The Litigation Game:
Modeling an Experiment with Symmetric Bargaining
& Two-Sided Incomplete Information

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Abstract

This paper analyzes a game-theoretic model of bargaining in the shadow of a trial created by Donald Wittman at University of California Santa Cruz. In this experiment, the researcher is presented with a legal court matter consisting of a plaintiff and a defendant. Both have symmetric cost for trial, but privately observe different signals of potential judgment if they are to proceed with trial. The plaintiff upon receiving their signal must make a demand. Simultaneously, the defendant upon receiving their signal must make an offer. If the offer is greater than or equal to the demand, then the case will settle at the average of the demand and offer. Otherwise the case proceeds to trial at which point the plaintiff and defendant both incur the cost of trial and the result of the judgment, the average of the two signals.

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Contents:

1 Introduction

Economists are greatly interested in how individuals interact in litigation when given different signals of the possible outcome. Game theoretic models are used to predict decision-making and determine best responses in different contexts. Litigation is present in court cases, both civil and criminal; the only difference is the outcome in a civil case is viewed as an award to the plaintiff rather than in a criminal case where the outcome is viewed as a punishment to the defendant. Bargaining games can represent simple models of litigation. Solving a realistic simplified version of litigation can have far reaching implications on how decisions are made in that context. Can seemingly irrational behavior actually be rational because of a large looming cost such as Trial? This paper delves into a simplified litigation game to analyze two-party decision-making, possible best responses, Nash equilibria, and possible implications of risk-preferring individuals.

Donald Wittman and Daniel Friedman published a paper "Litigation with Symmetric Bargaining and Two–Sided Incomplete Information" in 2011 that theorized results of realistic litigation trials. Their model was subsequently derived mathematically but does not provide empirical data supporting their claims. The game theoretic model creates a logical framework to understand litigation on a larger scale– this paper utilizes this model in order to expand its implications.

The paper analyzes empirical evidence to determine the validity of the game theoretic model of bargaining created by Donald Wittman. We derive data from a simulation that we analyze to predict the deviation between actual and theorized behavior. The model predicts that when trial costs are low, the probability of a trial is highest when the probability of the plaintiff winning is either very high or very low (Wittman and Friedman 2011). However, this prediction is inadequate if the plaintiff is risk neutral. The expectation is to estimate the willingness of subjects to settle instead of going to trial.

The game consists of two players, the plaintiff and defendant (in a criminal case the prosecutor and defendant), which observe two separate randomized signals and make a demand and offer respectively. When making their decision, they must consider the symmetric cost of trial (c) that varies each round. The game is meant to recreate a highly realistic litigation situation through symmetric information, namely the cost of trial, and two-sided incomplete information: since both parties make their respective offer and demand. Plaintiffs and defendants are only aware of their own information in a case; therefore, the signals they receive are private and parties are mutually aware they don't have access to all information. The symmetric game has predicted Nash Equilibrium (NE) strategies that are piecewise linear for both the plaintiff and defendant.

This paper uses the model as a framework to analyze the data in hopes of answering the following: Can the anticipated cost of trial affect the outcome of litigation? What are the plaintiff's and defendant's best responses to the symmetric cost and their asymmetric random signal of potential judgment? What is the Nash Equilibrium, if any? Answering the aforementioned questions allow me to determine the deviation between the predictive model and empirical evidence.

Wittman's model predicts that low costs scenarios will on average result in a trial and that high cost scenarios will on average result in a settlement. However, low signal scenarios will on average result in a settlement and high signal scenarios will on average result in a trial. The outcome is dependent upon the magnitude of the expectation differential. Ceteris Paribus, "the larger the expectation differential, the more likely the case will go trial." (Wittman 2006)

Thus, when one party is optimistic about the outcome and willing to deviate from the equilibrium the case will result in a trial. When the cost of trial is low the potential cost of trial is not as large of a concern for both parties therefore each requests more in their demand or offer especially if the plaintiff receives a high award signal. Subsequently the plaintiff's demand will often exceed the defendant's offer leading to a trial. At the breaking point of cost equaling ⅙, of the range of signals, the litigation will on average go to a settlement instead. The defendant's offer will exceed the plaintiff's demand because both parties are more aware of the looming cost of trial. The plaintiff will demand less and the defendant will offer more in hopes of avoiding trial.

We hypothesis that the evidence will follow Wittman's mathematically derived trends– at a low cost, trial will occur, and once the cost is over ⅙ then a settlement is more likely depending on the signals and the risks either party is willing to take. The best responses for the plaintiff and defendant should converge when the cost increases and in turn increasing the parameters for settlement. The treatment variable is the cost of trial and the performance variables are the observed signals and respective demands and offers.

2 Model

This section presents the experimental model and elaborates on the relationship between the symmetric cost, asymmetric random signal, demand and offer, judgment, and utility. The experimental model is a two-player game that refers to one of the players as the plaintiff and one of the players as the defendant. The game is made up of three stages. The preliminary stage of the game will inform players of the structure of the game, including the payoff function and the distribution of cost, signals, demands and offers. Both players will know that the lowest signal is

0 and the largest is 99. In particular, both players will know that lowest possible judgment is $L = 0$ and the largest possible judgment is $U = 99$.

