Task

Question.

How do the prices consumers pay for tickets change as the game date approaches?

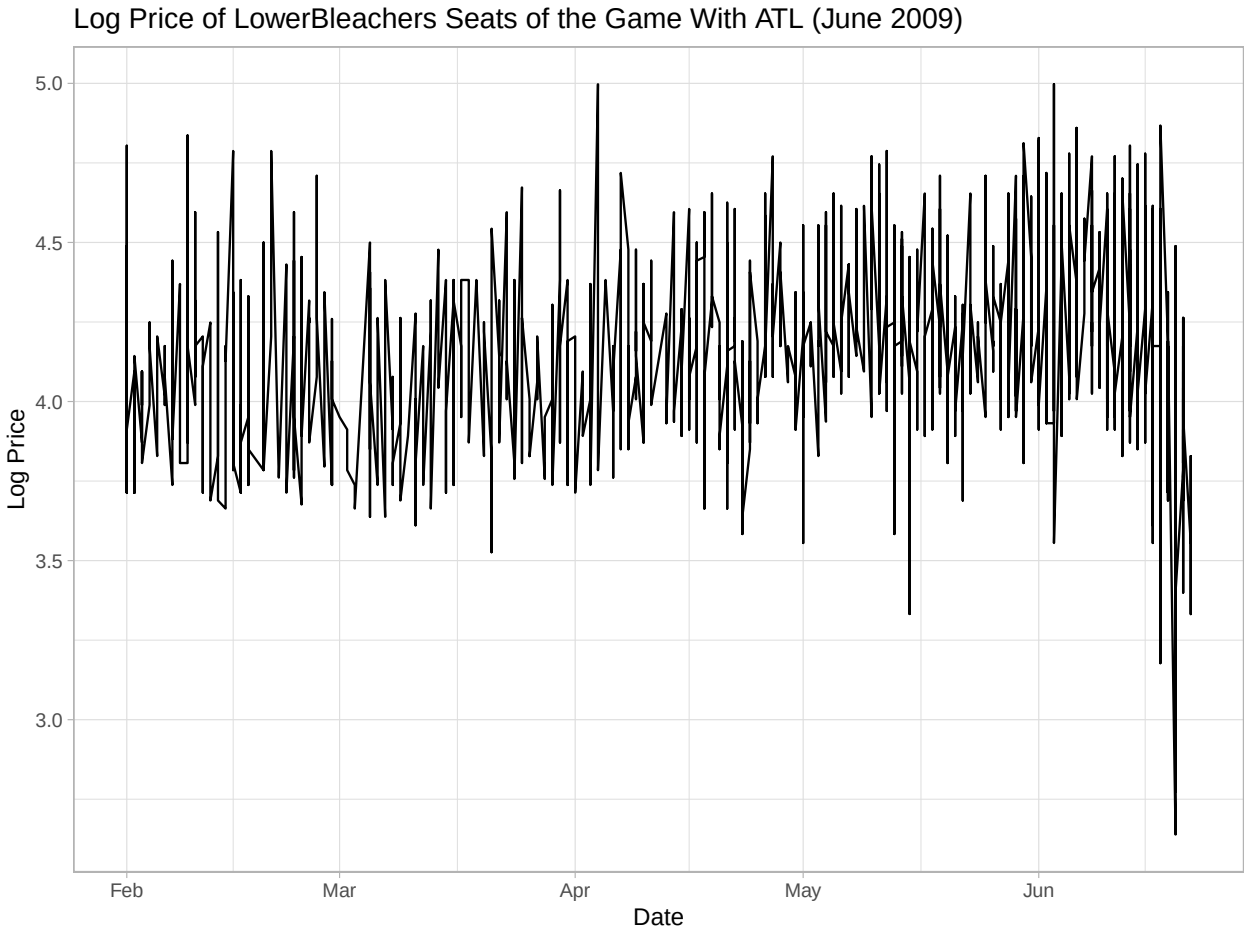
Before we answer this question with data, we can first try to approacah it with our own daily experiences. Typically, we can feel that as the event date gets closer, the ticket re-sellers on the StubHub marketplace will drop the prices to get rid of the inventory of the tickets. They would tend to make less money than to completely lost the profit since the value of the ticket is $0 after the event. However, there exists other cases where a event is so popular that the re-sellers would expect to run out of the stock at the certain point before the start time. Thus the question kinda depends on the last-minute demand supply relationship.

