

# Individual Analysis

*Dario Trujano Ochoa*

## Contents

Data	1
Graphs on Individual Behavior	1
Entry bias	2
Biased towards entry	4
Analysis by Treatment . . . . .	4
Conclusion	10

## Data

Let's import some data bases previously created from the treatments:

```
getwd()

## [1] "D:/Dario/Dropbox/Citizen-Candidate/ArticleCitizenCandidate"

participants_305075 <- read.csv("data/participants_305075.csv")[,2:8]
colnames(participants_305075)[3:5] <- c("Left", "Center", "Right")
participants_203080 <- read.csv("data/participants_203080.csv")[,2:8]
colnames(participants_203080)[3:5] <- c("Left", "Center", "Right")

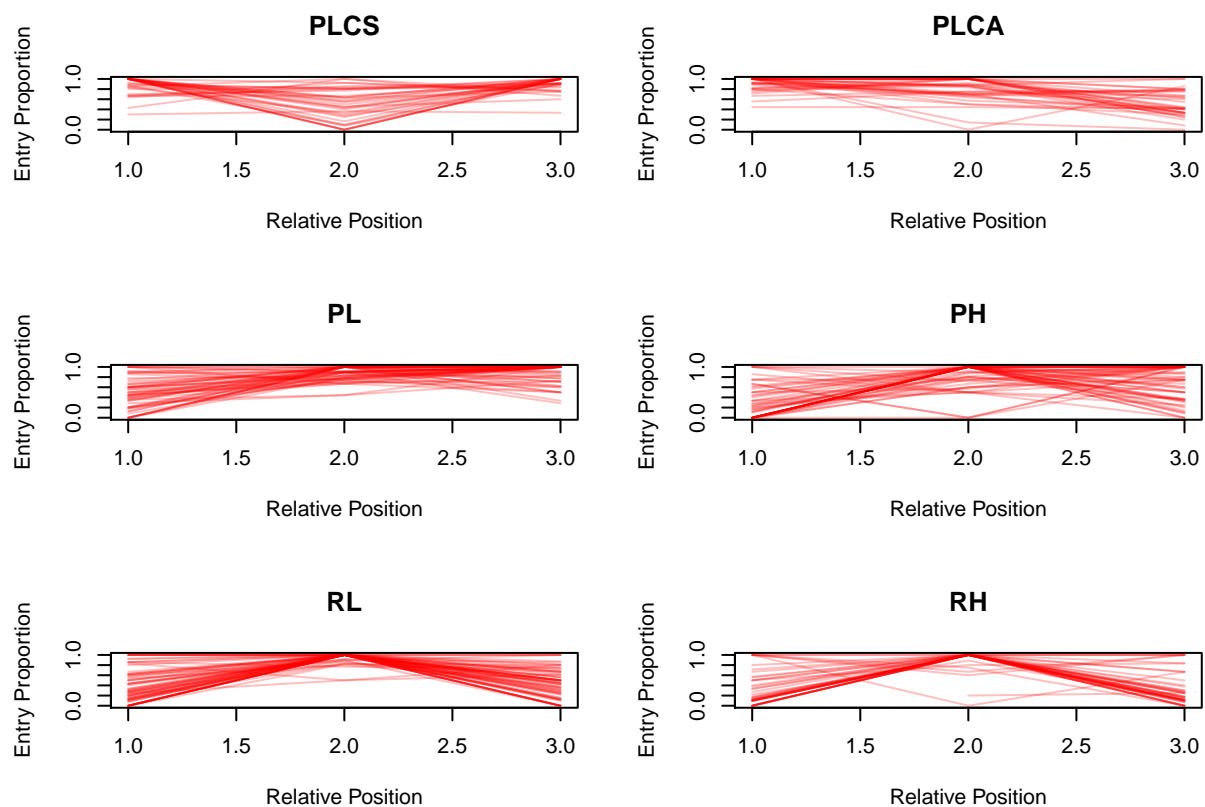
and now I merge them

participants <- rbind(participants_305075,participants_203080)

treatments <- names(table(participants$Game))
treatments_names <- cbind.data.frame(treatments,
                                     NewNames = c("PLCS", "PLCA", "PL", "PH", "RL", "RH"))
```

## Graphs on Individual Behavior

With the next graphs, we visually analyze heterogeneity among participants. The entry porportion by individual and by relative position are displayed; each red line relate data from each participant. For simplicity, we analyze the behavior according with the relative position, i.e., 1 stand for the left extreme candidate, 2 for that one in the middle, and the extreme right candidate is represented by 3. The precise postiiion depends of the treatment.