During the second stage, the plaintiff will privately observe a signal θ_P of the potential trial judgment drawn from the cumulative distribution function $(cdf)F^P$ and make a demand p. Simultaneously, the defendant privately observes an independent signal θ_d of the potential trial judgment drawn from the cumulative distribution function $(cdf)F^D$ and makes an offer d. Both the plaintiff's and defendant's cumulative distribution functions are uniform. This illustrates a situation where each player has private information on how well they will do in trial, but the trial outcome depends on both signals. If each player could observe the other player's signal, then they would know the outcome of their trial. However, even if they cannot observe the other player's signal they can still estimate the other signal and predict the outcome of trial because they know the expected outcome of the unobserved signal. In the third and final stage the award is determined based on the demand and offer. If the offer is greater than or equal to the demand $d \geq p$ then the case will settle at the average offer $\frac{[p+d]}{2}$ and trial will have been avoided. If the offer is less than the demand $d < p$ the plaintiff will proceed with trial. Each player will then incur the cost of trial $c \geq 0$ and a judgment will be awarded. The judgment will be $\frac{[\theta_p+\theta_d]}{2}$. The objective of the plaintiff is to maximize their utility payout including possible court costs that will incur if a trial takes place. The objective of the defendant is to minimize their expected utility payout including possible court costs that will incur if a trial takes place. The greater the expectation differential (demand – offer), the more likely there will be a trial. A settlement will only take place when neither player is risk seeking or optimistic. When the offer is greater than or equal to the demand, settlement is Pareto superior to trial; in that both sides are better off by settling considering the two-sided incomplete information.

3 Methods

The experiment was programmed and conducted with the software Python. In order to evaluate the deviation from the Nash Equilibrium of the Plaintiff's demands and the Defendant's offers the recorded data was exported from python into a .csv file. The csv file contains the ID of the experimental session, the values of the treatment variable or the cost of trial, the random signals for the Plaintiffs, the random signals for the Defendants, the value of the $P(\theta_p)$ for the corresponding treatments and Plaintiff signals, the respective minimum and maximum numbers to compare with $P(\theta_p)$ when truncating, the NE plaintiff demand, the actual demands made by the Plaintiffs for each corresponding round, the deviation from each of the Plaintiffs demands compared to the Nash Equilibrium demands, the value of the $D(\theta_d)$ for the corresponding treatments and defendant signals, the respective minimum and maximum numbers to compare with $D(\theta_d)$ when truncating, the NE defendant offers for each cost and signal, the observed Defendant offers, the deviation of NE defendant offers and observed offers and the corresponding round numbers.

To compute the Nash Equilibrium demands and offers we used the basic litigation game Nash Equilibrium proposed by Wittman and Friedman:

$$\Pi^P(p, \theta_p, D, F^D) = 0.5 \int_{D^{-1}(p)}^{1} [p + D(x)]\mathrm{d}x + 0.5 \int_{0}^{D^{-1}(p)} [\theta_p + x - 2c]\mathrm{d}x,$$

$$\Pi^D(d, \theta_d, P, F^P) = 0.5 \int_{0}^{P^{-1}(d)} [d + P(y)]\mathrm{d}y + 0.5 \int_{P^{-1}(d)}^{1} [\theta_d + y + 2c]\mathrm{d}y.$$

$$P(\theta_p) = \frac{2\theta_p}{3} - 2c + \frac{1}{2}$$

$$D(\theta_d) = \frac{2\theta_d}{3} + 2c - \frac{1}{6}$$

The equations for the plaintiff and defendant and are truncated at differing minimums and maximums. Since the range of the pilot's signals and cost is 0-99, the end of the equations above equal (1/2=49.5) and (1/6=16.5). The plaintiff's NE is truncated above at minimum $\{P(\theta_p)$, 1, 2c + 1/2} = $\{P(\theta_p)$, 99, 2c+49.5} and below at maximum $\{P(\theta_p)$, 0, 2c – 1/6} = $\{P(\theta_p)$, 0, 2c-16.5}. The defendant's NE is truncated above at minimum $\{D(\theta_d)$, 1, 7/6 – 2c} = $\{D(\theta_d)$, 99, 115.5 – 2c} and below maximum at $\{D(\theta_d)$, 0, -2c + 1/2} = $\{D(\theta_d)$, 0, -2c + 49.5}. The truncating process removed demands and offers that were outside of the range from 0 – 99, in other words it removed demands and offers that were negative and below the range or were positive and greater than the parameter of 99.

We then modified the Litigation Code to incorporate trial costs (that is when making demands, plaintiff and defendants account for trial costs as well as the signal of the outcomes). Judgements were adjusted to allow for exogenous shocks through a new parameter judge type. There are 2 kinds of judges (ones that favor plaintiff, and ones that favor defendant) either of which occur with equal probability. Judgements are no longer split evenly at the midpoint between the demand and offer parameters. Previously settlements were formulated by

$$Judgement = \frac{demand+offer}{2} + trial\ cost,$$

and now they are decided weighting one side more favorably, for example in the case of a judge who favors plaintiffs,

$$Judgement = \frac{w_1 demand + w_2 offer}{2} + trial\ cost, \text{ where } w_1 = (1+x), \quad w_2 = 2 - w_1 \text{ with}$$