In this report, I would tend to explain by using more graphs than using regressions or parameters cause I can't guarantee the robustness of the data and analysis.

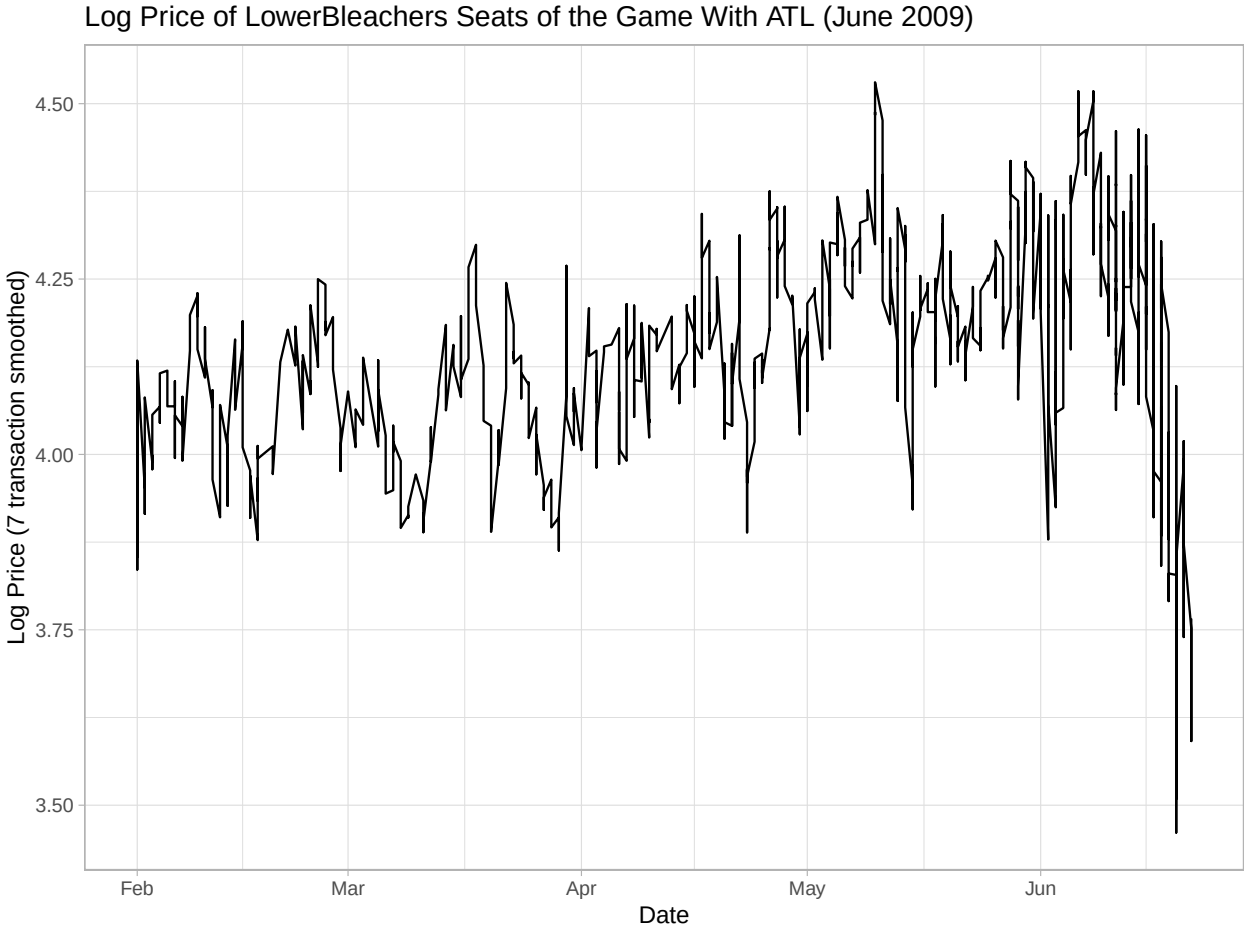
Evidence From Data (Examples).

