An Event Study of Patent Verdicts and Judicial Leakage

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An Event Study of Patent Verdicts and Judicial Leakage

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Abstract

To check for the impartiality of the United States judicial system, we investigate whether judicial decisions are leaked 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, patent infringement, judicial leakage, insider trading, trial court, appellate court

JEL Codes: G14, K41

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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, judicial 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 US's 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 analysis is capable of finding leaked information and insider trading.

To detect leaked information, we use an event study. In other words, we look to see whether a firm's stock prices made an abnormal change immediately prior to the verdict's public release. If the stock price changes drastically right before the news is released to the public, then the data suggests the information was leaked early and someone traded on the inside information. Following MacKinlay (1997), we first predict the change in a firm's stock price using the overall market return as measured by the S&P 500 index. We then find the abnormal returns for each observation, or judicial decision, by calculating the difference between the daily predicted returns and the daily actual returns over the event window. Lastly, we sum across the daily abnormal returns in the event window in order to calculate the cumulative abnormal returns for each decision. The size of these pre-decision cumulative abnormal returns can provide evidence the information was leaked within the judicial system.

We find evidence of large abnormal returns, or the leakage and use of nonpublic information, prior to the public release of the verdict at the appellate decision level. In particular, we reject a hypothesis of no leakage in nearly 10% of our observations at the appellate level, i.e., verdicts made by the United States Court of Appeals for the Federal Circuit. At the trial court level, our results do not provide clear evidence of illegal leakage although we do see their decisions have a material impact on their stock price after the decision. The abnormal return after the jury's decision is public may be because the juries do not leak information, the proceedings of the trials are publicly viewable and can be tracked and priced in prior to the announcement without seeing a large jump in the price, or a jury's group decision process is hard to model and predict by even those who sit on the jury. Although the event study approach is less than ideal for the trial court setting, the event study approach does apply well at the appellate level because 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. During the 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, i.e., our event window. As a result, abnormal returns during this period are highly suggestive of judicial leakage and insider trading.

Besides observing abnormal returns at the appellate level for specific decisions, we also calculate the cumulative average return across the trial and appellate court decisions, respectively. We fail to reject the sum to be statistically different from zero at both levels. In general, this method can improve the power of the test for abnormal returns as they might be small for any one event. However, we find large test statistics at the individual level. As a result, the lack of large abnormal cumulative returns across decisions is puzzling. However, we hypothesize that we have run into the 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 earnings releases. Earnings announcement studies use analyst predictions to separate announcements into positive and negative ones. Once separated, they analyze the results. To remedy the potential 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, i.e., the market on average gets the verdict correct. Using our alternative approach, we again find evidence of leakage at the appellate level.

In terms of checking our results, we employ two alternative robustness checks in addition to varying the estimation window. In Section 4.2 we employ a bootstrap method outlined in McWilliams and Siegel (1997). The method allows us to relax the normality assumption and approximate the distribution of the *CAR* statistics using the estimation window. In Section 4.3 we use a multi-factor model as discussed in Fama and French (1993). The alternative model provides a better fit when predicting returns. The factors come from the Kenneth R. French Online Data Library. The results are in line with the basic, or standard, event study results provided in Section 3.3. Varying the estimation window, as discussed in Section 4.1, does not change the results either. To reiterate, we have run a variety of alternative methods to check our results and they all support our primary results.

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 is adopted from MacKinlay (1997), the standard for 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

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

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

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

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

Given our focus on the leakage of private information, the event windows in equations 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 the results from the estimation window are used to make predictions over the event window. The event window and estimation window are calculated using trading days rather than calender days. The results of extended estimation windows are discussed in Section 4.1.

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 equation

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

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 the standard and controls for systematic risk following 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

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

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. Furthermore, we use the standard result

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

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 in our sample. Under the standard model, $\overline{CAR}$ is normally distributed with variance

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

or

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

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 relative to market expectations, and we do not measure the market expectation, the approach is flawed as a standard zero arbitrage model would find the *CAR* coefficients average out after controlling for the rate of interest. In other words, on average, the market would 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 groups 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 using the $\sigma_{\varepsilon_i}^2$ variances for each "i" drawn from a normal distribution. Given the random draws, we 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 accessible online sources. To begin, a list of trial 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 the trial court data, 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 trial data, we chose to include both the plaintiff and the defendant within the appeals data.

While we would have liked to have run the study with more event observations, the existing data for the appellate cases is somewhat limited. In order to eliminate cases whereby no large payments were on the line, we chose to include only cases whereby the previous damages as decided by the trial court exceeded $40 million. Additionally, many of the trial court cases with high damage verdicts have occurred in the last two years, and have not yet been ruled upon by the appellate court. Thus, the 45 observations we use represents the major appellate level rulings of publicly traded firms since 2005.

For both the trial and appellate results, 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 which was obtained from Kenneth French's 3 Factor Data sheet, located inth the Kenneth R French Online Data Library. Additionally, 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 ($t = 0$).

Since the trial data is composed of only those who have infringed, 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 must be

Figure 1: Trial Court Average Return over Time

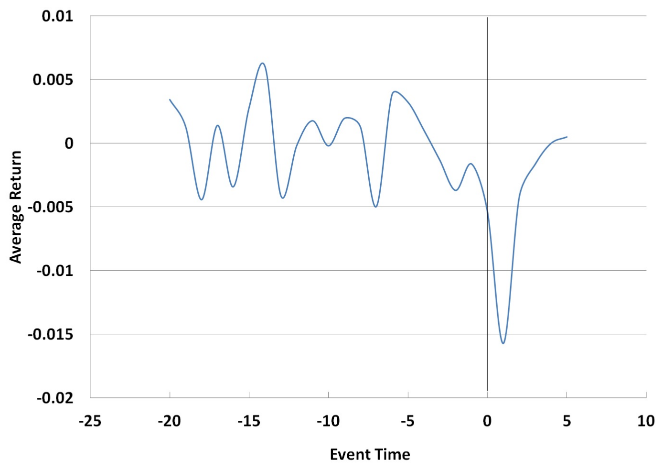
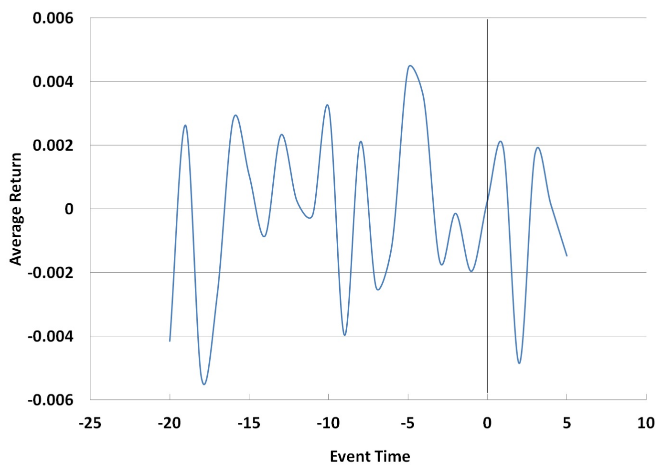