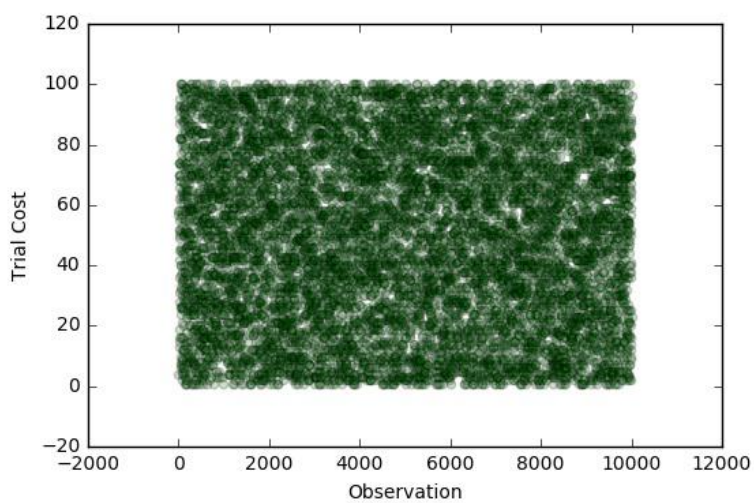
$$x \sim uniform\{0,1\}$$

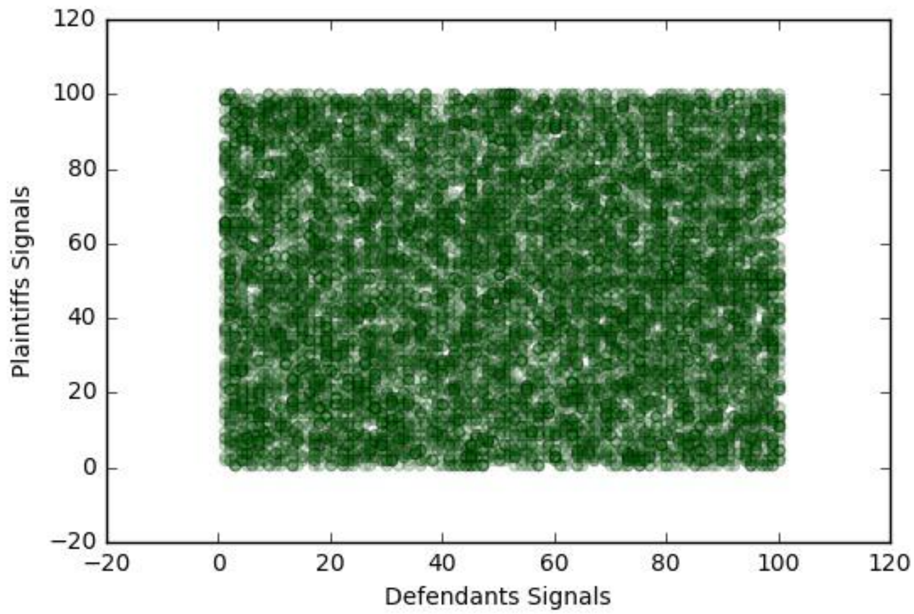
In the case of a judge which favors defendant, the weights w_1, w_2 are reversed.

Given a history of reputations of judges or courts and judgement outcomes, we implement machine learning to evaluate the suitability of different models in predicting judgement amounts. We implement a training portion (80%) of a 10,000 observation dataset and tested model prediction performance on the remaining test portion (20%). Assignment of observations between test and train sets is random. Two models we evaluated what Linear Models (OLS) and Random Forests.

We then constructed many plots to display our results. We focused the parameters of the figures based on the same cumulative distribution of the model from 1 to 100. The bandwidth represents the treatment or cost of trial and is distributed from 1 to 100. The binwidth did not have noise obtruding it so we decided to plot every individual data point. The y variable is the actual deviation from the chosen actions from the Nash Equilibrium. The range of the y variable is distributed from 1 to 100.