Let's look at how the question was answered in some examples.

Here I selected price data for LowerBleachers Seats from the first game in the dataset (ATL, June).



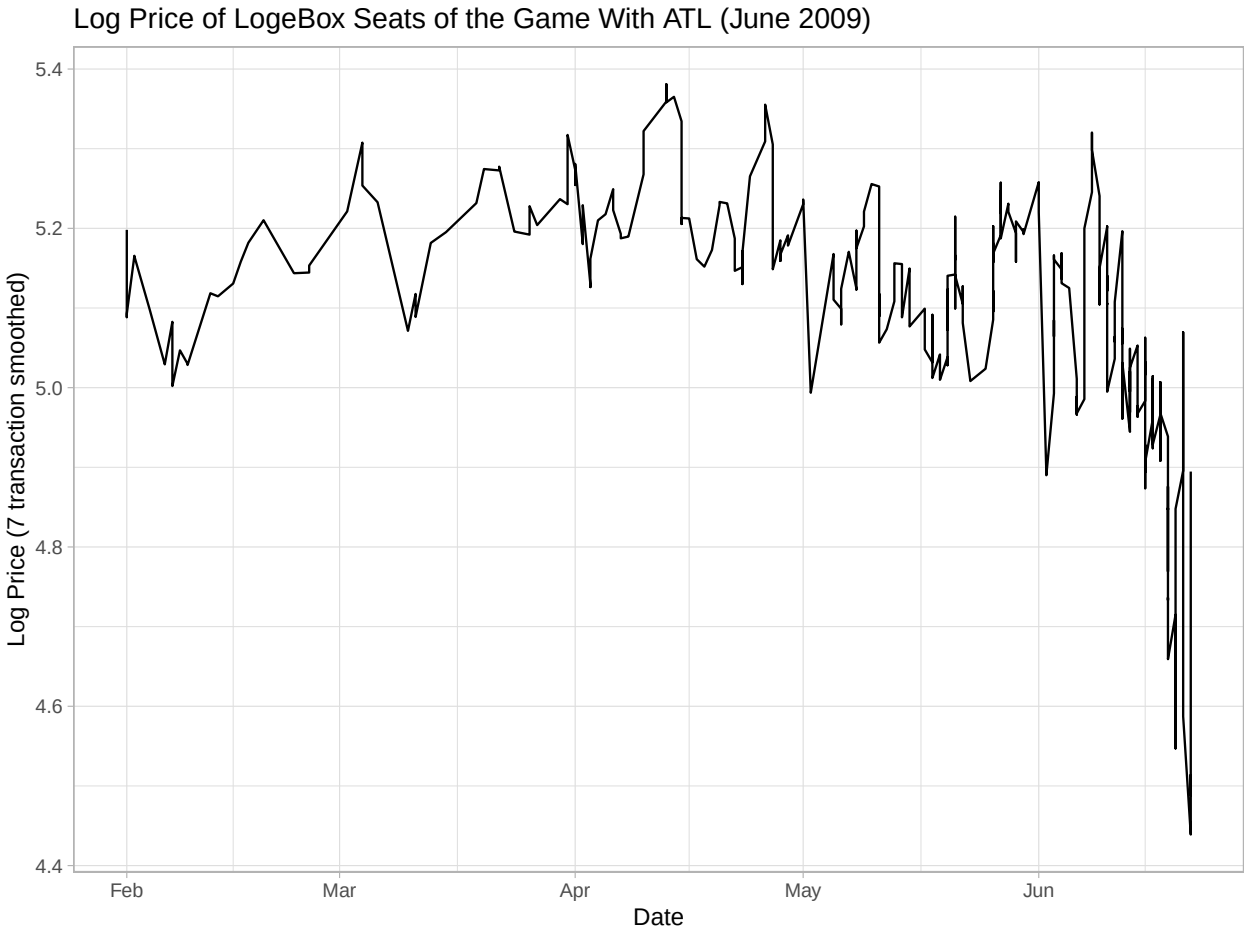
Well, the graph doesn't look very good. Except the drop of the price in the last few days, we can hardly see a trend. Here I use the seven transaction average method to smooth the line.



