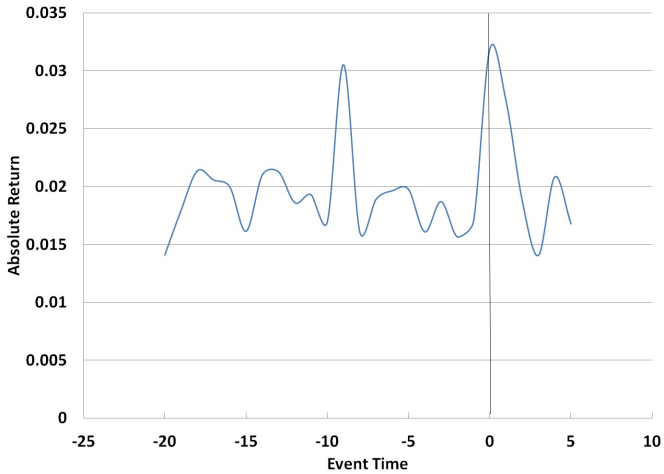
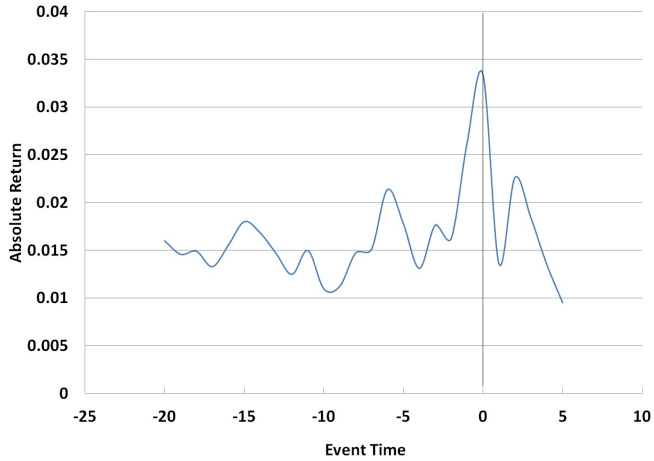


Figure 4: Absolute Average Return over Time



As shown by the curve in Figure 3, there is a clear increase in the average absolute value of the returns from $t = -1$ to $t = 1$. This increase represents the change in stock prices following the release of the jurys' verdicts. With respect to the days leading up the event however, we see no significant change in returns. This lack of change suggests that the juries are indeed keeping the information private or they are simply unsure of the outcome. As the verdict is decided by committee, it might be no one knows the eventual outcome until the vote and immediate announcement.

For the appeals study however, we see a significant increase in absolute average returns from $t = -2$ to $t = -1$. Since this increment falls before the official decision release date, the change functions as evidence to indicate that the appellate court is indeed leaking nonpublic information.

3.3 Cumulative abnormal returns

While the graphs do indeed help us to visualize the change in returns, we analyze the actual returns relative to the predicted market returns using statistics. Using the model, we were able to predict the cumulative abnormal return for each decision over each individual event window. Additionally, we generated a test statistic to test the significance of each *CAR* coefficient by type. Individual test statistics are tested against the hypothesis

$$H_0 : CAR_i = 0 \text{ for all } i(1,2.....N), \tag{14}$$

$$H_a : \text{At least one } CAR_i \neq 0. \tag{15}$$

The results can be seen in Tables 7 and 8 for the jury and appellate decisions, respectively. Multiple test statistics have an absolute value greater than 3, either with a window of -2 to -1, or -5 to -1, or both. As a result, we can reject the null at standard levels of significance.

Additionally, one can apply a Bonferroni Correction to our critical values. This correction requires a conservative critical value to limit type 1 errors as multiple tests are used. The correction requires the type 1 errors to be $\alpha = .05/N$ for a 95% significance level. To be clear, this is a conservative adjustment. For $N = 43$, the critical value is 3.261. As seen in Tables 7 and 8, we still reject the null on multiple decisions when using the conservative Bonferroni Correction.