4 Results




120
100
80
60
40
20
0
−20
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0
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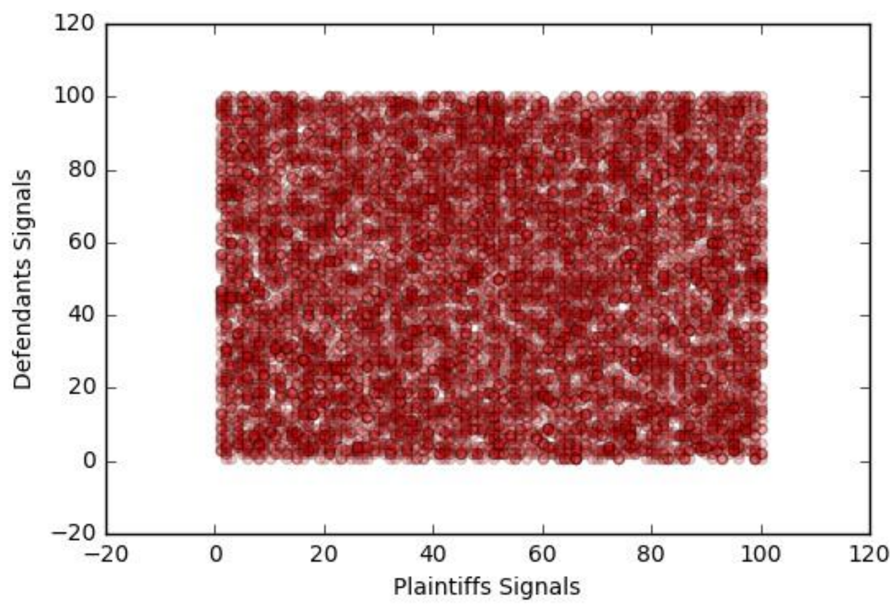
40
60
80
100
120
Plaintiffs Signals
Defendants Signals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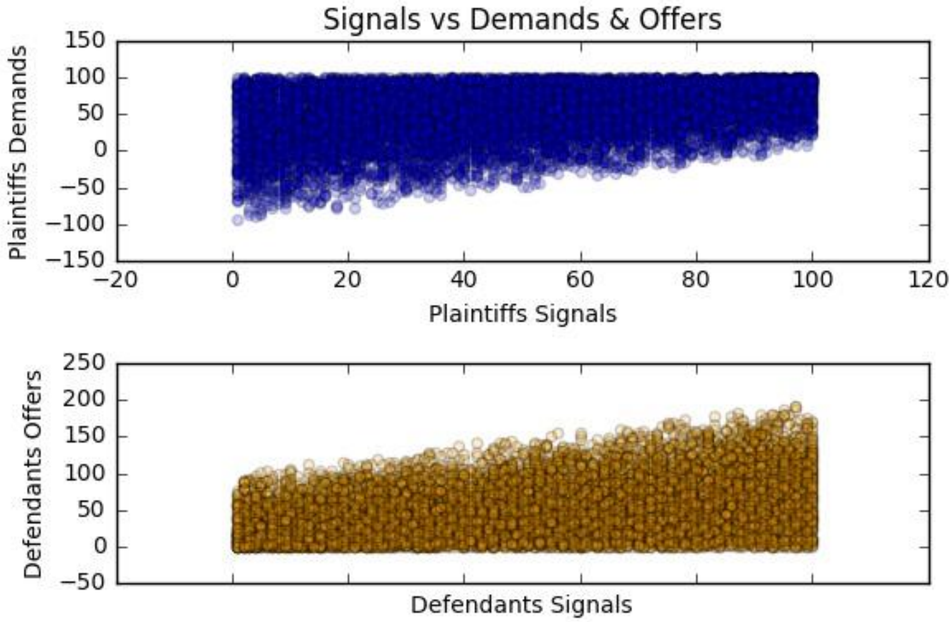
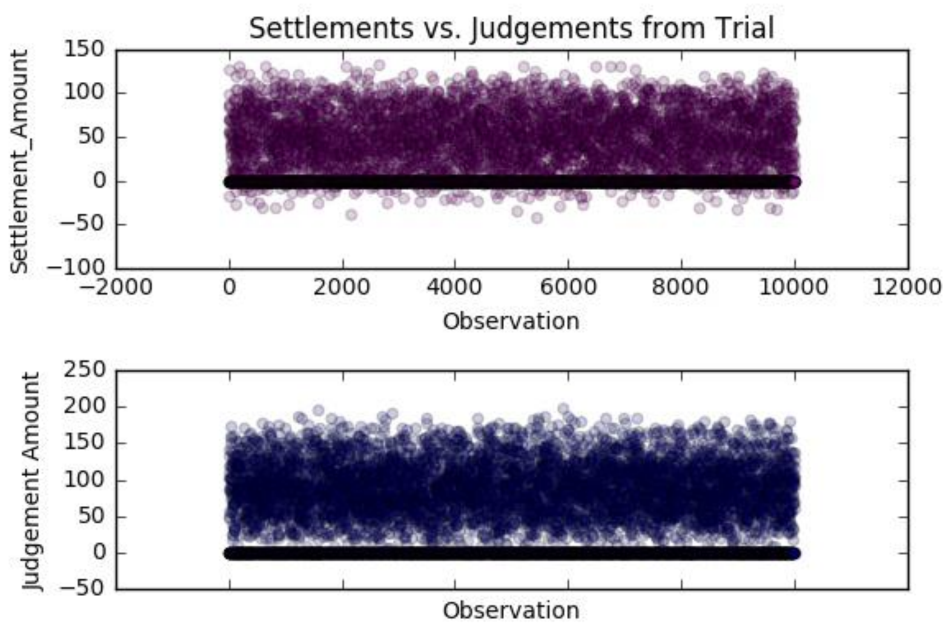
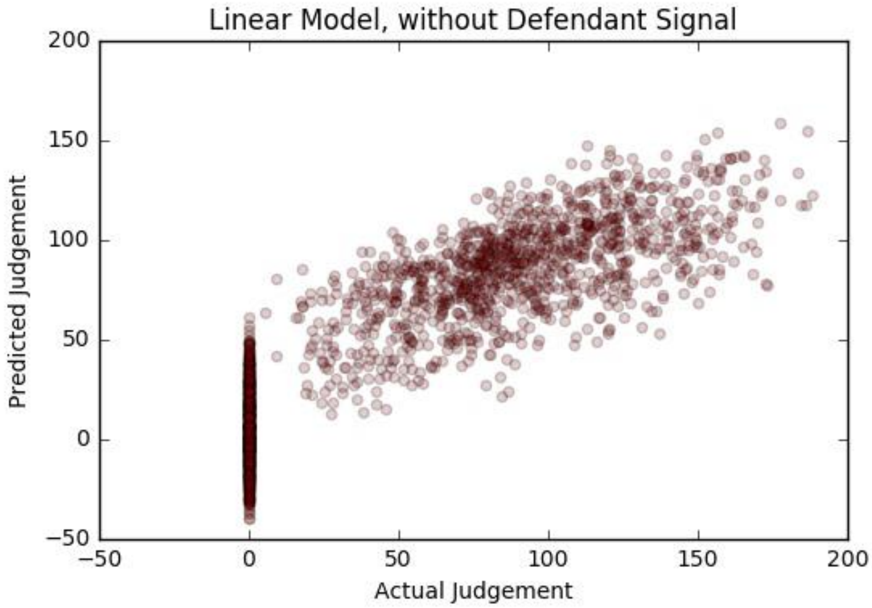
Defendants Signals
Plaintiffs Signals



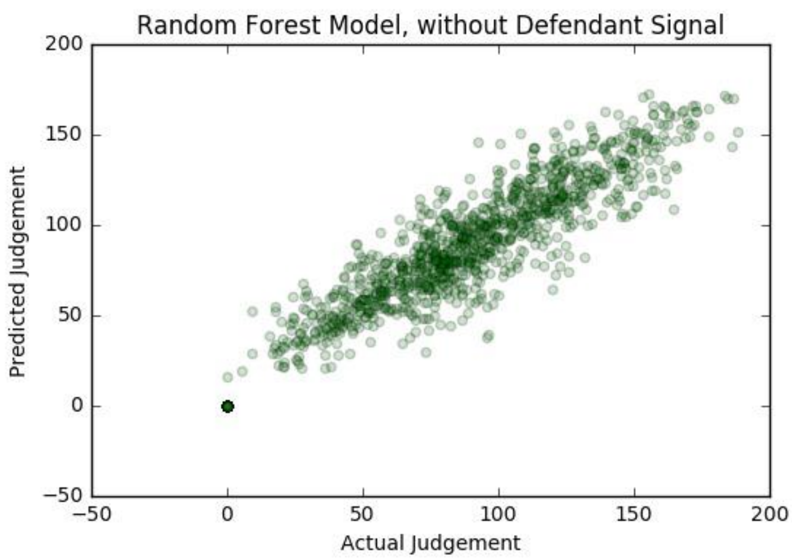
Signals vs Demands & Offers
Plaintiffs Demands
Plaintiffs Signals
Defendants Offers
Defendants Signals