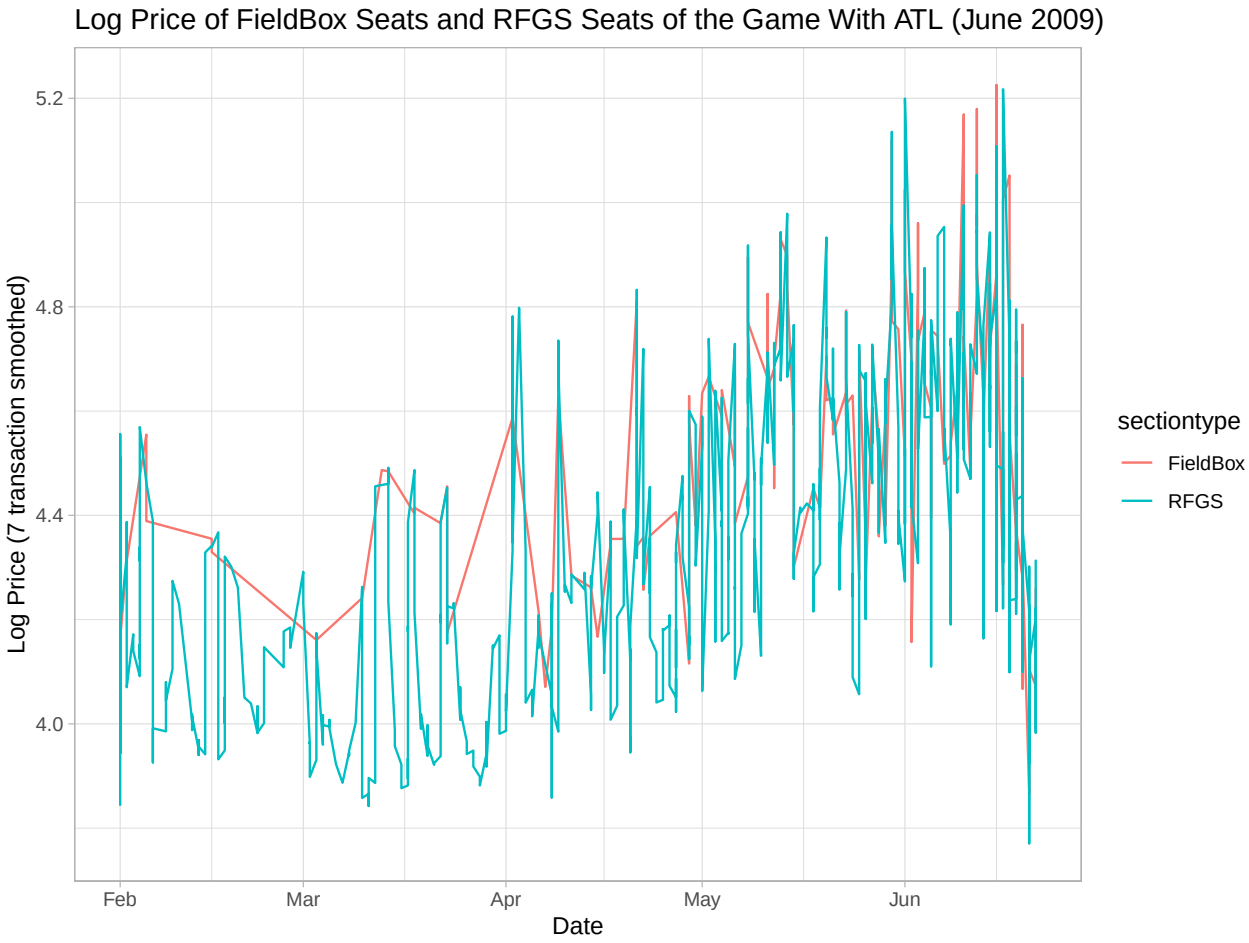
Right now it is much better, we can see that the price kept increasing until like 15 days before the event, then it falls dramatically as becoming closer to the event. So, it appears to be the first case that we discussed above. We want to know if other seats, other games, or other seasons have the same trend.