The behavior displayed is very similar among participants within treatments. Some participants deviate from the general path, but they are rare. Also, we can see that the variance increases for the position that should not enter according to Nash prediction.

## Entry bias

We considered the hypothesis of a biased decision towards entry.

First, let us consider the parameters of the treatments:

```
alpha = 0.1
costs = c(5,5,5,20,5,20) #costs in treatments
benefit = 25
D = 40 # penalty if no one enters
# what everybody does
n = 3 # number of players
Q_games = cbind(matrix(c(c(30, 50, 70),c(30, 50, 80),rep(c(20, 30, 80),4)),ncol=3,nrow=6,byrow = T)) #
parameters_games <- cbind(alpha, costs, benefit,D)
row.names(parameters_games) <- treatments
VotingRule <- c("Plurality Rule","Plurality Rule","Plurality Rule","Plurality Rule","Run-Off","Run-Off")
parameters_games2 <- data.frame(VotingRule,parameters_games,Q_games)
game_names <- treatments_names$NewNames
row.names(parameters_games2) <- game_names
colnames(parameters_games2)[6:8] <- c("Left", "Center", "Right")
Equilibria <- data.frame(
  Games= game_names,
```

```
OneCandidate= c(50,50,30,30,30,30),
TwoCandidate= c("30, 70",NA, "20, 80",NA,NA,NA) )
```

Second, we get the proportion of entry by session.

Finally, we merge the proportion of entry, the proportion of entry by session, and the expected payoffs of entry by session in a single data base.

```
str(entry_proportions_by_session)

## num [1:16, 1:3] 0.856 0.933 0.881 0.934 0.592 ...
## - attr(*, "dimnames")=List of 2
## ..$ : NULL
## ..$ : chr [1:3] "Left" "Center" "Right"

write.csv(entry_proportions_by_session, "data/entry_proportions_by_session.csv")

participants <- cbind.data.frame(participants,exp_val_participants,optimal_participants)
positions_should_entry <- c("ShouldLeftEntry", "ShouldCenterEntry","ShouldRightEntry")
positions_prop_entry <- names(participants[3:5])

errors <- participants[positions_prop_entry]-
  participants[positions_should_entry] # there are 3 participants that no played some position
names(errors) <- paste("Errors",names(errors))

errors1 <- errors > 0 # they entry when should not
errors2 <- errors < 0 # they do not enter when they should

Error1 <- rowSums(errors*errors1,na.rm = T) # when players never played some position there is NA
Error2 <- rowSums(errors*errors2,na.rm = T)

participants <- cbind(participants,errors>Error1>Error2)
str(participants)

## 'data.frame': 301 obs. of 21 variables:
## $ Game : Factor w/ 6 levels "ex70","ex80",...: 1 1 1 1 1 1 1 1 1 1 ...
## $ Session : int 1 1 1 1 1 1 1 1 1 1 ...
## $ Left : num 0.8 0.9 0.875 0.7 0.636 ...
## $ Center : num 0.8 0.8 0.0909 0.7692 0.8571 ...
## $ Right : num 0.9 1 1 1 0.917 ...
## $ Effective_Trials : int 30 30 30 30 30 30 30 30 30 30 ...
## $ Bankrupcy : int 0 0 0 0 0 0 1 0 0 0 ...
## $ LeftEntry : num 5.46 5.46 5.46 5.46 5.46 ...
## $ CenterEntry : num 0.0182 0.0182 0.0182 0.0182 0.0182 ...
## $ RightEntry : num 5.45 5.45 5.45 5.45 5.45 ...
## $ LeftPass : num -5.11 -5.11 -5.11 -5.11 -5.11 ...
## $ CenterPass : num -2.74 -2.74 -2.74 -2.74 -2.74 ...
## $ RightPass : num -5.24 -5.24 -5.24 -5.24 -5.24 ...
## $ ShouldLeftEntry : logi TRUE TRUE TRUE TRUE TRUE TRUE ...
## $ ShouldCenterEntry: logi TRUE TRUE TRUE TRUE TRUE TRUE ...
## $ ShouldRightEntry : logi TRUE TRUE TRUE TRUE TRUE TRUE ...
## $ Errors Left : num -0.2 -0.1 -0.125 -0.3 -0.364 ...
## $ Errors Center : num -0.2 -0.2 -0.909 -0.231 -0.143 ...
## $ Errors Right : num -0.1 0 0 0 -0.0833 ...
## $ Error1 : num 0 0 0 0 0 0 0 0 0 0 ...
## $ Error2 : num -0.5 -0.3 -1.034 -0.531 -0.59 ...
```