Figure 2: Appellate Court Average Return over Time



interpreted accordingly. 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 abnormal returns for both the trial and appellate cases. The time series plots are seen in Figures 3 and 4.

Figure 3: Trial Court Absolute Average Return over Time

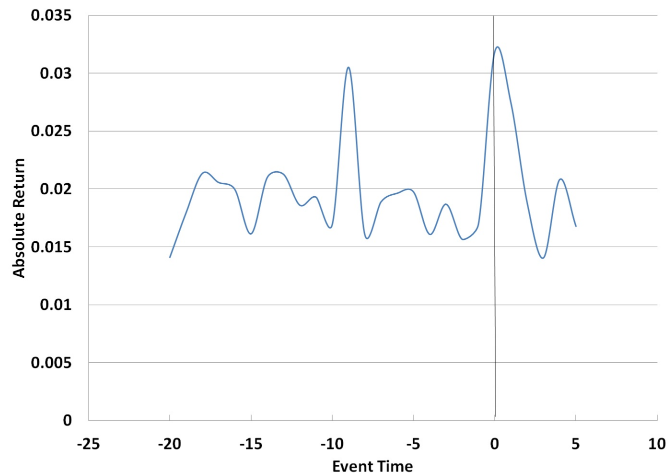
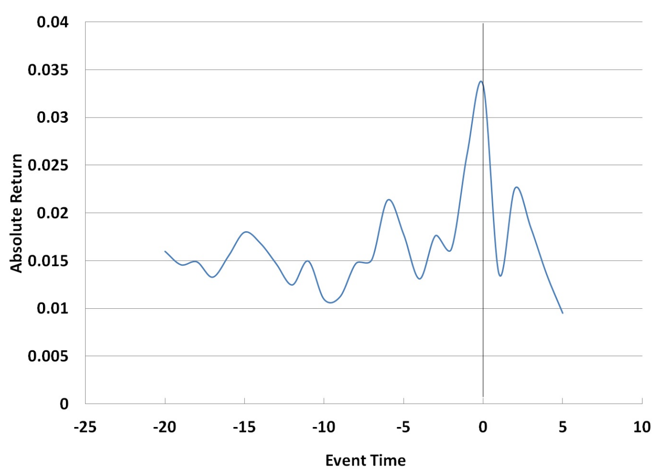


Figure 4: Appellate Court Absolute Average Return over Time



As shown by the curve in Figure 3, there is a clear increase in the average absolute value of the returns from $t = 0$ to $t = 1$. This increase represents the change in stock prices following the release of the trial court verdicts. However, the days leading up the event do not contain a large 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.

However, the appeals study data does have a significant increase in absolute average returns from $t = -2$ to $t = -1$. Since this increment falls before the public release, the change functions as evidence to indicate that the appellate court is indeed leaking nonpublic information.

3.3 Cumulative abnormal returns

While the graphs help visualize the change in returns, we analyze the actual returns relative to the predicted market returns using statistical inference. Using the model, we are able to predict the cumulative abnormal return for each decision over each individual event window. Additionally, we generate 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 13 and 14 for the trial and appellate decisions, respectively. Multiple test statistics have an absolute value greater than 3, either with a window of -2 to -1, -5 to -1, or both. As a result, we can reject the null at standard levels of significance. However, a standard significance level of 5% is inappropriate given the large number of tests.

As a conservative correction to adjust to an appropriate level of type I errors, we apply a Bonferroni Correction. To be clear, the correction provides 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 reiterate, this is a conservative adjustment. For $N = 43$, the critical value is 3.261. As seen in Tables 13 and 14, we still reject the null on multiple decisions when using the conservative Bonferroni Correction.

3.4 Average cumulative abnormal returns

In addition to testing each individual coefficient, we conduct an examination of the average of the *CAR* coefficients for both the trial and appellate level, or

$$H_0 : \overline{CAR} = 0, \tag{16}$$

$$H_a : \overline{CAR} \neq 0. \tag{17}$$

For both the appellate and trial results, we fail to reject the null at a 95% significance level for the time period prior to the decision's public release.[1] Refer to Tables 1 and 2 for the results. Given the graphical and individual

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

level results, we speculate the lack of power is a result of the impacts from the decisions averaging out. To put it differently, our results could have abnormal returns on the positive and negative side, as shown in Section 3.3, that are averaging out. Usually, an event study will put the events into positive and negative 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, i.e., the expected value is zero. Assuming the interest rate is sufficiently small, a standard no-arbitrage model would predict this result.

Table 1: $\overline{CAR}$ Significance Test for Trial Court Decisions

Event Window	$\overline{CAR}$	$var(\overline{CAR}(\tau_1,\tau_2))$	z−stat	p−value
$-5 \leq t \leq -1$	-0.00039	0.00005	-0.054	0.957
$-2 \leq t \leq -1$	-0.00252	0.00002	-0.543	0.587
$-2 \leq t \leq 2$	-0.02122	0.00005	-2.889	0.004
$0 \leq t \leq 1$	-0.02028	0.00002	-4.365	0

Table 2: $\overline{CAR}$ Significance Test for Appellate Court Decisions

Event Window	$\overline{CAR}$	$var(\overline{CAR}(\tau_1,\tau_2))$	z−stat	p−value
$-5 \leq t \leq -1$	-0.00246	0.00005	-0.334	0.738
$-2 \leq t \leq -1$	-0.00672	0.00002	-1.447	0.148
$-2 \leq t \leq 2$	-0.0148	0.00005	-2.014	0.044
$0 \leq t \leq 1$	-0.00437	0.00002	-0.941	0.347

3.5 Sum of the absolute value of the cumulative abnormal returns

To resolve the zero mean concern, we examine the events using the absolute value method outlined in Equation 12. The $|CAR|$ coefficients are assessed under the hypothesis

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

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

Given that these results are not normally distributed, we use a Monte Carlo simulation to predict the critical values for the event windows. In other words, we draw observations from normal distributions with variances equal to the estimated variances, or $\sigma_i^2(\tau_1,\tau_2)$ for all i, and sum the absolute values of the draws. We repeat this process to approximate the distribution.