3.4 Sum of cumulative abnormal returns

In addition to testing each individual coefficient, we conduct a cross examination of the *CAR* coefficients summed over all events. First, we test the mean *CAR* statistics for both event studies, jurors and judges, against the hypothesis test

$$H_0 : \frac{\sum_{i=1}^{N} CAR_i}{N} = 0, \tag{16}$$

$$H_a : \frac{\sum_{i=1}^{N} CAR_i}{N} \neq 0. \tag{17}$$

For both the judicial and jury study, we fail to reject the null at a 95% significance level.[1] Refer to Tables 1 and 2 for the results. We speculate the lack of power is a result of a canceling out. However, we could still be seeing abnormal returns on the positive and negative side. Usually, an event study will put the events into good and bad bins. For instance, earnings releases are broken into three groups - exceeding analyst predictions, in line with analyst predictions, and below analyst predictions. Given our lack of knowledge pertaining to investor expectations relative to the actual award, we suspect the positive and negative reactions relative to market expectations may be combining to yield a mean of zero.

[1] Although the results are not included, we confirm these findings using the sign test and rank tests as described in MacKinlay (1997), Section 8 among many others.

Table 1: Jury Summary Statistics: (CAR) Significance Test

Event Window	CAR	Test Statistic	Standard Error	$P < \|t\|$
$-2 \leq t \leq -1$	-0.003	-0.9	0.003	0.376
$-5 \leq t \leq -1$	-0.003	-0.53	0.005	0.6
$-2 \leq t \leq 2$	-0.023	-1.82	0.013	0.075
$0 \leq t \leq 1$	-0.022	-1.69	0.013	0.099

Note:A test statistic greater than 1.96 would indicate significance at the 95 percent level

Table 2: Judicial Summary Statistics: (CAR) Significance Test

Event Window	Mean CAR	Test Statistic	Standard Error	$P > \mid t \mid$
$-2 \leq t \leq -1$	-0.007	-0.67	0.011	0.505
$-5 \leq t \leq -1$	-0.004	-0.4	0.011	0.695
$-2 \leq t \leq 2$	-0.016	-0.95	0.017	0.348
$0 \leq t \leq 1$	-0.004	-0.39	0.010	0.695

Note: A test statistic greater than 1.96 would indicate significance at the 95 percent level

3.5 Sum of the absolute value of the cumulative abnormal returns

To resolve the issue of cancellation, we also examine the events using the absolute value method outlined in Equation 12. The $|CAR|$ coefficients are then assessed using the hypothesis test

$$H_0 : \sum_{i=1}^{N} |CAR_i| = 0 \tag{18}$$

$$H_a : \sum_{i=1}^{N} |CAR_i| \neq 0. \tag{19}$$

Given that these results are no longer normally distributed, we use a Monte Carlo simulation to predict the critical values for the event windows.

For the jury study, we fail to reject the null in both the $-5 \leq t \leq -1$ window and the $-2 \leq t \leq -1$ window. We do however reject the null with 99% confidence in the $-2 \leq t \leq 2$ window, as well as the $0 \leq t \leq 1$ window. Given that no significant absolute abnormal returns are found within either of the two pre-decision event windows, this test fails to find any leakage occurring within the jury trials on aggregate. However, individual decisions may have been leaked as found in Section 3.3. The summary statistics for jury-based absolute value test are found in Table 3.

Given the individual results find significance across several different decisions, these results suggest on average the information is unavailable due to the unpredictability of jurors, it is priced in prior to the event window as the evidence comes to light during the trial, or the information simply isn't being leaked on an aggregate enough scale. However, we do see results on the individual level that are being washed out by the number of observations with insignificant

critical values.

Table 3: Jury Summary Statistics: $|CAR|$ Significance Test

Event Window	$\|CAR\|$	90% critical value	95% critical value	99% critical value
$-2 \leq t \leq -1$	0.727	1.002	1.049	1.142
$-5 \leq t \leq -1$	1.061	1.584	1.660	1.807
$-2 \leq t \leq 2$	1.993	1.584	1.660	1.805
$0 \leq t \leq 1$	1.696	1.002	1.050	1.143

Note: The simulation uses random draws from the normal distribution with observed variance $\sigma^2_{\varepsilon_i}$ estimated from the estimation window.