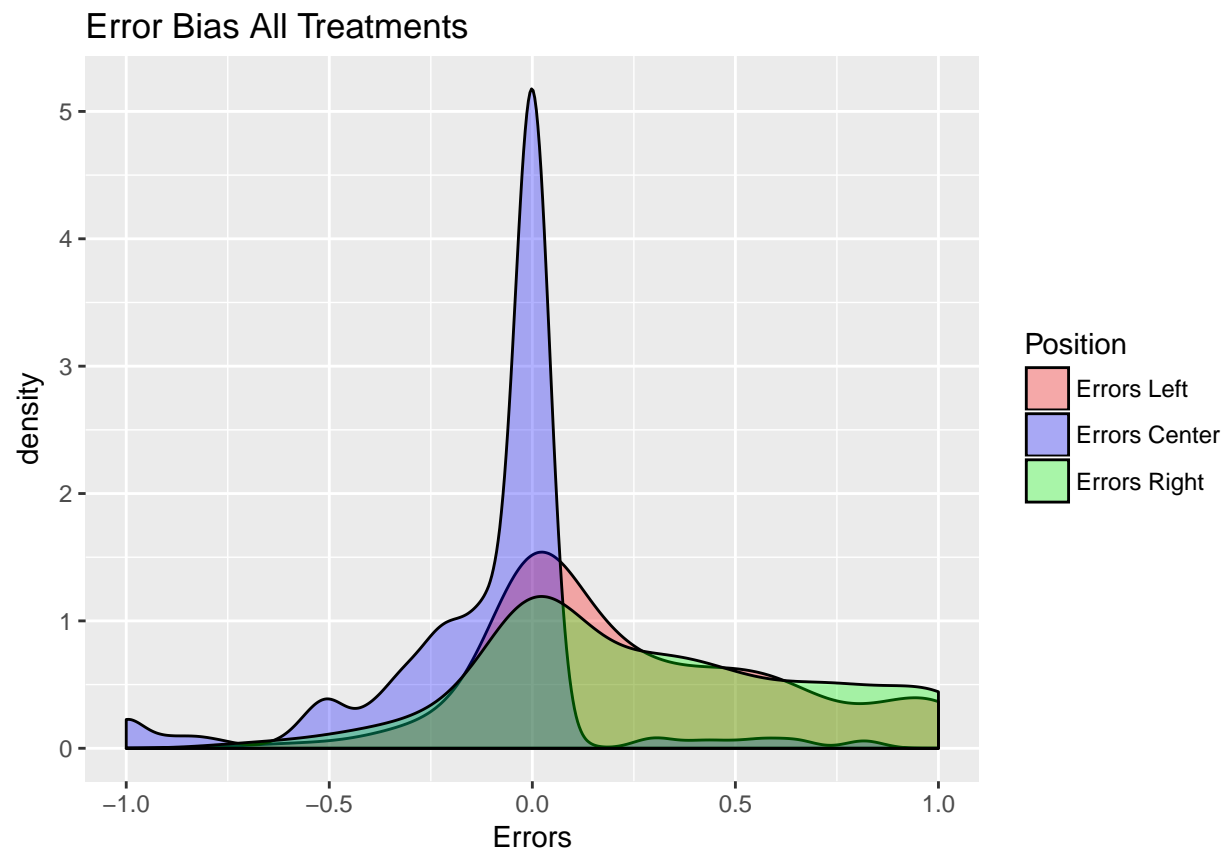
```
write.csv(participants,file = "data/participants.csv")
```

## Biased towards entry

In order to analyze the error bias, we considered the difference between the entry proportion and the optimal decision, e.g. if the optimal decision was to enter, and the proportion observed was 0.5, we calculate a negative error of 0.5. Then, a positive error indicates overentry, and negative subentry relative with the optimal decision. It can be seen that errors range from -1 to 1, and zero means optimal behavior.

We ran the analysis by position, as we saw a difference in the individual behavior according with this variable. Also, we analyzed the treatment effect over error distributions. In each graph, a density was adjusted and data from the three positions are set for comparison.