For the trial results, our findings are in Table 3. 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, we fail to find any leakage occurring within the trial decisions on aggregate.

Given the individual results find significance across several different decisions, the aggregate 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.

Table 3: $|CAR|$ Significance Test for Trial Court Decisions

Event Window	$\|CAR\|$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	1.063	1.591	1.667	1.814
$-2 \leq t \leq -1$	0.698	1.006	1.054	1.148
$-2 \leq t \leq 2$	1.988	1.591	1.667	1.814
$0 \leq t \leq 1$	1.696	1.006	1.054	1.148

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

For the appellate results, our findings are in Table 4. In this case we reject the null under all the event windows at the 10% significance level. For the shorter window prior to the decisions' public release, we reject the nuall at the 1% significance level. As a result, and in contrast to the trial results, we find evidence leakage is occurring at the appellate level prior to its public release.

In interpreting the results, we find the large window has a larger p-value. This is likely due to the increased variation from additional days. Also, we are finding leakage, but this doesn't mean judges are selling the information. It is likely the information is being 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: $|CAR|$ Significance Test for Appellate Court Decisions

Event Window	$\|CAR\|$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	1.696	1.654	1.729	1.875
$-2 \leq t \leq -1$	1.444	1.046	1.093	1.185
$-2 \leq t \leq 2$	2.271	1.654	1.729	1.875
$0 \leq t \leq 1$	1.573	1.046	1.093	1.185

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

3.6 Sum of the square of the cumulative abnormal returns

In addition to 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 trial results, we again fail to reject the null for both pre-decision windows, 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 trial litigations. The $(CAR)^2$ summary statistics for the trial results are in Table 5.

Table 5: $(CAR)^2$ Significance Test for Trial Court Decisions

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	0.046	0.144	0.169	0.229
$-2 \leq t \leq -1$	0.02	0.058	0.068	0.091
$-2 \leq t \leq 2$	0.295	0.145	0.169	0.228
$0 \leq t \leq 1$	0.299	0.058	0.067	0.091

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

As shown in Table 6, when using the $(CAR)^2$ procedure with the appellate data, 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, all the tests present strong evidence that the appellate court is leaking information.

Table 6: $(CAR)^2$ Significance Test for Appellate Court Decisions

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	0.244	0.14	0.158	0.199
$-2 \leq t \leq -1$	0.234	0.056	0.063	0.08
$-2 \leq t \leq 2$	0.575	0.14	0.158	0.199
$0 \leq t \leq 1$	0.205	0.056	0.063	0.08

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

4 Robustness

Given their is strong evidence of pre-decision leakage at the appellate level, we analyze the appellate data further using a variety of approaches including an extended event window, bootstrap model, and multi-factor model.

4.1 Expanded Event Windows

To verify our results, we have considered several different estimation windows for the appellate decisions. The results from an estimation window of $-180 \leq t < -10$ are provided in Table 15 although other windows were evaluated and returned similar results. The results include the four event windows as described in Equations (1)-(4).

The cumulative abnormal returns for each decision are provided in Table 15. The results are largely consistent with those yielded by the original event window and support the conclusion that the appellate court is leaking information. Although we observe some significance values drop slightly, it is balanced by others rising.

The cumulative return results are provided in Tables 7-9. The results are in line with or stronger than the previous results where the null of no leakage was rejected after controlling for the issue of averaging out.

Table 7: $\overline{CAR}$ Significance Test for Appellate Court Decisions, Expanded Event Window

Event Window	$\overline{CAR}$	$var(\overline{CAR}(\tau_1, \tau_2))$	z−stat	p−value
$-5 \leq t \leq -1$	-0.00387	0.00005	-0.527	0.598
$-2 \leq t \leq -1$	-0.00647	0.00002	-1.393	0.164
$-2 \leq t \leq 2$	-0.01327	0.00005	-1.807	0.071
$0 \leq t \leq 1$	-0.00285	0.00002	-0.614	0.539

Table 8: $|CAR|$ Significance Test for Appellate Court Decisions, Expanded Event Window

Event Window	$\|CAR\|$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	2.163	1.666	1.743	1.892
$-2 \leq t \leq -1$	1.337	1.053	1.102	1.195
$-2 \leq t \leq 2$	2.036	1.666	1.742	1.891
$0 \leq t \leq 1$	1.569	1.054	1.102	1.196

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

4.2 Bootstrap Model

To further verify the appellate results, we employ the bootstrap method described in McWilliams and Siegel (1997). The bootstrap enables the model to relax the normal distribution assumption of the error terms. Due to the nature of the procedure, we used the expanded estimation window to control for the possibility of a large abnormality that may not have occurred in the smaller window. The method uses the AR data from the estimation window to approximate

Table 9: $(CAR)^2$ Significance Test for Appellate Court Decisions, Expanded Event Window

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	0.665	0.146	0.164	0.206
$-2 \leq t \leq -1$	0.228	0.058	0.066	0.083
$-2 \leq t \leq 2$	0.582	0.146	0.165	0.207
$0 \leq t \leq 1$	0.216	0.058	0.066	0.083

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

the distribution of the *CAR* distribution. In particular, for each event window, we independently and randomly drew the appropriate number of days from the estimation window abnormal returns, summed across the abnormal returns across the appropriate number of draws, and repeated the process to generate an empirical distribution for the CAR statistic using the estimation window estimates. To evaluate the hypothesis of no abnormal return, we evaluate the proportion of generated *CAR* statistics that were greater than the actual calculated *CAR* statistic for that particular event window. This statistic, or p-value, provides an estimate of the likelihood of randomly obtaining a *CAR* statistic greater than or equal to those found in event window. The results are provided in Table 16.