With respect to the appellate judges, we reject the null for both of the post-decision event windows. Furthermore, we find significant results within the pre-decision windows. Specifically, we reject the null for the $-2 \leq t \leq -1$ window with 99% confidence, and we reject the null for the $-5 \leq t \leq -1$ window with 90% confidence. Shown in Table 4, these significant absolute abnormal returns within the pre-decision window are indeed an indicator that judicial leakage is occurring.

In interpreting the results, we find the large window has a smaller p-value. This is likely due to the increased variation from additional observations. Also, we are finding leakage, but this doesn't mean judges are selling the information. It is likely the information could be stolen as a result of insufficient protection of the appellate court's computer networks. None the less, the source of the leak should be investigated no matter what the cause because trading on insider information is illegal whether it is being done by a judge or not.

Table 4: Judicial Summary Statistics: $|CAR|$ Significance Test

Event Window	$\|CAR\|$	90% critical value	95% critical value	99% critical value
$-2 \leq t \leq -1$	1.433	1.053	1.100	1.192
$-5 \leq t \leq -1$	1.679	1.665	1.740	1.887
$-2 \leq t \leq 2$	2.260	1.664	1.739	1.885
$0 \leq t \leq 1$	1.571	1.052	1.100	1.192

Note: The simulation uses random draws from the normal distribution with observed variance $\sigma^2_{\varepsilon_i}$ estimated from the estimation window.

3.6 Sum of the square of the cumulative abnormal returns

In addition examining the factors in absolute value, we check our results by means of the squared value of the test statistic. The hypothesis test is

$$H_0 : \sum_{i=1}^{N} (CAR)^2 = 0 \tag{20}$$

$$H_a : \sum_{i=1}^{N} (CAR)^2 \neq 0 \tag{21}$$

With respect to the jury study, we again fail to reject the null for both the $-5 \leq t \leq -1$ window and the $-2 \leq t \leq -1$ window, but reject the null at a 99% significance level for both of the post-decision event windows. These results confirm our previous findings that no significant abnormal returns exist within the pre-event window on aggregate for the jury litigations. The $(CAR)^2$ summary statistics for the jury study can be found in Table 5.

Table 5: Jury Summary Statistics: $(CAR)^2$ Significance Test

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-2 \leq t \leq -1$	0.021	0.057	0.067	0.091
$-5 \leq t \leq -1$	0.044	0.143	0.168	0.227
$-2 \leq t \leq 2$	0.300	0.144	0.168	0.228
$0 \leq t \leq 1$	0.299	0.057	0.067	0.091

Note: The squared test is different in the sense that it allows our larger coefficients to have more influence than the smaller ones.

As shown in Table 6, when using the $(CAR)^2$ procedure on the judge study, we reject the null with 99% confidence in all four of our event windows. The test confirms our previous finding from the $|CAR|$ procedure that significant abnormal returns do indeed exist within the pre-event window for the appellate court. All together, both tests present strong evidence that the appellate court is leaking information.

Table 6: Judicial Summary Statistics: $(CAR)^2$ Significance Test

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-2 \leq t \leq -1$	0.231	0.056	0.063	0.079
$-5 \leq t \leq -1$	0.239	0.141	0.159	0.199
$-2 \leq t \leq 2$	0.563	0.141	0.158	0.199
$0 \leq t \leq 1$	0.204	0.056	0.063	0.079

Note: The squared test is different in the sense that it allows our larger coefficients to have more influence than the smaller ones.

4 Conclusion

The US court system is often considered one of the most powerful and influential organizations in the country. With jurisdiction over nearly all legal matters, the courts are unconditionally obligated to continuously present both fair and impartial decisions. However, the nonpublic nature of the decision provides an incentive to leak and potentially manipulate a verdict for personal gain.