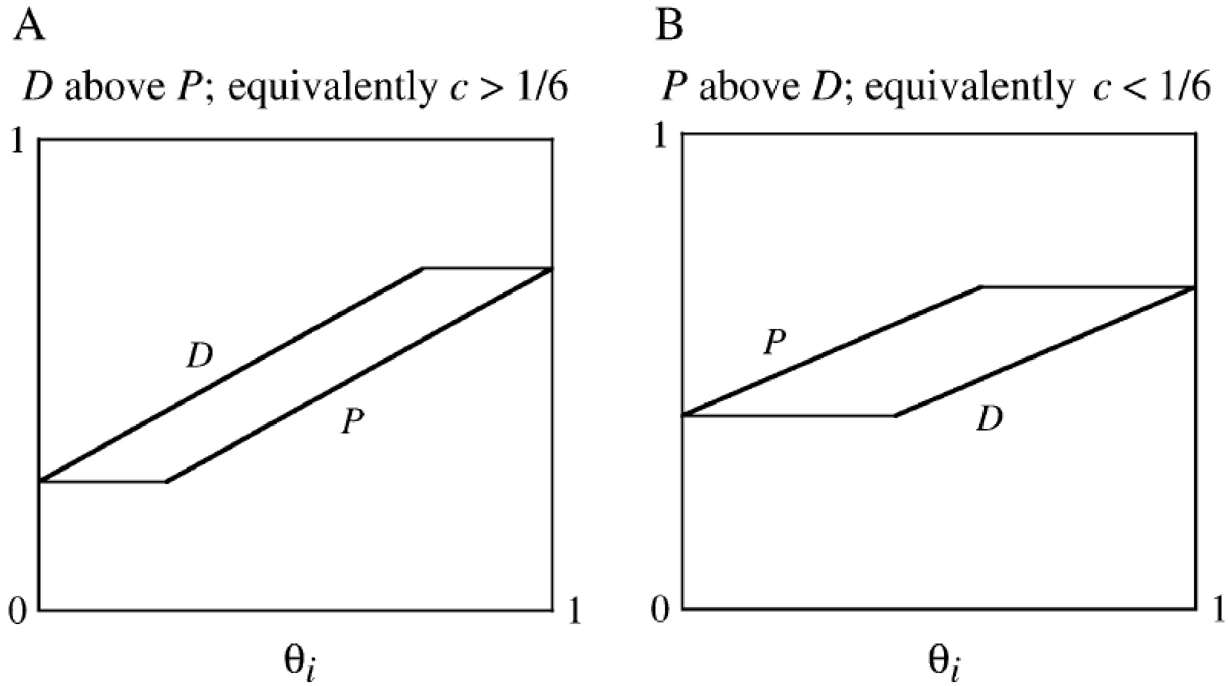
Settlements vs. Judgements from Trial
Settlement_Amount
Observation
Judgement Amount
Observation