As a whole, the bootstrapped results are largely consistent with previously calculated p-values from the normal distribution. For events with small p-values, we found that little or no randomly generated *CAR* statistics would exceed those yielded by the event study. To the contrary, for events with large p-values, we found that a large majority of the random *CAR* values would exceed those found under the standard procedure.

4.3 Multifactor Model

As an additional robustness check, we also ran a multifactor model using the appellate data. Following Fama and French (1993), we employed a 3 Factor Model with the following time series regression.

$$R_i - R_f = \alpha_i + b_i \left(R_m - R_f\right) + s_i SMB + h_i HML + \varepsilon_i \tag{22}$$

where *SMB* (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios. Additionally, *HML* is the average return on the two value portfolios minus the average return on the two growth portfolios. Finally, $R_m - R_f$ represents the market return minus the risk free rate. The data comes from the Kenneth R. French library Online Data Library.

Table 17 provides the *CAR* and test statistic for each event across all 4 event windows. As seen in the table, the *CAR* statistics are consistent with those yielded by the market model where multiple individual events reject the null using the Bonferroni correction.

The cumulative return results are provided in Tables 10-12. The results are in line with the previous results where the null of no leakage was rejected after controlling for the issue of averaging out.

Table 10: $\overline{CAR}$ Significance Test for Appellate Court Decisions, Multifactor Model

Event Window	$\overline{CAR}$	$var(\overline{CAR}(\tau_1,\tau_2))$	z−stat	p−value
$-5 \leq t \leq -1$	-0.00079	0.00005	-0.113	0.91
$-2 \leq t \leq -1$	-0.00683	0.00002	-1.558	0.119
$-2 \leq t \leq 2$	-0.0127	0.00005	-1.831	0.067
$0 \leq t \leq 1$	-0.00455	0.00002	-1.038	0.299

Table 11: $|CAR|$ Significance Test for Appellate Court Decisions, Multifactor Model

Event Window	$|CAR|$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	1.694	1.519	1.59	1.728
$-2 \leq t \leq -1$	1.457	0.961	1.006	1.093
$-2 \leq t \leq 2$	2.207	1.519	1.59	1.728
$0 \leq t \leq 1$	1.506	0.961	1.006	1.093

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

Table 12: $(CAR)^2$ Significance Test for Appellate Court Decisions, Multifactor Model

Event Window	$(CAR)^2$	90% critical value	95% critical value	99% critical value
$-5 \leq t \leq -1$	0.225	0.125	0.142	0.18
$-2 \leq t \leq -1$	0.223	0.05	0.057	0.072
$-2 \leq t \leq 2$	0.521	0.125	0.142	0.18
$0 \leq t \leq 1$	0.191	0.05	0.057	0.072

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

5 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 jurors 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 analyzing whether such an incentive is being acted upon. 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 verdicts. As a result, we conclude court decisions are being leaked prior to their public release and the inside information is being used for profit.

The question of whether the inside information is warping judicial decisions is still open ended. Using the data from this study, we did not find any consistent patterns related to a firm being publicly traded. However, the analysis was limited due to the limited number of observations in our study.

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Table 13: Trial Court Cumulative Abnormal Return Statistics

Stock		$\tau_1=-5,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=2$		$\tau_1=0,\ \tau_2=1$	
Ticker	Decision Date	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$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
AAPL	Apr 23,2009	0.018	0.49	-0.014	-0.591	-0.013	-0.345	-0.011	-0.454
AAPL	Oct 01,2010	-0.021	-0.85	-0.006	-0.362	0.007	0.291	-0.013	-0.810
AAPL	Jul 08,2011	0.046	1.971	0.015	0.984	0.021	0.878	0.004	0.304
ABT	Feb 19,2009	0.01	0.273	0.015	0.69	0.038	1.074	0.015	0.657
ABT	Jun 29,2009	0.002	0.049	0.012	0.412	-0.001	-0.026	-0.006	-0.205
AOL	Nov 06,2012	0.008	0.265	0.006	0.332	0.096	3.381	0.114	6.369
BAX	Jan 30,2009	0.035	0.772	0.004	0.149	0.058	1.272	0.028	0.955
BBRY	Jul 13,2012	0.032	0.473	0.038	0.882	-0.043	-0.63	-0.065	-1.523
BDX	Nov 09,2009	0.01	0.443	0.015	1.069	0.031	1.36	0.006	0.411
BSX	Feb 11,2008	0.08	1.818	-0.009	-0.324	0.019	0.438	0.025	0.896
CAMT	Mar 05,2009	-0.059	-0.635	-0.041	-0.693	-0.281	-3.005	-0.245	-4.132
CSCO	May 17,2010	-0.018	-0.87	-0.049	-3.8	-0.066	-3.209	-0.016	-1.236
CSCO	Mar 22,2013	-0.027	-1.323	-0.031	-2.462	-0.04	-2.006	-0.002	-0.190
CTXS	Jun 18,2012	0.001	0.016	0.009	0.285	-0.013	-0.262	-0.02	-0.642
ELY	Mar 05,2010	-0.013	-0.355	0.049	2.156	0.065	1.79	-0.002	-0.102
GMED	Jun 14,2013	-0.027	-0.679	-0.001	-0.04	0.006	0.154	0.022	0.858
HAS	Mar 24,2008	0.012	0.225	0.026	0.76	0.021	0.389	0.014	0.424
HOLX	Oct 17,2011	-0.024	-0.815	-0.004	-0.203	-0.039	-1.33	-0.028	-1.531
ILMN	Mar 14,2013	-0.001	-0.013	-0.014	-0.422	-0.008	-0.143	0	-0.012
IO	Aug 16,2012	-0.014	-0.49	0.007	0.378	-0.12	-4.147	-0.121	-6.615
JCP	Nov 18,2011	-0.031	-0.844	0.015	0.638	0.001	0.033	0.002	0.094
JNJ	Jan 28,2011	-0.035	-3.249	-0.008	-1.125	-0.007	-0.621	-0.005	-0.669
LLNW	Feb 29,2008	-0.013	-0.138	-0.032	-0.523	-0.348	-3.616	-0.401	-6.591
MDT	Dec 05,2008	0.095	2.172	0.055	2.011	0.06	1.387	0.015	0.530
MDT	Jan 26,2012	-0.002	-0.043	-0.002	-0.083	-0.025	-0.66	-0.014	-0.579
MGI	Sep 24,2009	-0.068	-0.464	-0.034	-0.369	-0.066	-0.447	-0.075	-0.804
MRVL	Dec 26,2012	-0.005	-0.085	0.004	0.099	-0.096	-1.667	-0.128	-3.508
MSFT	May 20,2009	0.035	0.69	-0.012	-0.385	-0.014	-0.274	-0.001	-0.042
MSFT	Mar 16,2010	0.014	0.689	0.007	0.499	0.005	0.246	-0.003	-0.241
NUVA	Sep 20,2011	0.014	0.365	-0.008	-0.33	-0.037	-0.946	-0.084	-3.429
PAY	Jun 08,2012	-0.044	-1.135	-0.041	-1.662	-0.154	-3.952	-0.03	-1.211
PII	Apr 16,2009	0.061	0.939	-0.008	-0.184	0.07	1.083	0.103	2.495
QCOM	Oct 24,2013	-0.047	-2.496	-0.029	-2.396	-0.019	-0.996	0.008	0.697
SNE	Nov 17,2008	-0.008	-0.196	0.005	0.197	-0.02	-0.5	0.007	0.279
SPLS	Dec 21,2010	0.015	0.693	-0.011	-0.791	0.006	0.257	0.003	0.198
T	Mar 20,2013	-0.012	-0.771	0.002	0.153	0.005	0.293	0.002	0.221
VAR	Feb 23,2012	-0.021	-1.225	-0.012	-1.095	-0.021	-1.214	-0.002	-0.230
VZ	Mar 08,2011	-0.029	-1.101	-0.007	-0.412	0.003	0.127	0.011	0.686
VZ	Aug 02,2011	0.016	1.077	0.013	1.33	0.03	1.994	0.016	1.720
XLNX	May 18,2012	0.008	0.376	-0.006	-0.422	-0.008	-0.364	0.002	0.115
YHOO	May 15,2009	0.011	0.194	-0.009	-0.265	0.005	0.098	0.013	0.381
ZMH	Feb 05,2013	-0.021	-1.657	-0.015	-1.84	-0.003	-0.21	0.012	1.497