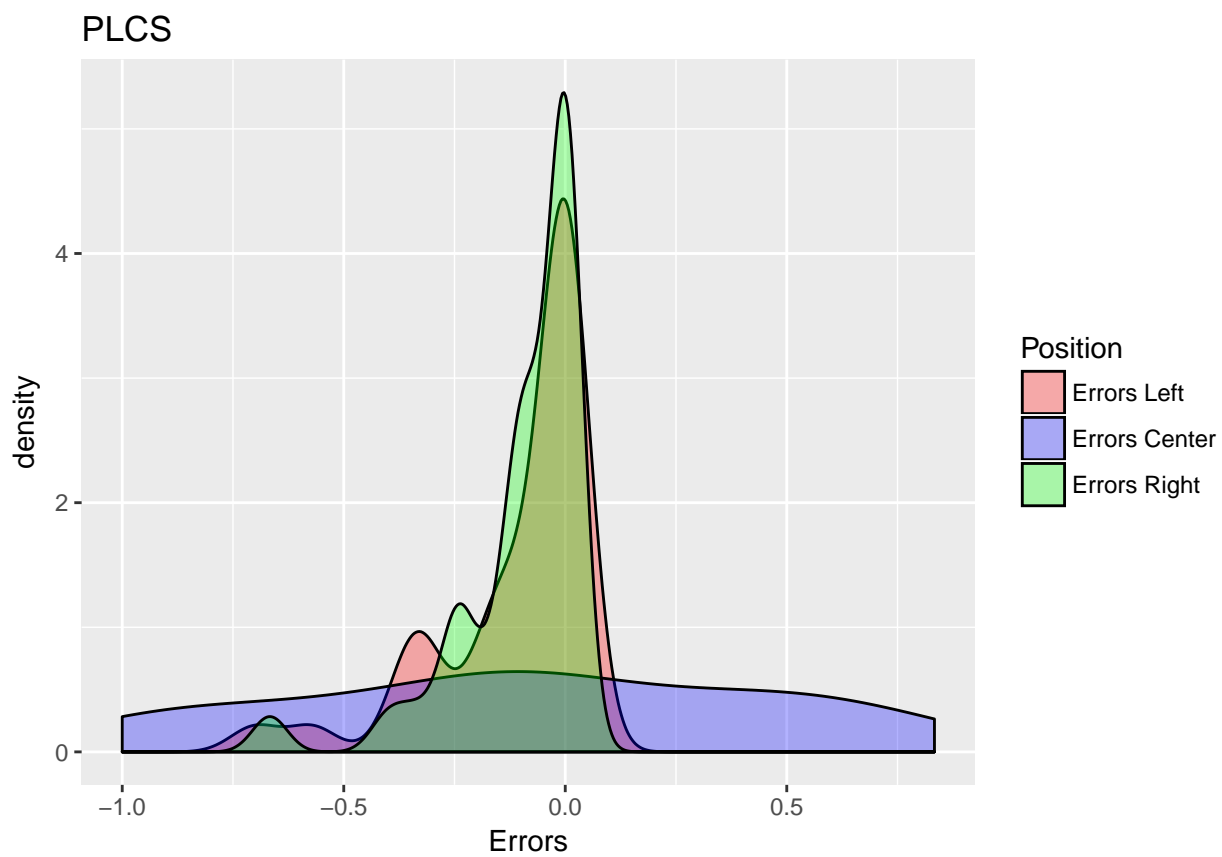
```
## Warning: Removed 3 rows containing non-finite values (stat_density).
```