As a result of this potential conflict of interest, we take the first step in deciding whether such an incentive is

being used. To investigate the hypothesis, an event study of patent litigations involving roughly 45 publicly traded firms is used. We find statistically significant abnormal returns occurring prior to the public release of the nonpublic information. As a result, we conclude court decisions are being leaked and used to profit.

Given our results, further work needs to be done to determine how the information is being leaked and whether it is manipulating decisions. As a first step, we investigated whether a correlation exists between high abnormal returns and whether an appellate decision went in favor or against the original decision. However, the limited number of observations limited our analysis. Whatever the eventual conclusion, unbiased judges and juries are key to the integrity of the judicial system.

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Table 7: Jury Cumulative Abnormal Return Statistics

Stock Ticker	Decision Date	$\tau_1 = -5,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = 2$		$\tau_1 = 0,\ \tau_2 = 1$	
		CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
BSX	Feb 11, 2008	0.051	1.165	-0.017	-0.631	-0.006	-0.13	0.011	0.39
LLNW	Feb 29, 2008	-0.051	-0.557	-0.039	-0.665	-0.357	-3.871	-0.401	-6.872
HAS	Mar 24, 2008	0.004	0.079	0.029	0.852	0.025	0.459	0.012	0.338
SNE	Nov 17, 2008	-0.009	-0.245	0.007	0.28	-0.037	-0.992	-0.016	-0.659
MDT	Dec 05, 2008	0.078	2.057	0.046	1.945	0.043	1.145	0.013	0.554
BAX	Jan 30, 2009	0.032	0.709	0.003	0.12	0.059	1.295	0.029	1
ABT	Feb 19, 2009	0.013	0.368	0.016	0.721	0.039	1.127	0.014	0.629
CAMT	Mar 05, 2009	-0.061	-0.647	-0.041	-0.693	-0.282	-3.012	-0.245	-4.14
PII	Apr 16, 2009	0.065	0.987	-0.011	-0.268	0.068	1.035	0.105	2.515
AAPL	Apr 23, 2009	0.019	0.506	-0.013	-0.557	-0.014	-0.392	-0.013	-0.553
YHOO	May 15, 2009	0.005	0.092	-0.012	-0.339	0.001	0.015	0.012	0.339
MSFT	May 20, 2009	0.029	0.572	-0.012	-0.364	-0.017	-0.324	-0.004	-0.121