Table 14: Appellate Court Cumulative Abnormal Return Statistics, Base Specification

Stock		$\tau_1=-5,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=2$		$\tau_1=0,\ \tau_2=1$	
Ticker	Decision Date	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	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
AAPL	Sep 04,2012	0	0.023	-0.012	-1.02	-0.015	-0.824	0.006	0.49
AAPL	May 18,2015	0.008	0.288	0.012	0.709	0.021	0.77	0.008	0.448
ABT	Feb 23,2011	0.025	1.909	0.021	2.53	0.033	2.474	0.007	0.856
ALU	Sep 11,2009	0.059	0.944	0.006	0.152	0.083	1.315	0.032	0.813
ALU	Sep 25,2008	-0.04	-0.652	0.053	1.376	-0.069	-1.136	-0.049	-1.272
AOL	Aug 15,2014	-0.005	-0.166	0.01	0.566	0.019	0.697	0.008	0.441
ARIA	Mar 22,2010	-0.04	-0.724	-0.134	-3.815	-0.033	-0.592	0.122	3.478
BBRY	Aug 22,2014	-0.054	-0.789	-0.033	-0.756	-0.06	-0.871	-0.017	-0.391
BSX	Sep 18,2012	0.025	0.54	0.006	0.201	0.019	0.423	0.003	0.116
CSCO	Jun 25,2013	0.021	0.808	-0.003	-0.165	-0.005	-0.185	-0.005	-0.284
DD	May 09,2014	0.027	2.125	0.01	1.274	-0.008	-0.633	-0.017	-2.187
ENZ	Mar 16,2015	0.172	2.62	0.082	1.988	-0.017	-0.254	-0.078	-1.879
ERIC	Aug 05,2005	-0.019	-1.268	-0.008	-0.781	-0.004	-0.247	-0.007	-0.728
FCS	Mar 26,2013	-0.007	-0.269	0.011	0.642	0.018	0.705	0.004	0.243
FNSR	Apr 18,2008	0.016	0.135	0.044	0.602	-0.05	-0.43	-0.078	-1.063
HD	Nov 14,2011	0.034	1.488	0.001	0.071	0.007	0.302	0.001	0.06
HRS	Aug 05,2005	-0.035	-0.622	-0.014	-0.396	-0.015	-0.273	0.005	0.153
IO	Jul 02,2015	0.075	0.82	0.091	1.57	0.106	1.159	0.113	1.944
LLNW	May 13,2015	-0.014	-0.233	0.017	0.448	0.027	0.449	0.003	0.067
LLY	Mar 22,2010	0.003	0.13	0.005	0.349	0.001	0.061	0.001	0.039
MDT	Sep 18,2012	0.008	0.403	0.011	0.873	0.018	0.889	-0.002	-0.149
MDT	Sep 09,2010	0.007	0.405	-0.01	-0.853	0.014	0.76	0.025	2.159
MGI	Dec 07,2010	-0.084	-1.227	-0.058	-1.341	-0.019	-0.273	0.062	1.432
MON	May 09,2014	0.056	2.496	0.015	1.065	0.016	0.709	-0.008	-0.557
MSFT	Nov 16,2007	-0.013	-0.735	-0.006	-0.578	0.026	1.533	0.017	1.531
MSFT	Sep 25,2008	0.016	0.337	0.029	1.005	0.061	1.33	0.045	1.538
MSFT	Dec 22,2009	-0.004	-0.124	0.017	0.787	0.018	0.513	0.003	0.148
MSFT	Sep 11,2009	0.006	0.128	-0.009	-0.306	-0.003	-0.058	0	-0.004
MSFT	Jan 04,2011	-0.016	-0.698	-0.005	-0.333	0.023	1.023	-0.002	-0.145
PAY	Oct 17,2014	0.069	3.563	0.077	6.324	0.069	3.586	-0.019	-1.554
POWI	Mar 26,2013	-0.022	-0.425	-0.025	-0.762	-0.041	-0.777	-0.019	-0.577
RMBS	May 13,2011	0.028	0.725	0.018	0.724	-0.337	-8.791	-0.252	-10.401
SAP	May 01,2013	0.049	2.251	0.015	1.123	0.027	1.24	-0.011	-0.818
SATS	Apr 20,2011	-0.017	-0.324	-0.038	-1.137	-0.033	-0.626	0.007	0.208
SLB	Jul 02,2015	-0.041	-1.327	-0.021	-1.092	-0.027	-0.872	-0.011	-0.583
STJ	Sep 11,2013	0.012	0.483	-0.01	-0.678	-0.035	-1.432	-0.013	-0.822
SYK	Dec 19,2014	0.004	0.255	0.016	1.612	0.01	0.653	-0.019	-1.91
TIVO	Apr 20,2011	0.016	0.27	-0.008	-0.209	0.16	2.681	0.171	4.519
VAR	Apr 10,2014	0.007	0.348	-0.011	-0.918	-0.027	-1.45	-0.016	-1.357
VAR	Jun 09,2009	-0.042	-0.865	-0.021	-0.699	0.019	0.383	0.033	1.07
VG	Sep 26,2007	-0.408	-3.876	-0.422	-6.336	-0.618	-5.872	-0.242	-3.636
VZ	Sep 26,2007	0.016	0.571	-0.005	-0.26	-0.005	-0.178	0.007	0.391
VZ	Aug 24,2012	-0.053	-3.646	-0.017	-1.882	-0.018	-1.204	0.005	0.499
WU	Dec 07,2010	-0.012	-0.539	0.003	0.205	0.005	0.222	0.01	0.718
ZMH	Dec 19,2014	-0.011	-0.518	-0.002	-0.116	-0.032	-1.454	-0.012	-0.87