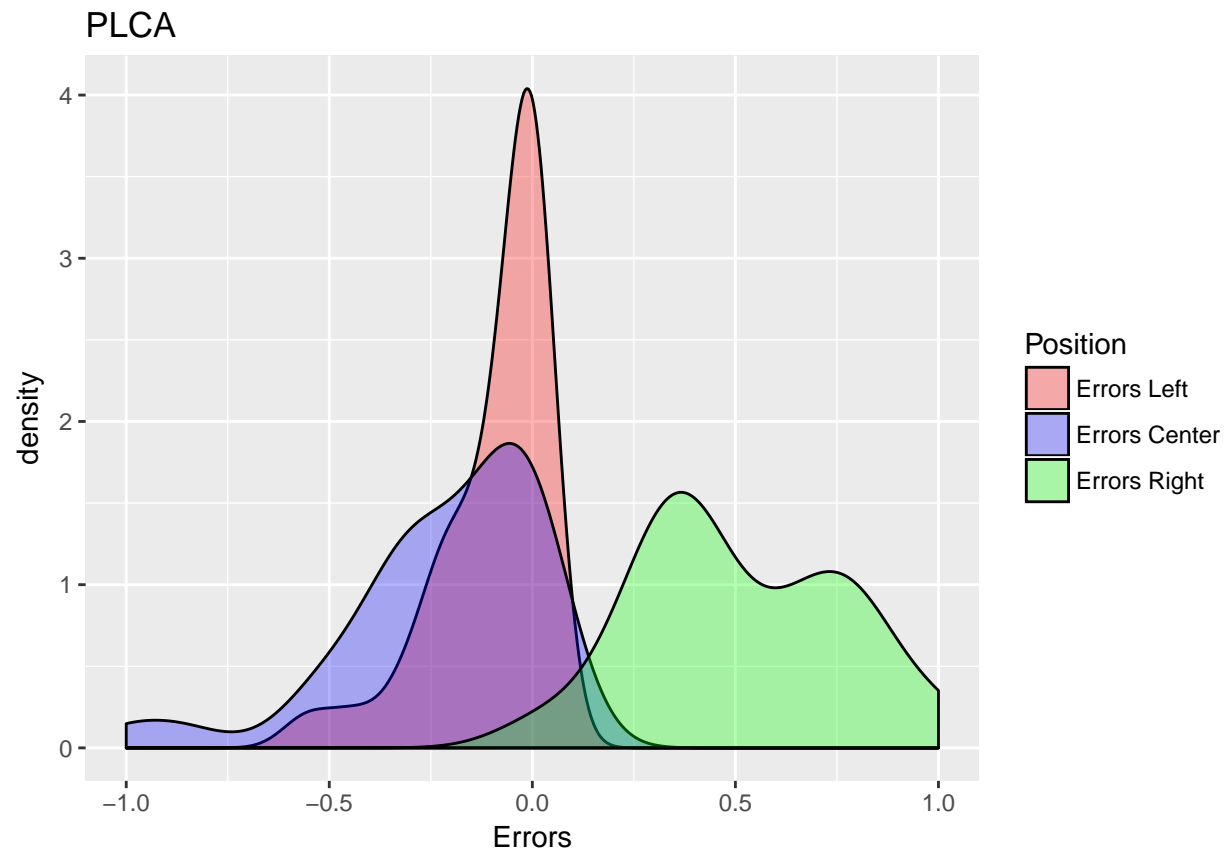


In the graph that shows the joined behavior in all treatments by position, we can see that extreme positions are more commonly biased towards over entering, i.e., participants are prone to enter in those positions even against their interest. On the other hand, in central position, participants tend to make less mistakes and, if so, they enter less than predicted.