Let's look at another example from the price of FieldBox Seats of the same game.

Note that LogeBox Seats are more expensive than LowerBleachers Seats, thus we would expect that there were only few transactions before the months leading up to the game.



Different from LowerBleachers Seats, the price of LogeBox Seats peaked between April and May instead of early June. This may have been caused by a sudden increase in demand for better seats in April. Then prices dropped from their peak as supplies increased and then plummeted about 10 days before the game.



These are the situations of other seats. We can observe that these graphs generally follow a same pattern: increases or floats at the beginning, peaks at a certain point, and then drops rapidly a dozen days before the game.

Sum up our goal.

Our object right now is clear: we want to find that certain point that prices started to fall. Why are they important? Imaging you are going to an event, you know that the ticket price would drop and the last minute price is always the cheapest so you want to buy the ticket when you get there. But in fact you are also taking the risk that you could miss out on it.

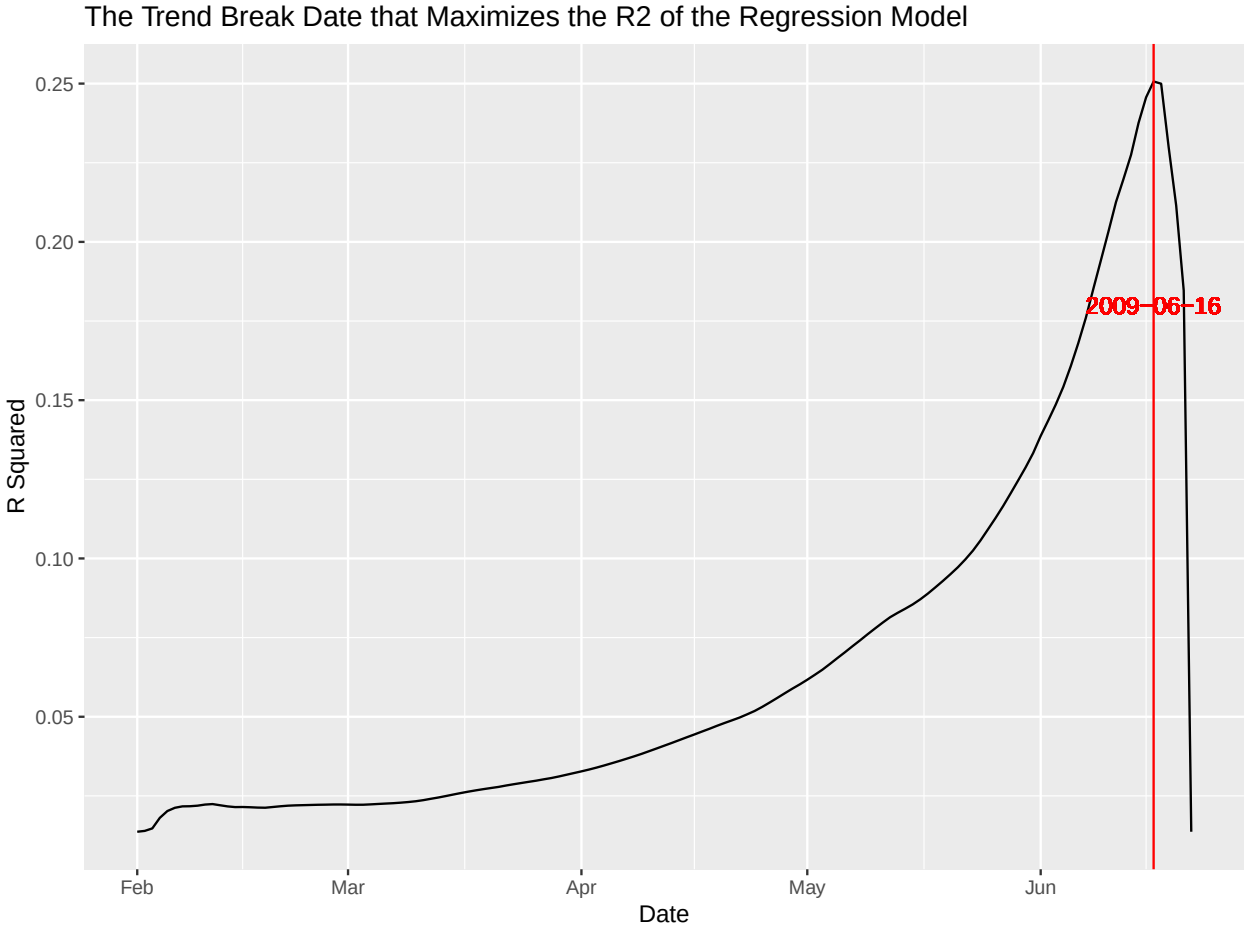
The information on that "turning point" can help you (**here I define the turning point as the point such that after that point, we can tell there is a trend, so it's not the point that started decreasing**). If the turning point is like 10 days ahead of the event, that means the demand of the tickets started to decrease so you are probably safe to buy the last minute ticket. But, if the turning point is the last day or even no turning point, which means the event is so popular that you are gonna miss the event.

Thus knowing the turning point can help people better react the changes of the price and assist them to pick up the best worth ticket without missing the event.