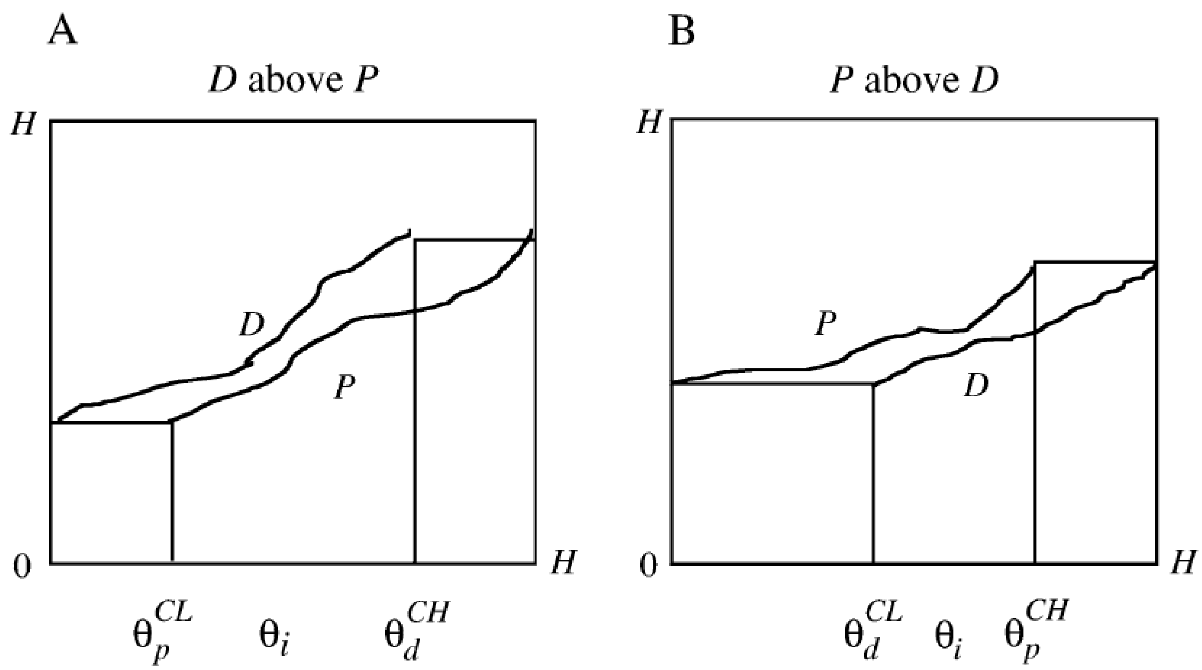


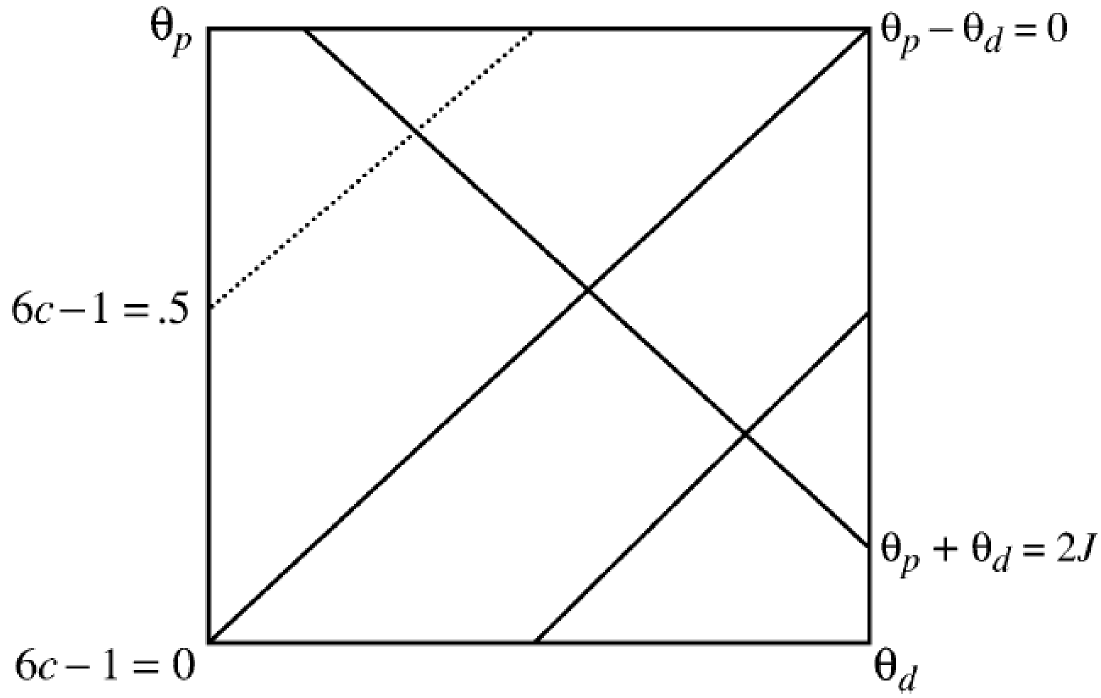
MSE for linear was 599.05765513774054.



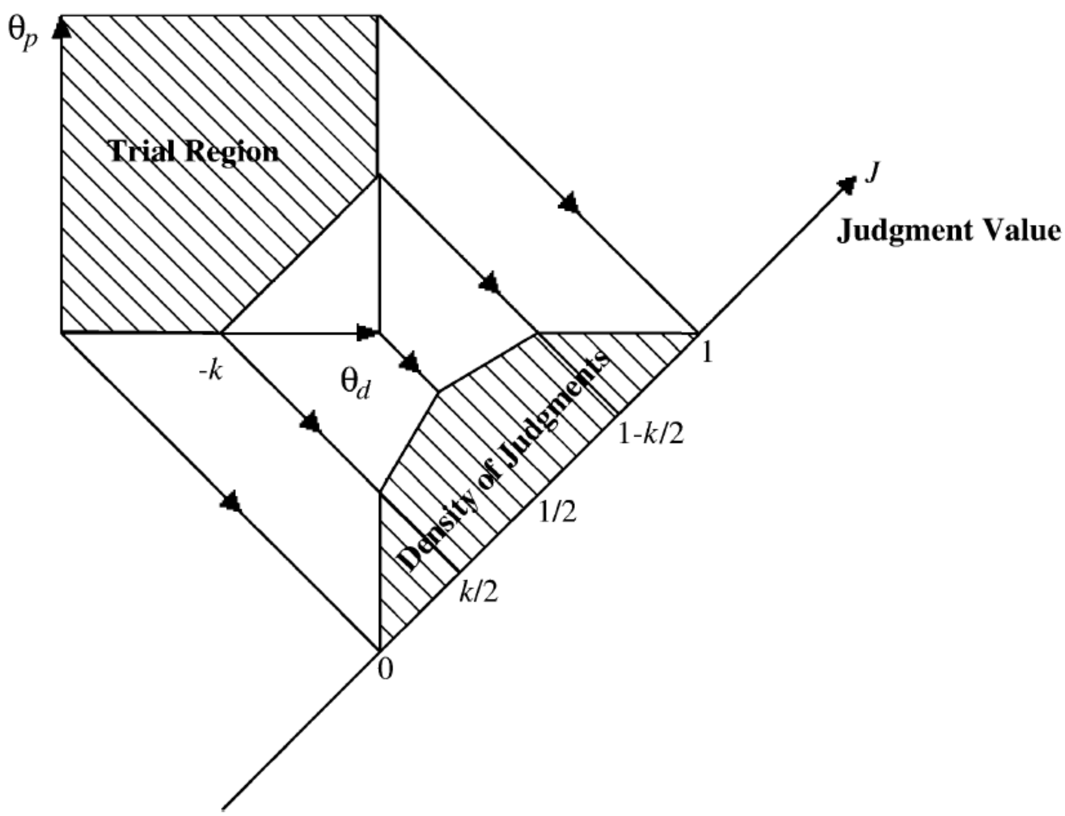
MSE for random forest was 147.94465483050789.