## Analysis by Treatment

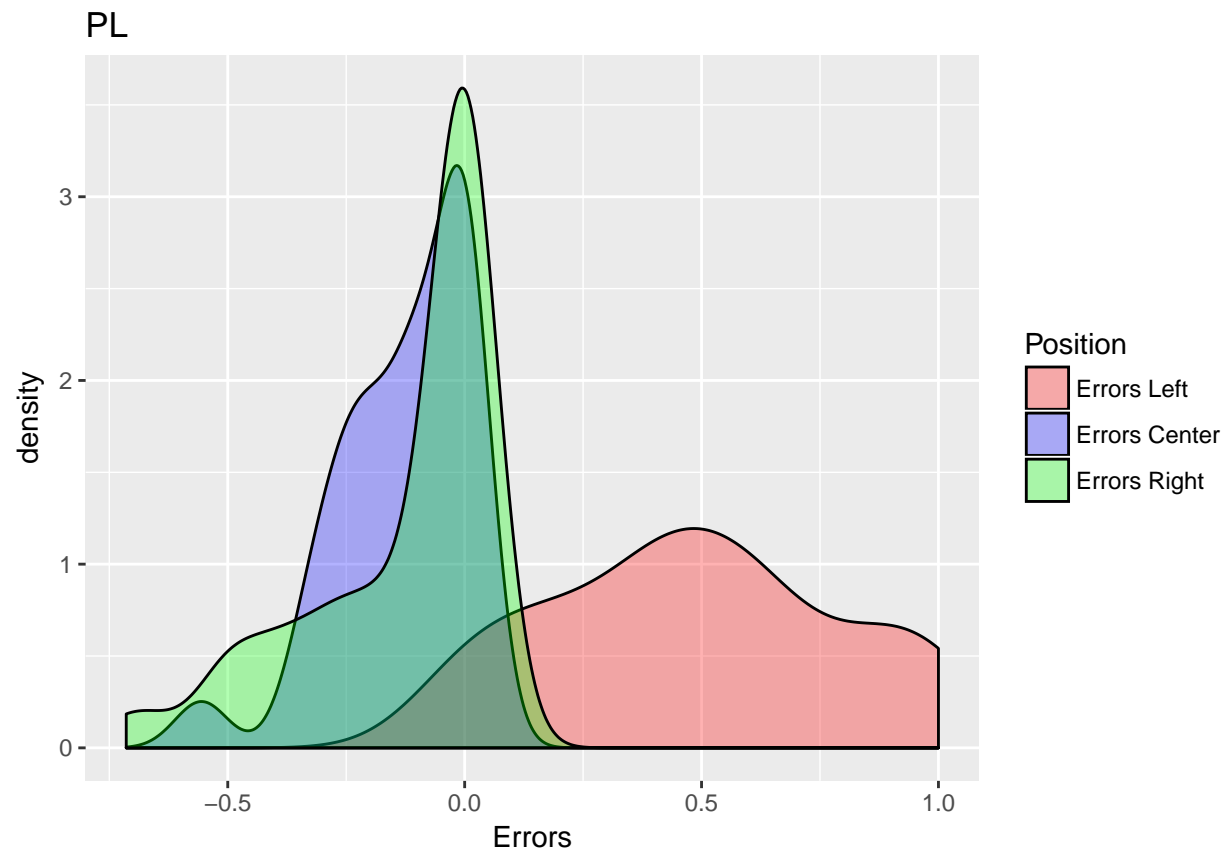
In this section, we analyze error distribution in the six treatments.



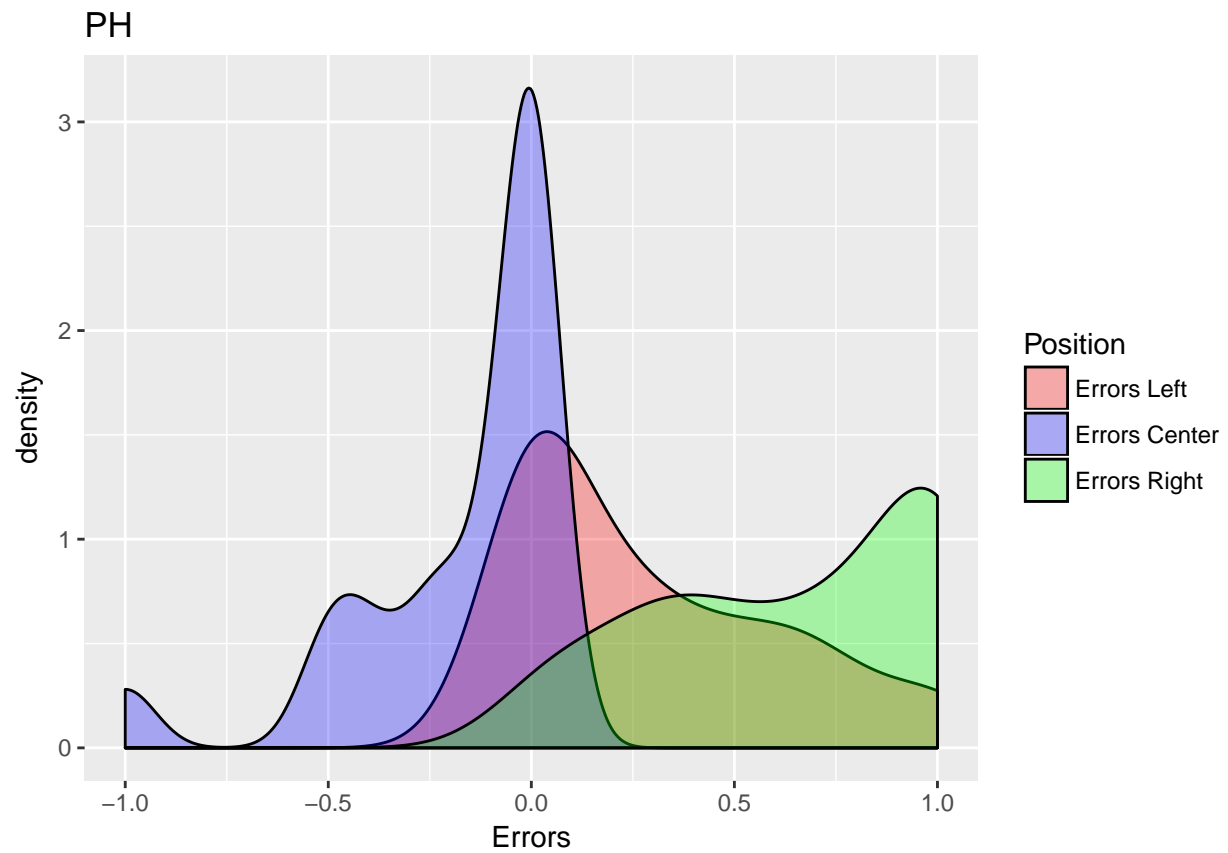


```
## Warning: Removed 1 rows containing non-finite values (stat_density).
```

```
## Warning: Removed 1 rows containing non-finite values (stat_density).
```