Table 15: Appellate Court Cumulative Abnormal Return Statistics, Expanded Event Window

Stock Ticker	Decision Date	$\tau_1=-5,\ \tau_2=-1$ CAR$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$\tau_1=-2,\ \tau_2=-1$ CAR$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$\tau_1=-2,\ \tau_2=2$ CAR$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$\tau_1=0,\ \tau_2=1$ CAR$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
AAPL	Sep 04, 2012	0.006	0.231	0.007	0.418	0.012	0.435	0.005	0.288
AAPL	May 18, 2015	0.008	0.247	-0.014	-0.682	-0.023	-0.69	0.005	0.240
ABT	Feb 23, 2011	0.023	1.449	0.024	2.381	0.038	2.389	0.009	0.935
ALU	Sep 11, 2009	0.104	1.419	0.007	0.16	0.062	0.85	0.017	0.364
ALU	Sep 25, 2008	-0.057	-1.055	0.065	1.888	-0.032	-0.594	-0.045	-1.312
ARIA	Mar 22, 2010	-0.012	-0.114	-0.131	-1.927	-0.022	-0.204	0.129	1.902
BBRY	Aug 22, 2014	0.016	0.21	-0.01	-0.204	0.002	0.022	0.008	0.164
BSX	Sep 18, 2012	0.007	0.189	0	0.015	0.004	0.13	-0.002	-0.077
CSCO	Jun 25, 2013	-0.009	-0.278	-0.01	-0.487	-0.009	-0.296	-0.004	-0.187
DD	May 09, 2014	0.016	1.032	0.008	0.825	-0.004	-0.25	-0.01	-1.040
ENZ	Mar 16, 2015	0.041	0.594	0.073	1.678	-0.037	-0.54	-0.086	-1.984
ERIC	Aug 05, 2005	0.004	0.133	0	0.005	0.014	0.424	0.002	0.110
FCS	Mar 26, 2013	-0.011	-0.345	0.008	0.389	0.011	0.34	0	-0.023
FNSR	Apr 18, 2008	-0.069	-0.688	0.034	0.529	-0.066	-0.657	-0.071	-1.115
HD	Nov 14, 2011	0.05	2.122	-0.002	-0.129	0.011	0.475	0.004	0.299
HRS	Aug 05, 2005	0.005	0.101	-0.004	-0.137	0.009	0.21	0.017	0.589
IO	Jul 02, 2015	0.165	2.057	0.073	1.439	0.069	0.857	0.103	2.036
LLNW	May 13, 2015	0.019	0.342	0.025	0.731	0.047	0.85	0.011	0.309
LLY	Mar 22, 2010	0.012	0.513	0.003	0.195	0.002	0.107	0.006	0.428
MDT	Sep 18, 2012	0.005	0.197	-0.01	-0.579	0.011	0.407	0.023	1.341
MDT	Sep 09, 2010	0.016	0.855	0.013	1.083	0.021	1.106	0	-0.015
MGI	Dec 07, 2010	-0.019	-0.29	-0.051	-1.231	-0.006	-0.086	0.066	1.596
MON	May 09, 2014	0.049	2.378	0.011	0.867	0.009	0.458	-0.009	-0.691
MSFT	Nov 16, 2007	0.05	1.34	0.031	1.296	0.06	1.603	0.051	2.172
MSFT	Sep 25, 2008	-0.008	-0.174	-0.011	-0.373	-0.013	-0.281	-0.005	-0.193
MSFT	Dec 22, 2009	0.011	0.306	0.016	0.722	0.02	0.555	0.006	0.262
MSFT	Sep 11, 2009	-0.004	-0.163	-0.003	-0.207	0.027	1.16	-0.002	-0.121
MSFT	Jan 04, 2011	-0.015	-0.59	-0.008	-0.483	0.018	0.738	0.014	0.920
PAY	Oct 17, 2014	0.066	1.698	0.084	3.404	0.074	1.902	-0.021	-0.855
POWI	Mar 26, 2013	0.001	0.013	-0.014	-0.509	-0.007	-0.152	-0.005	-0.184
RMBS	May 13, 2011	-0.177	-6.396	0.011	0.643	-0.355	-12.857	-0.26	-14.889
SAP	May 01, 2013	0.039	1.684	0.013	0.915	0.021	0.903	-0.016	-1.080
SATS	Apr 20, 2011	0.02	0.562	-0.03	-1.307	-0.004	-0.124	0.023	1.002
SLB	Jul 02 , 2015	-0.018	-0.541	-0.026	-1.238	-0.027	-0.828	-0.004	-0.170
STJ	Sep 11, 2013	0.015	0.666	-0.002	-0.167	-0.02	-0.878	-0.009	-0.627
SYK	Dec 19, 2014	-0.001	-0.055	0.016	1.671	0.015	0.982	-0.017	-1.712
TIVO	Apr 20, 2011	0.23	4.195	-0.02	-0.569	0.135	2.467	0.163	4.720
VAR	Apr 10, 2014	-0.012	-0.551	-0.006	-0.471	-0.027	-1.26	-0.021	-1.534
VAR	Jun 09, 2009	-0.005	-0.087	-0.016	-0.453	0.03	0.541	0.036	1.022
VG	Sep 26, 2007	-0.717	-6.421	-0.422	-5.976	-0.634	-5.676	-0.258	-3.656
VZ	Sep 26, 2007	-0.025	-1.581	-0.013	-1.341	-0.008	-0.506	0.008	0.788
VZ	Aug 24, 2012	0.02	0.978	-0.005	-0.394	-0.009	-0.412	0.004	0.268
WU	Dec 07, 2010	-0.006	-0.217	0.005	0.295	0.009	0.337	0.011	0.639