A
D above P; equivalently c > 1/6
B
P above D; equivalently c < 1/6
1
0
1
D
P
θi


A
D above P
B
P above D
H
0
D
P
θp CL
θi
θd CH
θd CL
θp CH



θ_p
$\theta_p - \theta_d = 0$
$6c-1=.5$
$\theta_p + \theta_d = 2J$
$6c-1=0$
θ_d



θ_p
Trial Region
J
Judgment Value
-k
θ_d
1
Density of Judgments
1-k/2
1/2
k/2
0

5 Conclusion

The motivation for this project was to construct a simulation in python that provides empirical evidence for the Wittman model, which has implications in two-sided bargaining, litigation, and how individuals should make decisions in the shadow of a trial. The game is meant to recreate a highly realistic litigation situation through symmetric information (the cost of trial) and two-sided incomplete information -- both parties make their respective offer and demand simultaneously. The model predicts that when trial costs are low, the probability of a trial is highest when the probability of the plaintiff winning is either very high or very low

The results from simulations were disparate from what we would expect to see if individuals were engaged in rational decision making, indicating that the random demands and offers were not dependent on the best response strategies of the plaintiff or defendant. While this is not ideal, the simulation provided insight on necessary protocol changes to obtain accurate estimates in future experimental sessions. Our aim would be to create a function in python that would utilize a tobit model in order to create the range for the Nash equilibrium best response in consideration of the possible distribution with information of the trial cost and signal. Possible future analysis could include clustering standard errors between sessions, changing the pairing every round, testing a correlation of demographics to performance, adding another treatment variable of presenting results after each round or not, running matched pair testing, bootstrap analysis, and a logit regression model.

6 Appendix

6.1: Experimental Protocol

- All participants will play 23 rounds (including the 3 practice rounds)
- There will be 16 participants total in 2 different groups of 8 rotating defendant and plaintiff and their pairing every round.
- During the practice rounds all of the group's payoffs, demands, and offers are projected for everyone to analyze.
- In actual rounds players only get to see the payoffs of their pairing (defendant and plaintiff).
- Signal will be explained as an estimate of the award judgment
- After explaining the instructions all participants will take a quiz to evaluate their understanding of the relationship between their signal, utility, and cost of trial. The examples will have a numerical signal of both the plaintiff and defendant and the associated cost.
- The participants will have to input the payoff for the defendant and the plaintiff using the equations provided in the instructions.
- There will be one example of a case that is settled and one that goes to trial. During this period talking is not permitted unless it is with a proctor who can help a participant that cannot figure it out.
-

6.2: Experiment Instructions

<u>Instructions:</u>

Experiment Instructions:

Welcome to the LEEPS lab! Today you will be playing a game designed to help us understand how people make decisions.

Each round will consist of three stages.

- Stage Null:
    - You are assigned either the role of “plaintiff” or “defendant” in a possible trial court matter.
    - You will be paired with one other individual in the room who will have the opposing role in your case.
    - Your pair assignment will change every round.
    - You will be given a signal, which represents the associated cost of trial if your pair does not settle.
    - You will observe a private signal from 0-99 about the potential judgment if your pair is to proceed to trial rather than settle.
- Stage 1:
    - Each player will make a simultaneous choice from 0-99; the “plaintiff” will make a demand and the “defendant” will make an offer.
- Stage 2:
    - If the offer is greater than or equal to the demand then the case is settled at the average
        - (demand + offer) / 2
    - If the offer is less than the demand the case will go to trial and the outcome will be decided by a judgment.
        - The judgment is (signal of plaintiff + signal of defendant)/2

- Each player will incur the cost of trial

End of the Round

6.3: Post-Experiment Questionnaire

Post-Experiment Questionnaire

1. How old are you?

2. Male or Female?

3. Ethnicity (White, Black, Asian, Mexican, etc.)?

4. Are you employed?

5. Did you work last week?

6. Do you have a high school diploma?

7. Do you have insurance?

8. Are you married?

9. Are you going to school?

10. If so, what is your major?

11. When would you graduate?

12. Are you a graduate student?

13. Did you find any of the instructions confusing? If so, what was most confusing?

14. Please comment on how you made your choices in this experiment. For example, what would make you want to change your strategy?