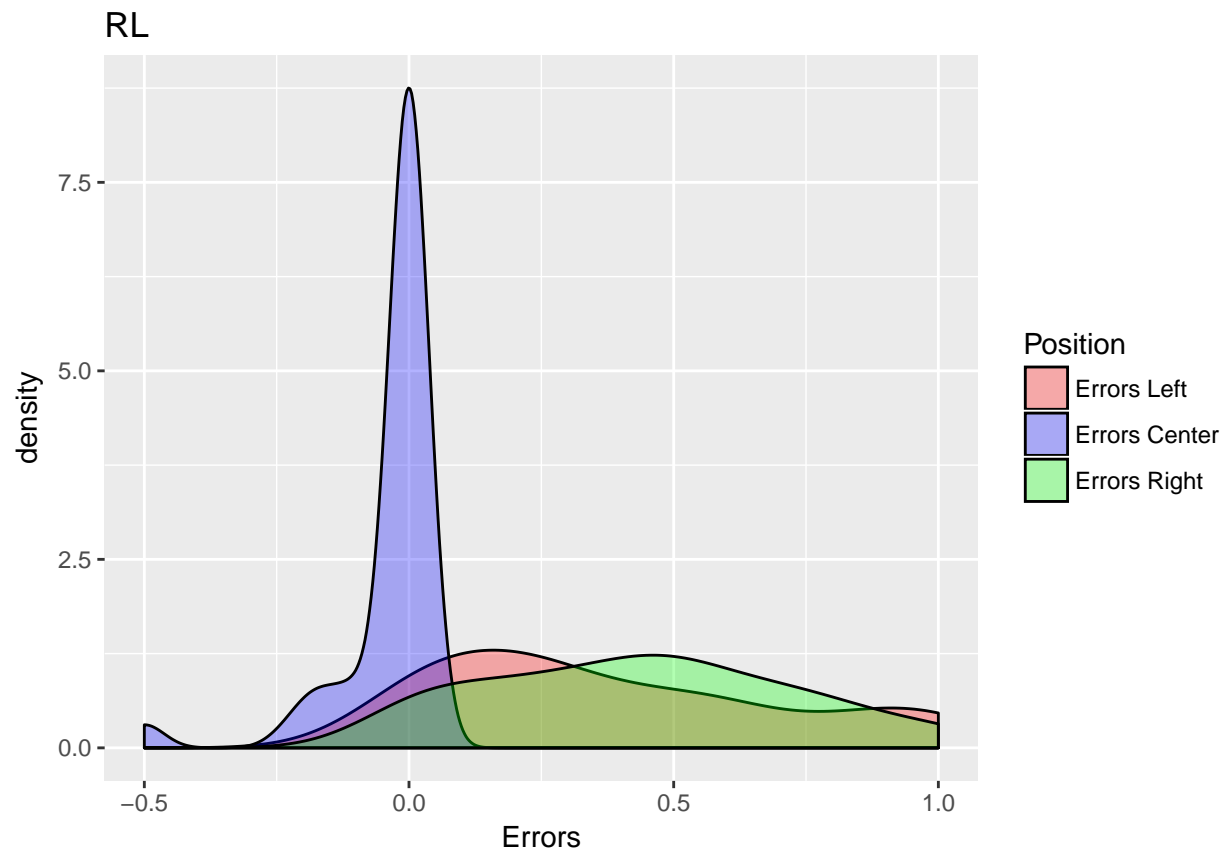
## Warning: Removed 1 rows containing non-finite values (stat\_density).