Table 16: Appellate Court Cumulative Abnormal Return Statistics, Bootstrap Model

Stock Ticker	Decision Date	$\tau_1=-5,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=-1$		$\tau_1=-2,\ \tau_2=2$		$\tau_1=0,\ \tau_2=1$	
		$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$(\% > CAR)$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$(\% > CAR)$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$(\% > CAR)$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$	$(\% > CAR)$
AAPL	Sep 04 , 2012	0.231	0.795	0.418	0.64	0.435	0.629	0.288	0.746
AAPL	May 18 , 2015	0.247	0.81	-0.682	0.421	-0.69	0.463	0.24	0.769
ABT	Feb 23 , 2011	1.449	0.133	2.381	0.028	2.389	0.019	0.935	0.307
ALU	Sep 11 , 2009	1.419	0.155	0.16	0.858	0.85	0.381	0.364	0.679
ALU	Sep 25 , 2008	-1.055	0.289	1.888	0.055	-0.594	0.561	-1.312	0.172
ARIA	Mar 22 , 2010	-0.114	0.895	-1.927	0.052	-0.204	0.804	1.902	0.053
BBRY	Aug 22 , 2014	0.21	0.824	-0.204	0.824	0.022	0.978	0.164	0.859
BSX	Sep 18 , 2012	0.189	0.839	0.015	0.987	0.13	0.885	-0.077	0.923
CSCO	Jun 25 , 2013	-0.278	0.718	-0.487	0.478	-0.296	0.697	-0.187	0.776
DD	May 09 , 2014	1.032	0.293	0.825	0.361	-0.25	0.803	-1.04	0.273
ENZ	Mar 16 , 2015	0.594	0.507	1.678	0.089	-0.54	0.555	-1.984	0.062
ERIC	Aug 05 , 2005	0.133	0.865	0.005	0.996	0.424	0.606	0.11	0.898
FCS	Mar 26 , 2013	-0.345	0.723	0.389	0.677	0.34	0.727	-0.023	0.982
FNSR	Apr 18 , 2008	-0.688	0.424	0.529	0.472	-0.657	0.461	-1.115	0.186
HD	Nov 14 , 2011	2.122	0.037	-0.129	0.879	0.475	0.585	0.299	0.710
HRS	Aug 05 , 2005	0.101	0.888	-0.137	0.812	0.21	0.747	0.589	0.338
IO	Jul 02 , 2015	2.057	0.046	1.439	0.135	0.857	0.373	2.036	0.053
LLNW	May 13 , 2015	0.342	0.721	0.731	0.449	0.85	0.386	0.309	0.757
LLY	Mar 22 , 2010	0.513	0.591	0.195	0.825	0.107	0.902	0.428	0.618
MDT	Sep 18 , 2012	0.197	0.798	-0.579	0.409	0.407	0.607	1.341	0.087
MDT	Sep 09 , 2010	0.855	0.384	1.083	0.28	1.106	0.271	-0.015	0.987
MGI	Dec 07 , 2010	-0.29	0.767	-1.231	0.194	-0.086	0.927	1.596	0.101
MON	May 09 , 2014	2.378	0.021	0.867	0.337	0.458	0.63	-0.691	0.433
MSFT	Nov 16 , 2007	1.34	0.165	1.296	0.151	1.603	0.107	2.172	0.045
MSFT	Sep 25 , 2008	-0.174	0.838	-0.373	0.614	-0.281	0.75	-0.193	0.802
MSFT	Dec 22 , 2009	0.306	0.698	0.722	0.331	0.555	0.482	0.262	0.707
MSFT	Sep 11 , 2009	-0.163	0.865	-0.207	0.825	1.16	0.243	-0.121	0.902
MSFT	Jan 04 , 2011	-0.59	0.485	-0.483	0.519	0.738	0.394	0.92	0.264
PAY	Oct 17 , 2014	1.698	0.077	3.404	0.013	1.902	0.054	-0.855	0.273
POWI	Mar 26 , 2013	0.013	0.987	-0.509	0.5	-0.152	0.837	-0.184	0.795
RMBS	May 13 , 2011	-6.396	0	0.643	0.456	-12.857	0	-14.889	0.000
SAP	May 01 , 2013	1.684	0.091	0.915	0.309	0.903	0.326	-1.08	0.244
SATS	Apr 20 , 2011	0.562	0.546	-1.307	0.156	-0.124	0.884	1.002	0.260
SLB	Jul 02 , 2015	-0.541	0.569	-1.238	0.181	-0.828	0.384	-0.17	0.859
STJ	Sep 11 , 2013	0.666	0.466	-0.167	0.857	-0.878	0.356	-0.627	0.473
SYK	Dec 19 , 2014	-0.055	0.953	1.671	0.085	0.982	0.323	-1.712	0.082
TIVO	Apr 20 , 2011	4.195	0.002	-0.569	0.433	2.467	0.031	4.72	0.003
VAR	Apr 10 , 2014	-0.551	0.506	-0.471	0.542	-1.26	0.151	-1.534	0.082
VAR	Jun 09 , 2009	-0.087	0.932	-0.453	0.608	0.541	0.56	1.022	0.248
VG	Sep 26 , 2007	-6.421	0	-5.976	0	-5.676	0	-3.656	0.015
VZ	Sep 26 , 2007	-1.581	0.104	-1.341	0.164	-0.506	0.59	0.788	0.386
VZ	Aug 24 , 2012	0.978	0.318	-0.394	0.666	-0.412	0.671	0.268	0.772
WU	Dec 07 , 2010	-0.217	0.803	0.295	0.71	0.337	0.694	0.639	0.429

Note: $(\% > CAR)$ corresponds to the percentage of randomly generated values that were greater than the CAR statistic.