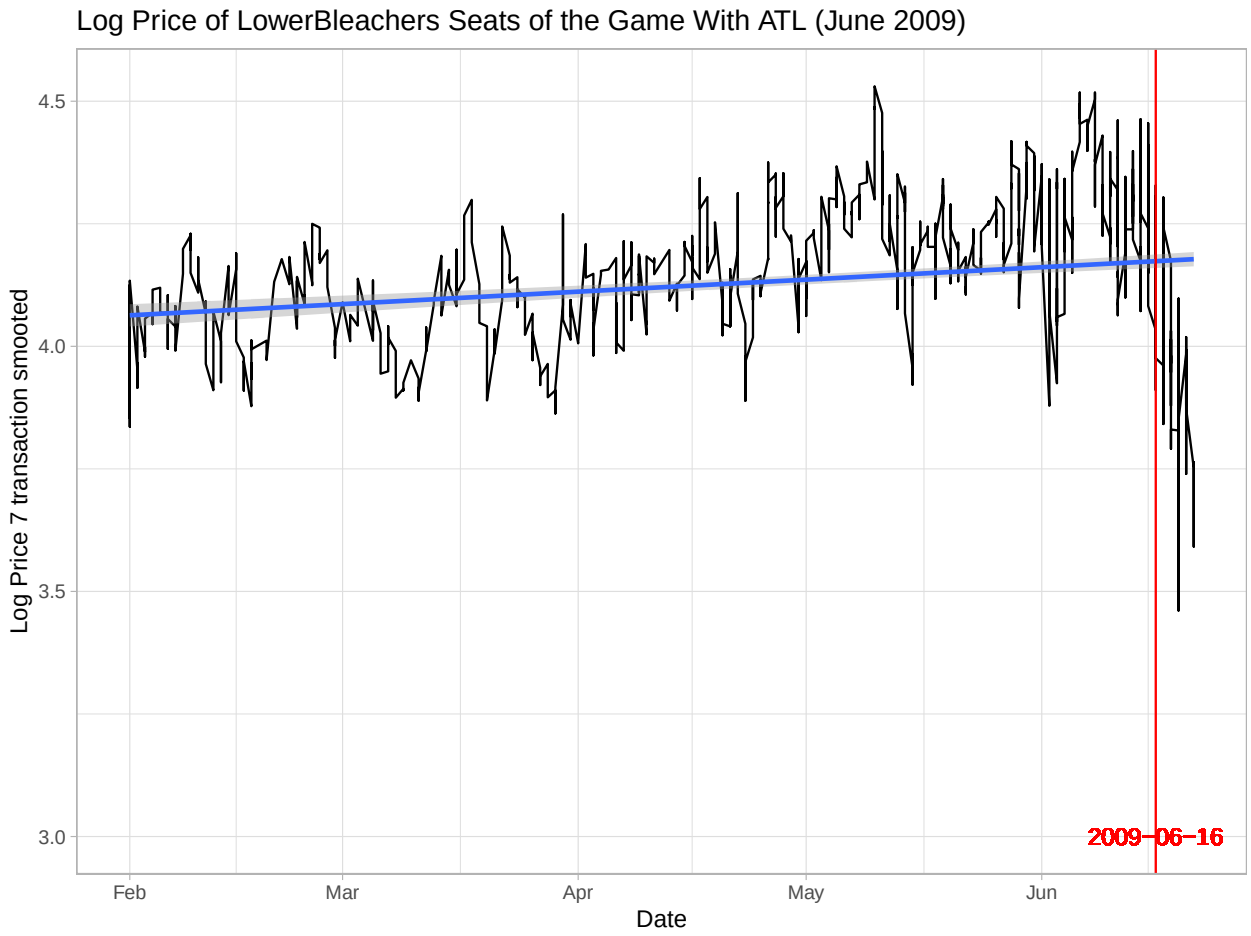
Measuring the turning point.

Again, we start with the same example(game with ATL and LowerBleachers).

We measure the "trend break" at some point between Feb and June. In other words, I calculate and report the trend break day that maximizes the R^2 of the regression model.



Here we observe that June 16 is the best day that we can confirm a down trend of the price. It is the day that we should start to keep close track on the price and consider purchasing the ticket.