ABT	Jun 29, 2009	0.003	0.056	0.012	0.404	-0.001	-0.029	-0.006	-0.201
MGI	Sep 24, 2009	-0.078	-0.525	-0.039	-0.415	-0.076	-0.513	-0.079	-0.848
BDX	Nov 09, 2009	0.008	0.345	0.016	1.095	0.029	1.287	0.004	0.284
ELY	Mar 05, 2010	-0.009	-0.251	0.05	2.176	0.065	1.8	-0.003	-0.124
MSFT	Mar 16, 2010	0.014	0.672	0.005	0.386	0.002	0.085	-0.004	-0.313
CSCO	May 17, 2010	-0.011	-0.562	-0.045	-3.493	-0.058	-2.849	-0.013	-1.033
AAPL	Oct 01, 2010	-0.02	-0.778	-0.005	-0.334	0.007	0.287	-0.013	-0.843
SPLS	Dec 21, 2010	0.016	0.723	-0.011	-0.781	0.005	0.234	0.002	0.163
JNJ	Jan 28, 2011	-0.038	-3.512	-0.008	-1.152	-0.009	-0.787	-0.007	-1.013
VZ	Mar 08, 2011	-0.027	-1.027	-0.005	-0.328	0.006	0.233	0.011	0.657
AAPL	Jul 08, 2011	0.046	1.97	0.015	1.014	0.022	0.922	0.005	0.339
VZ	Aug 02, 2011	0.018	1.219	0.014	1.526	0.033	2.28	0.017	1.852
NUVA	Sep 20, 2011	0.015	0.386	-0.009	-0.367	-0.038	-0.971	-0.086	-3.475
HOLX	Oct 17, 2011	-0.024	-0.821	-0.005	-0.277	-0.042	-1.447	-0.028	-1.54
JCP	Nov 18, 2011	-0.03	-0.801	0.015	0.644	0.003	0.071	0.004	0.164
MDT	Jan 26, 2012	-0.002	-0.056	-0.001	-0.031	-0.024	-0.636	-0.014	-0.6
VAR	Feb 23, 2012	-0.022	-1.305	-0.013	-1.22	-0.021	-1.297	-0.002	-0.202
XLNX	May 18, 2012	0.011	0.496	-0.006	-0.418	-0.009	-0.435	0.002	0.113
PAY	Jun 08, 2012	-0.047	-1.181	-0.043	-1.723	-0.157	-3.962	-0.03	-1.207
CTXS	Jun 18, 2012	-0.004	-0.071	0.008	0.244	-0.012	-0.24	-0.019	-0.588
BBRY	Jul 13, 2012	0.029	0.428	0.037	0.846	-0.045	-0.663	-0.067	-1.541
IO	Aug 16, 2012	-0.014	-0.431	0.009	0.476	-0.116	-3.689	-0.118	-5.916
AOL	Nov 06, 2012	0.008	0.273	0.006	0.328	0.096	3.385	0.115	6.376
MRVL	Dec 26, 2012	0.012	0.213	0.01	0.277	-0.083	-1.431	-0.126	-3.42
ZMH	Feb 05, 2013	-0.023	-1.832	-0.016	-2.081	-0.005	-0.388	0.012	1.528
ILMN	Mar 14, 2013	-0.002	-0.035	-0.015	-0.44	-0.01	-0.181	-0.002	-0.046
T	Mar 20, 2013	-0.013	-0.85	0.001	0.11	0.002	0.098	0.002	0.212
CSCO	Mar 22, 2013	-0.028	-1.378	-0.031	-2.455	-0.042	-2.082	-0.004	-0.275
GMED	Jun 14, 2013	-0.027	-0.669	-0.001	-0.043	0.006	0.155	0.022	0.863
QCOM	Oct 24, 2013	-0.049	-2.579	-0.03	-2.483	-0.022	-1.154	0.007	0.603