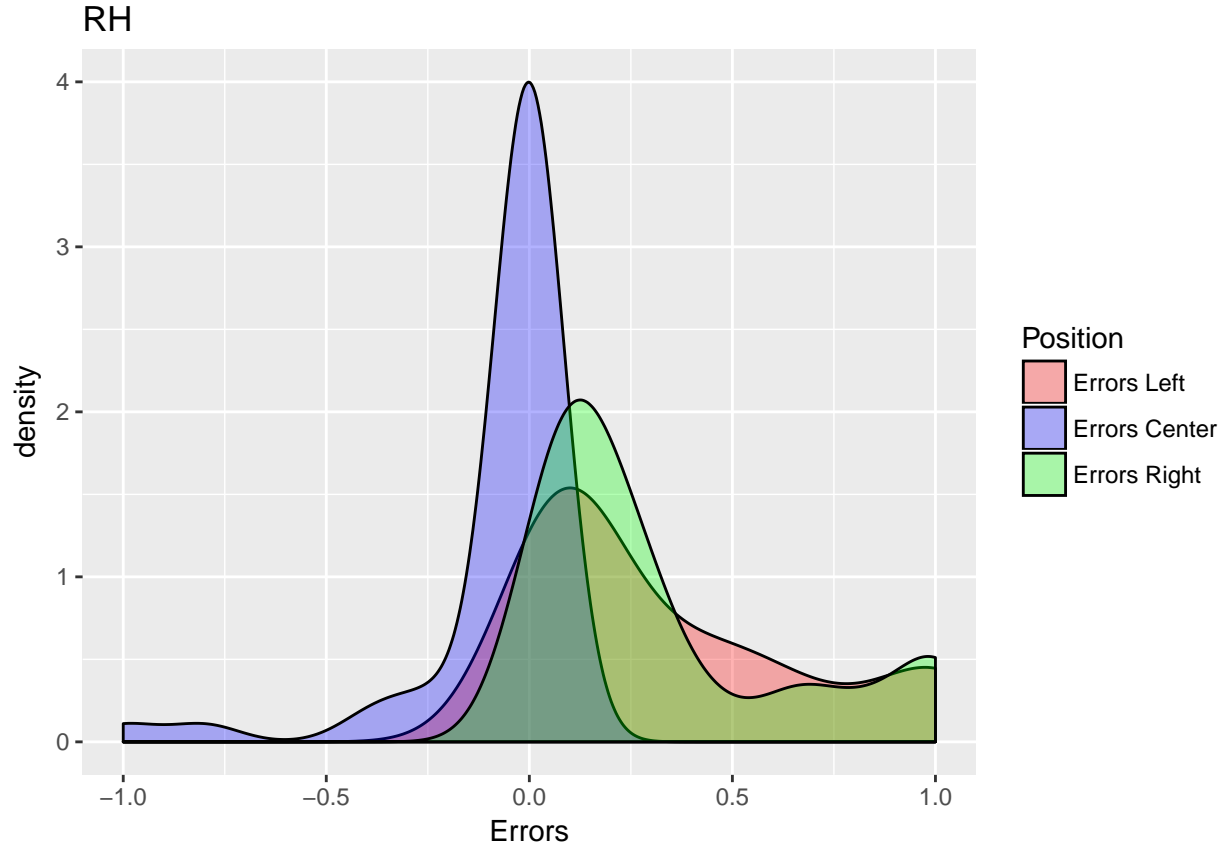
```
## Warning: Removed 2 rows containing non-finite values (stat_density).
```

```
## Warning: Removed 2 rows containing non-finite values (stat_density).
```





## Warning: Removed 2 rows containing non-finite values (stat\_density).



According with the graphs, treatments PH, RL and RH display a similar behavior in general: overentry in the extreme positions, and less error in the central one. Among other treatments, there is more heterogeneity. In the PLCS treatment, we observe that in extreme position participants make less mistakes, and error is uniformly distributed in central position. In the PLCA treatment, there are less mistakes in the left position, and overentry in the right position. Finally, in the PL treatment we observe the opposite; more mistakes in the left positions, and more optimal behavior when participants were in the right position.

## Conclusion

There are differences in the error distributions along the treatments. These errors reflect the behavior observed in comparison with the Nash Equilibria. In all the treatment, but in PLCS, central position entering alone was predicted. As we saw in the first graphs, there are differences in the entry rate between extreme positions along the treatments and the errors behave accordingly; when an extreme position enters more than the other, the positive error is greater.