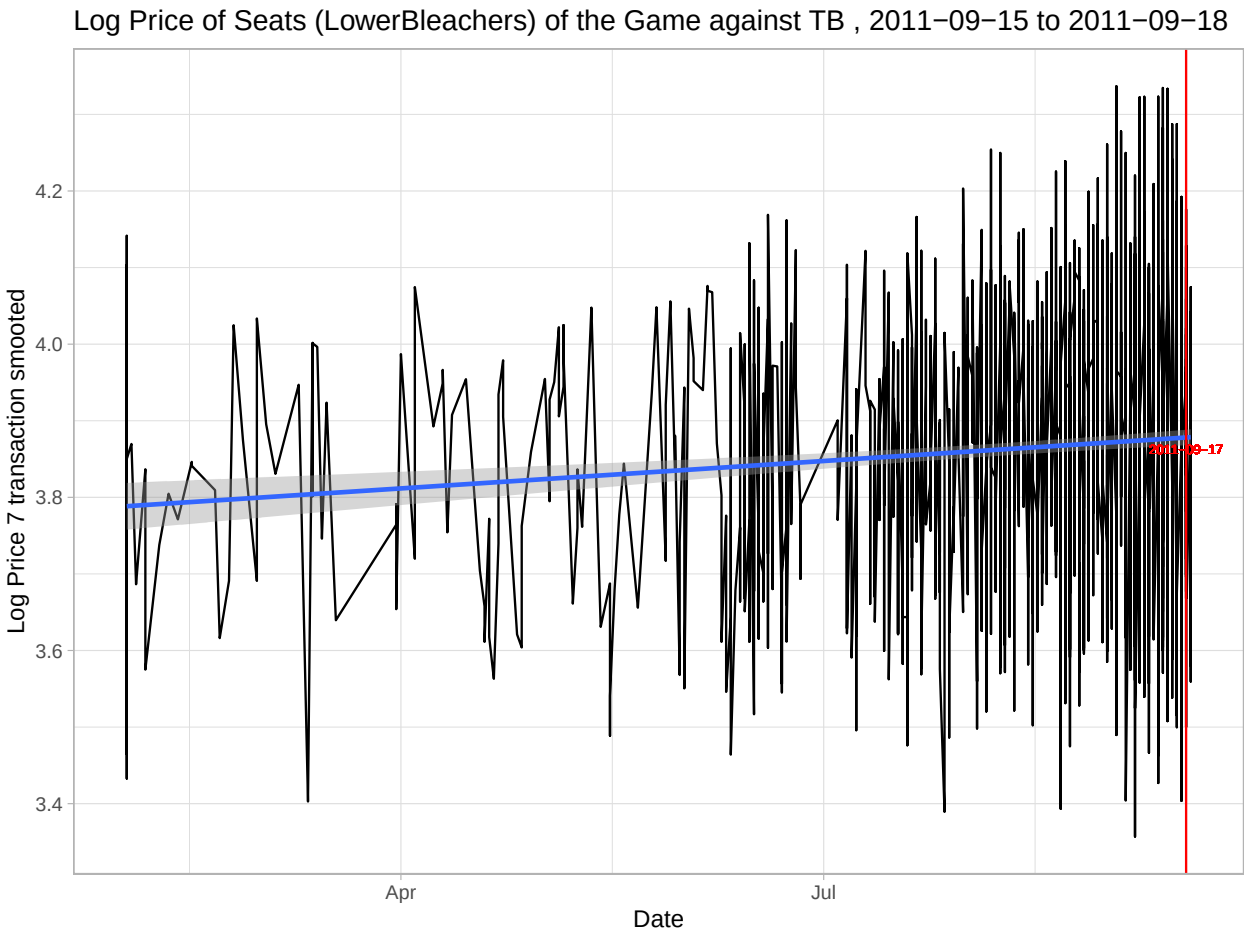
Let's look at how does the turning point do in the trend of prices. The blue line the OLS fit of the graph and clearly it doesn't fit very well, esepcially for the later part of the data. While the red line, tells us we can safely expect a incoming down slope of the graph, and it fits the graph well.

Conclusion

From previous examples, we can observe the trend of prices goes up slowly then goes down (the turning point) 5 days before this event.

What about others? I made a function called *turningPoint* that only takes 4 inputs. It will give the plot that shows the trend of prices, OLS regression line, and the turning point.

```
source("turning_point_maker.R")
turningPoint(data = red_sox, seats = c("LowerBleachers"),
             game_startdate =  "2011-09-15", game_enddate = "2011-09-18")
```



Here is an example: I consider the game that started at "2011-09-15", ended at "2011-09-18", and the "LowerBleachers" seats. We can see that the turning point is almost the last day of the game, which means this event is so popular that we can only tell the trend of prices at the very end, no matter it kept increasing or decreasing. In this case, we better buy the ticket early.

Right now we can analyze the trend of prices for specific game and specific seats. Maybe we can analyze all seats in one game and take the weights by the total numbers. Or maybe we can conclude all the games in each year and compare them with each other to see if there is a difference between seasons. Anyway, the rest is the just labor work, and I won't show it here.