Table 17: Appellate Court Cumulative Abnormal Return Statistics, Multifactor Model

Stock		$\tau_1 = -5,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = -1$		$\tau_1 = -2,\ \tau_2 = 2$		$\tau_1 = 0,\ \tau_2 = 1$	
Ticker	Decision Date	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$_i$	$\frac{CAR_i}{\sigma_i^2(\tau_1,\tau_2)}$
AAPL	May 18, 2015	0.007	0.242	0.012	0.702	0.019	0.689	0.006	0.355
AAPL	Sep 04, 2012	-0.002	-0.140	-0.012	-1.223	-0.009	-0.621	0.006	0.638
ABT	Feb 23, 2011	0.032	2.849	0.021	2.950	0.037	3.356	0.006	0.883
ALU	Sep 11, 2009	0.035	0.546	-0.005	-0.128	0.057	0.883	0.024	0.595
ALU	Sep 25, 2008	-0.056	-0.908	0.045	1.148	-0.082	-1.316	-0.059	-1.488
AOL	Aug 15, 2014	-0.018	-0.651	0.003	0.156	0.006	0.230	0.005	0.276
ARIA	Mar 22, 2010	0.031	0.650	-0.088	-2.874	-0.018	-0.374	0.083	2.712
BBRY	Aug 22, 2014	-0.045	-0.673	-0.033	-0.776	-0.051	-0.772	-0.012	-0.283
BSX	Sep 18, 2012	0.020	0.449	0.004	0.135	0.026	0.601	0.006	0.224
CSCO	Jun 25, 2013	0.022	0.996	-0.011	-0.756	-0.004	-0.189	0.001	0.088
DD	May 09, 2014	0.026	2.127	0.009	1.120	-0.009	-0.737	-0.017	-2.271
ENZ	Mar 16, 2015	0.124	1.976	0.066	1.650	-0.013	-0.201	-0.070	-1.765
ERIC	Aug 05, 2005	-0.032	-2.502	-0.020	-2.436	-0.028	-2.137	-0.010	-1.191
FCS	Mar 26, 2013	-0.012	-0.445	0.011	0.692	0.022	0.850	0.005	0.309
FNSR	Apr 18, 2008	0.033	0.285	0.049	0.685	-0.057	-0.501	-0.090	-1.245
HD	Nov 14, 2011	0.033	1.422	0.000	0.012	0.014	0.587	0.006	0.400
HRS	Aug 05, 2005	-0.021	-0.385	0.006	0.172	0.018	0.323	0.006	0.174
IO	Jul 02, 2015	0.119	1.411	0.121	2.276	0.162	1.919	0.141	2.641
LLNW	May 13, 2015	-0.015	-0.261	0.018	0.480	0.032	0.552	0.004	0.105
LLY	Mar 22, 2010	-0.029	-1.362	-0.018	-1.291	-0.009	-0.400	0.005	0.392
MDT	Sep 09, 2010	-0.001	-0.051	-0.011	-0.969	0.012	0.644	0.023	1.998
MDT	Sep 18, 2012	0.006	0.301	0.012	0.959	0.022	1.092	-0.001	-0.043
MGI	Dec 07, 2010	-0.053	-0.850	-0.094	-2.379	-0.047	-0.750	0.069	1.736
MON	May 09, 2014	0.066	3.226	0.022	1.699	0.022	1.093	-0.015	-1.191
MSFT	Sep 25, 2008	0.045	1.113	0.046	1.809	0.090	2.240	0.062	2.438
MSFT	Sep 11, 2009	0.025	0.587	0.006	0.212	0.025	0.591	0.005	0.193
MSFT	Dec 22, 2009	0.019	0.604	0.012	0.611	0.009	0.300	0.000	0.008
MSFT	Jan 04, 2011	-0.003	-0.121	0.004	0.327	0.031	1.473	-0.001	-0.042
MSFT	Nov 16, 2007	0.014	1.018	0.000	0.032	0.020	1.429	0.006	0.673
PAY	Oct 17, 2014	0.071	3.774	0.063	5.311	0.064	3.436	-0.017	-1.472
POWI	Mar 26, 2013	-0.014	-0.263	-0.020	-0.603	-0.025	-0.465	-0.013	-0.372
RMBS	May 13, 2011	0.015	0.472	0.020	0.955	-0.303	-9.342	-0.229	-11.153
SAP	May 01, 2013	0.046	2.207	0.019	1.436	0.032	1.526	-0.013	-0.976
SATS	Apr 20, 2011	-0.045	-0.966	-0.035	-1.202	-0.044	-0.954	-0.007	-0.241
SLB	Jul 02, 2015	-0.023	-0.871	-0.010	-0.582	-0.008	-0.288	-0.001	-0.034
STJ	Sep 11, 2013	0.015	0.624	-0.009	-0.590	-0.028	-1.177	-0.008	-0.498
SYK	Dec 19, 2014	0.003	0.217	0.015	1.564	0.004	0.240	-0.021	-2.141
TIVO	Apr 20, 2011	-0.038	-0.675	-0.041	-1.140	0.091	1.610	0.138	3.862
VAR	Apr 10, 2014	0.015	0.841	-0.013	-1.115	-0.022	-1.191	-0.013	-1.100
VAR	Jun 09, 2009	-0.037	-0.875	-0.014	-0.511	0.033	0.781	0.036	1.351
VG	Sep 26, 2007	-0.385	-3.911	-0.406	-6.522	-0.583	-5.931	-0.247	-3.975
VZ	Aug 24, 2012	-0.053	-3.659	-0.017	-1.866	-0.017	-1.142	0.004	0.471
VZ	Sep 26, 2007	0.021	0.775	-0.009	-0.523	-0.003	-0.127	0.015	0.884
WU	Dec 07, 2010	-0.008	-0.342	0.002	0.134	0.008	0.372	0.012	0.881
ZMH	Dec 19, 2014	-0.009	-0.417	0.001	0.092	-0.027	-1.193	-0.011	-0.767