6.4: Python Code

```
"""
Created on Wed Apr 19 14:21:25 2017

@author: William
"""
def litigation():
    import random

    # first generate a symmetric trial cost for both
    trial_cost = random.randrange(1,100+1)

    # create a random signal for both
    p_signal = random.randrange(1, 100+1)
    d_signal = random.randrange(1, 100+1)
    p=p_signal
    d=d_signal

    # simulate Plaintiff demand, which should be higher than other outcome (trial)
    # this will be from p to 100, at worst they can get the trial outcome
    demand = random.randrange(p+1-trial_cost, 101+1)-1

    # simulate Defendant offer, which should be lower than the outcome
    # at worst they go to trial and pay d_signal, so they should offer less
    offer = random.randrange(-1, d-1+trial_cost+1)+1

    # initial values
    settle = 0
    judgement = 0
    c = random.randrange(0,1+1)

    # if the offer exceeds the demand, they settle and split the surplus
    if offer >= demand:
        settle = float(offer + demand)/2 #avg on hi low
```

```
    # else the offer is too low and trials occurs
    if offer < demand:
        # let's suppose there are 2 types of judges, plaintiff, defendant
        whigh = 1 + random.uniform(0, 1)
        wlow = 2-whigh

        # plaintiff
        if c == 0:
            judgement = float((whigh*p_signal) + (wlow*d_signal))/2 + trial_cost

        # defendant
        if c == 1:
            judgement = float((wlow*p_signal) + (whigh*d_signal))/2 + trial_cost

    return([trial_cost, p_signal, d_signal, demand, offer, settle, judgement, c])
import csv

with open('lit2.csv', "w", newline='') as f:
    writer = csv.writer(f)
    #writer.writerow(['trial_cost', 'p_signal', 'd_signal', 'demand', 'offer', 'settle',
'judgement'])
    for i in range(10000):
        rowi = litigation()
        print(rowi)
        writer.writerow(rowi)

# - Machine learning, visualization
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
# load the simulation data
df = pd.read_csv('lit2.csv', header=None, names=['Trial_Cost', 'Plaintiffs_Signals',
'Defendants_Signals', 'Plaintiffs_Demands', 'Defendants_Offers', 'Settlement_Amount',
'Judgement_Amount', 'Court_Type'])
df['Observation'] = df.index
columns = df.columns.tolist()
columns = [c for c in columns if c not in ["Defendants_Signals", "Judgement_Amount",
"Observation"]]
target = "Judgement_Amount"

df_train = df.sample(frac=0.8, random_state=1)
df_test = df.loc[~df.index.isin(df_train.index)]

df_train2 = df_train.copy(deep=True)
df_test2 = df_test.copy(deep=True)

df_train2['Court_Type'] = pd.get_dummies(df_train2['Court_Type'])
df_test2['Court_Type'] = pd.get_dummies(df_test2['Court_Type'])
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
# Initialize the model class.
model1 = LinearRegression()
# Fit the model to the training data. It is then saved as a Pandas dataframe.
model1.fit(df_train[columns], df_train[target])
predictions1 = model1.predict(df_test[columns])
df_test.is_copy = False
df_test['hat1'] = predictions1
from sklearn.metrics import mean_squared_error
mean_squared_error(predictions1, df_test[target])
from sklearn.ensemble import RandomForestRegressor
# Initialize the model with some parameters.
model2 = RandomForestRegressor(n_estimators=100, min_samples_leaf=10, random_state=1)
model2.fit(df_train[columns], df_train[target])
# Make predictions.
predictions2 = model2.predict(df_test[columns])
# Compute the error.
df_test['hat2'] = predictions2
mean_squared_error(predictions2, df_test[target])
df_test.head()

# plot A
```

```
plt.scatter(df_test['Judgement_Amount'], df_test['hat1'], c='darkred', alpha=0.2)
plt.xlabel('Actual Judgement')
plt.ylabel('Predicted Judgement')
plt.title('Linear Model, without Defendant Signal')
plt.savefig('plotA.jpg')
plt.show()

# plot B
plt.scatter(df_test['Judgement_Amount'], df_test['hat2'], c='green', alpha=0.2)
plt.xlabel('Actual Judgement')
plt.ylabel('Predicted Judgement')
plt.title('Random Forest Model, without Defendant Signal')
plt.savefig('plotB.jpg')
plt.show()

df = df_test

# plot 1
plt.scatter(df['Plaintiffs_Signals'], df['Defendants_Signals'], c='r', alpha=0.2)
plt.xlabel('Plaintiffs Signals')
plt.ylabel('Defendants Signals')
plt.savefig('plot01.jpg')
plt.show()

# plot 2
plt.scatter(df['Defendants_Signals'], df['Plaintiffs_Signals'], c='g', alpha=0.2)
plt.xlabel('Defendants Signals')
plt.ylabel('Plaintiffs Signals')
plt.savefig('plot02.jpg')
plt.show()

# plot 3
plt.scatter(df['Plaintiffs_Signals'], df['Plaintiffs_Demands'], c='b', alpha=0.2)
plt.xlabel('Plaintiffs Signals')
plt.ylabel('Plaintiffs Demands')
plt.savefig('plot03.jpg')
plt.show()

# plot 4
plt.scatter(df['Defendants_Signals'], df['Defendants_Offers'], c='orange', alpha=0.2)
plt.xlabel('Defendants Signals')
plt.ylabel('Defendants Offers')
plt.savefig('plot04.jpg')
plt.show()

# Panel 1
ax1 = plt.subplot(211)
plt.scatter(df['Plaintiffs_Signals'], df['Defendants_Signals'], c='r', alpha=0.2)
plt.xlabel('Plaintiffs Signals')
plt.ylabel('Defendants Signals')
plt.title('Signals plotted against each other')

# share x only
ax2 = plt.subplot(212, sharex=ax1)
plt.scatter(df['Defendants_Signals'], df['Plaintiffs_Signals'], c='g', alpha=0.2)
plt.xlabel('Defendants Signals')
plt.ylabel('Plaintiffs Signals')
plt.setp(ax2.get_xticklabels(), visible=False)
plt.tight_layout()
plt.savefig('panel1.jpg')
plt.show()

# Panel 2
ax1 = plt.subplot(211)
plt.scatter(df['Plaintiffs_Signals'], df['Plaintiffs_Demands'], c='b', alpha=0.2)
plt.xlabel('Plaintiffs Signals')
plt.ylabel('Plaintiffs Demands')
plt.title('Signals vs Demands & Offers')

# share x only
ax2 = plt.subplot(212, sharex=ax1)
```

```
plt.scatter(df['Defendants_Signals'], df['Defendants_Offers'], c='orange', alpha=0.2)
plt.xlabel('Defendants Signals')
plt.ylabel('Defendants Offers')
plt.setp(ax2.get_xticklabels(), visible=False)
plt.tight_layout()
plt.savefig('panel2.jpg')
plt.show()

# plot 5
plt.scatter(df['Observation'], df['Trial_Cost'], c='darkgreen', alpha=0.2)
plt.xlabel('Observation')
plt.ylabel('Trial Cost')
plt.savefig('plot05.jpg')
plt.show()

# plot 6
plt.scatter(df['Observation'], df['Settlement_Amount'], c='purple', alpha=0.2)
plt.xlabel('Observation')
plt.ylabel('Settlement_Amount')
plt.savefig('plot06.jpg')
plt.show()

# plot 7
plt.scatter(df['Observation'], df['Judgement_Amount'], c='navy', alpha=0.2)
plt.xlabel('Observation')
plt.ylabel('Judgement Amount')
plt.savefig('plot07.jpg')
plt.show()

# Panel 1
ax1 = plt.subplot(211)
plt.scatter(df['Observation'], df['Settlement_Amount'], c='purple', alpha=0.2)
plt.xlabel('Observation')
plt.ylabel('Settlement_Amount')
plt.title('Settlements vs. Judgements from Trial')

# share x only
ax2 = plt.subplot(212, sharex=ax1)
plt.scatter(df['Observation'], df['Judgement_Amount'], c='navy', alpha=0.2)
plt.xlabel('Observation')
plt.ylabel('Judgement Amount')
plt.setp(ax2.get_xticklabels(), visible=False)
plt.tight_layout()
plt.savefig('panel1.jpg')
plt.show()
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7 References

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