Table 8: Appellate Judge Cumulative Abnormal Return Statistics

Stock Ticker	Decision Date	$\tau_1 = -5,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = 2$		$\tau_1 = 0,\ \tau_2 = 1$	
		CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	CAR_i	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
ERIC	Aug 05, 2005	-0.013	-0.84	-0.006	-0.634	0	0.012	-0.005	-0.543
HRS	Aug 05, 2005	-0.027	-0.476	-0.013	-0.379	-0.012	-0.214	0.006	0.163
VG	Sep 26, 2007	-0.4	-3.831	-0.417	-6.315	-0.606	-5.806	-0.237	-3.587
VZ	Sep 26, 2007	0.012	0.42	-0.008	-0.425	-0.011	-0.4	0.005	0.268
MSFT	Nov 16, 2007	-0.018	-1.041	-0.008	-0.692	0.02	1.148	0.015	1.335
FNSR	Apr 18, 2008	0.005	0.047	0.023	0.317	-0.074	-0.654	-0.073	-1.015
ALU	Sep 25, 2008	-0.037	-0.607	0.056	1.458	-0.061	-0.998	-0.048	-1.236
MSFT	Sep 25, 2008	0.022	0.45	0.028	0.918	0.055	1.117	0.049	1.578
VAR	Jun 09, 2009	-0.044	-0.906	-0.023	-0.752	0.014	0.297	0.03	0.98
ALU	Sep 11, 2009	0.056	0.845	0.007	0.175	0.08	1.208	0.03	0.717
MSFT	Sep 11, 2009	0.004	0.091	-0.008	-0.285	-0.004	-0.082	-0.001	-0.037
MSFT	Dec 22, 2009	-0.003	-0.095	0.018	0.797	0.019	0.545	0.004	0.187
ARIA	Mar 22, 2010	-0.043	-0.775	-0.136	-3.863	-0.034	-0.605	0.125	3.554
LLY	Mar 22, 2010	0.001	0.026	0.004	0.246	0.001	0.026	0.002	0.162
MDT	Sep 09, 2010	0.006	0.322	-0.011	-0.949	0.013	0.737	0.024	2.151
MGI	Dec 07, 2010	-0.087	-1.256	-0.056	-1.288	-0.017	-0.253	0.062	1.409
WU	Dec 07, 2010	-0.015	-0.667	0.005	0.336	0.006	0.273	0.01	0.68
MSFT	Jan 04, 2011	-0.017	-0.753	-0.006	-0.408	0.018	0.808	-0.005	-0.35
ABT	Feb 23, 2011	0.025	1.896	0.021	2.47	0.033	2.479	0.007	0.858
SATS	Apr 20, 2011	-0.021	-0.394	-0.042	-1.205	-0.037	-0.68	0.008	0.234
TIVO	Apr 20, 2011	0.011	0.185	-0.011	-0.291	0.153	2.563	0.169	4.464
RMBS	May 13, 2011	0.029	0.731	0.017	0.675	-0.342	-8.745	-0.255	-10.322
HD	Nov 14, 2011	0.032	1.425	0	-0.034	0.007	0.292	0.002	0.112
VZ	Aug 24, 2012	-0.053	-3.632	-0.017	-1.877	-0.017	-1.195	0.004	0.461
AAPL	Sep 04, 2012	0.001	0.062	-0.012	-1.019	-0.013	-0.707	0.007	0.634
BSX	Sep 18, 2012	0.026	0.559	0.006	0.218	0.02	0.423	0.004	0.148
MDT	Sep 18, 2012	0.009	0.434	0.012	0.881	0.019	0.866	-0.001	-0.074
FCS	Mar 26, 2013	-0.009	-0.349	0.009	0.541	0.016	0.602	0.002	0.139
POWI	Mar 26, 2013	-0.026	-0.485	-0.028	-0.827	-0.044	-0.841	-0.021	-0.643
SAP	May 01, 2013	0.05	2.269	0.016	1.144	0.027	1.248	-0.012	-0.899
CSCO	Jun 25, 2013	0.026	1.021	-0.003	-0.167	-0.005	-0.209	-0.007	-0.42
STJ	Sep 11, 2013	0.014	0.57	-0.008	-0.522	-0.033	-1.358	-0.014	-0.904
VAR	Apr 10, 2014	0.003	0.133	-0.01	-0.784	-0.029	-1.499	-0.018	-1.463
DD	May 09, 2014	0.022	1.775	0.006	0.771	-0.011	-0.859	-0.015	-1.83
MON	May 09, 2014	0.054	2.349	0.013	0.91	0.015	0.657	-0.006	-0.411
AOL	Aug 15, 2014	-0.004	-0.163	0.01	0.568	0.019	0.691	0.007	0.425
BBRY	Aug 22, 2014	-0.056	-0.809	-0.034	-0.787	-0.06	-0.862	-0.017	-0.381
PAY	Oct 17, 2014	0.076	3.672	0.086	6.567	0.078	3.804	-0.019	-1.492
SYK	Dec 19, 2014	0.005	0.345	0.016	1.598	0.009	0.615	-0.02	-2.04
ZMH	Dec 19, 2014	-0.009	-0.421	-0.002	-0.134	-0.032	-1.498	-0.013	-0.972
ENZ	Mar 16, 2015	0.174	2.553	0.084	1.945	-0.017	-0.244	-0.078	-1.803
LLNW	May 13, 2015	-0.013	-0.219	0.018	0.454	0.027	0.436	0.003	0.067
AAPL	May 18, 2015	0.007	0.265	0.011	0.649	0.02	0.748	0.008	0.473
IO	Jul 02, 2015	0.074	0.809	0.091	1.562	0.105	1.142	0.112	1.937
SLB	Jul 02, 2015	-0.041	-1.344	-0.021	-1.092	-0.027	-0.883	-0.011	-0.592