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# Decision Making In A Sequential Game: The Case Of Pitting In Nascar

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Decision Making in a Sequential Game: The Case of Pitting in NASCAR

This paper uses data from NASCAR to examine strategic decision making with professional players and high stakes. We look at driver decisions to pit, enabling car performance to be improved at the cost of track position. Pitting decisions are sequential, unlike choices that have previously been used sports to test game-theoretic play. Optimal decision making should result in the subgame perfect equilibrium outcome. After estimating the likelihood of passing another driver based upon the decision to pit or not, we find little evidence that drivers make optimal decisions. Instead we find that too often cars simply follow the preceding car.

Key Words: Backward Induction, NASCAR, Sequential Decision Making

"If we didn't pit, I can assure you that 90% of the guys behind us would have pitted and we would have definitely lost the race if that's the case." – Sprint Cup Driver Denny Hamlin[1]

Given the prevalence with which game theory is used to analyze strategic behavior in a wide variety of settings, it is important to empirically validate its predictions. Most of this work has been done using the methodology of controlled laboratory experiments where the researcher has complete information and controls the game. Sports provide another testing ground for game-theoretic predictions of behavior. Like controlled laboratory experiments (and unlike most naturally occurring data) sports have clearly defined strategy spaces and observable actions and outcomes. Unlike the laboratory, the players are professionals with considerable experience and training and they are often playing for large stakes. Walker and Wooders (2001) find evidence to support minimax play by professional tennis players. Chiappori, et al. (2002) and Palacios-Huerta (2003) report that the mixed strategy equilibrium describes the penalty kick behavior of professional soccer players. These results are encouraging, but are limited to simultaneous play games. However, as argued by Levitt, et al. (2011, p. 975), "backward induction represents one of the most basic concepts in game theory." Are there opportunities to study backwards induction and sequential decision making in the sports world? Yes.[2]

The National Association of Stock Car Auto Racing (NASCAR) Sprint Cup series is stock car racing's premier league and it is big business. Trevor Bayne, the winner of the 2011 Daytona 500 race won nearly $1.5 million in prize money that afternoon.[3] Amato, et al. (2010) report that NASCAR's 75 million fans contribute $3 billion towards its profitability. NASCAR is second only to the National Football League in viewership (Chang 2007) and sponsorship for a single Cup car can be $20 million (Brown 2008 as cited by Groothuis, et al. 2010). NASCAR fans are notoriously loyal to drivers and sponsors (Groothuis, et al. 2010). O'Roark, et al. (2009) find that fans can more readily identify the brands of winning drivers. Thus, drivers have both direct (race purse) and indirect (greater value to sponsors) incentives to win races. Several studies have also looked at how the tournament structure of prize money impacts behavior (see Bothner, et al. 2007, Von Allmen 2001, and Schwartz, et al. 2007).

While many choices factor into winning a race from engine set-up to driver ability, one important decision is pitting strategy late in a race. Pit road refers to a side area on the race course where the driver can stop to refuel and have corrective adjustments made to the car. Pit crews, as the people who work on a car are called, can refuel the car and change all four tires in less than 15 seconds, but with people driving at speeds in excess of 200 m.p.h. the loss of this much time can put a driver far behind the competition. So while adjustments to the car improve performance, a driver that pulls onto pit road risks being passed by those behind him. Races are normally several hundred miles in duration so that cars will have to stop multiple times to refuel.

When an accident or a safety concern occurs on the track, race officials wave a yellow caution flag (as opposed to the normal all clear green flag). Under yellow flag conditions racers must remain in their relative positions and are not allowed to pass. Speeds are also significantly reduced during a caution. Thus, there is an advantage to pitting during a caution in that the distance between the leader and the car that pitted is smaller than it would be under green flag conditions. Therefore when a caution flag comes out late in the race, drivers face sequential strategic choices.

Pit road has a single entrance point on the track and a driver approaching the entrance to pit road has only a split second to react to the decisions of the drivers ahead of him and anticipate the reactions of the drivers behind him. This paper analyzes data from the 2009 NASCAR Sprint Cup series to determine the optimal sequential pitting decision for drivers. We find that drivers do not follow the optimal strategy and instead tend to imitate the driver who is directly ahead of them in the race. While previous experimental work has questioned the ability of players to backwards induct (see Levitt, et al. 2011 for a review), we believe this to be the first direct evidence from naturally occurring data that professionals have difficultly engaging in backwards induction.[4]

**A Model of Pitting**

In order to evaluate driver decisions to pit or not pit under caution late in a race, we develop a simple sequential model of pitting. First, we assume that drivers are attempting to maximize their chance of winning the race. Each of the $n$ drivers has to choose an action $A \in$ {Pit, Not pit}. Driver $i \in \{1, n\}$ is in the $i^{th}$ position and makes his decision after observing the actions of Drivers 1, …, $i$-1 and before Drivers $i$+1, …, $n$ make their decisions. After each of the drivers has made their decision the cars are reordered according to the following rules:

1. If Driver $i$ and Driver $j$ chose different strategies then the driver that chose Not Pit restarts ahead of the driver that chose Pit.

2. If Driver *i* and Driver *j* chose the same strategy then Driver *i* restarts ahead of Driver *j* iff $i < j$.

The first rule simply states that all drivers who pit are passed by the drivers who do not pit. The second rule covers two cases. If both cars do not pit then the caution rules dictate that the relative order remains unchanged. If both cars pit then the actual time in the pits depends on the specific modifications that are made during the stop, but rule 2 assumes that the expected duration is equal thus maintaining the ordering.

Once the cars are reordered and the caution is over, the drivers race to the finish. The likelihood that a car successfully passes another car is a function of the actions taken by the two cars (and other factors such as the number of laps remaining and the length of a lap[5]). Let N denote the probability that a car that did not pit successfully passes another car that did not pit. Similarly, let P denote the probability that a car that pitted successfully passes another car that pitted. Let D denote the probability that a car that pitted successfully passes a car that took the different action of not pitting. Given the way cars are reordered, no car that did not pit is behind a car that did pit and hence there is no need for a fourth term. For simplicity, we assume that cars which are higher ranked at the restart have the first opportunity to pass.[6]

Figure 1 shows the extensive form game for the cases of two racers. In three of the four outcomes Driver 1 restarts in first place and his chance of winning is simply 1 minus the probability that he is passed. However, if Driver 1 pits and Driver 2 does not pit, then Driver 1 will restart in second place and must pass Driver 2. The standard solution concept is that of subgame perfection. If Driver 1 chooses to not pit then Driver 2 will pit if D > N and if Driver 1 does pit then Driver 2 will pit if $P > 1 - D$. Driver 1's choice ultimately depends on how he (correctly) anticipates Driver 2 will react in each subgame.

This game can be extended to any number of drivers in a straightforward manner. We introduce the notation $\{A_1, \ldots, A_n\}$ to denote a path through the game where $A_i$ is the action taken by Driver *i*. While the equilibrium path will depend on the specific parameters, if we assume that $D > N$, which seems reasonable given that pitting offers the opportunity to improve car performance, then at least one driver should pit in equilibrium. This is formalized in the following proposition.

Proposition: If $D > N$ then $\{N, \ldots, N\}$ cannot be a subgame perfect Nash equilibrium path.

Proof: Suppose that $\{N, \ldots, N\}$ is a subgame perfect equilibrium path. Consider the decision of Driver *n*. Since none of the previous drives has opted to pit, then not pitting results in a $(N)^{n-1}$ chance of winning while pitting results in a $(D)^{n-1}$ chance of winning. By assumption $1 \geq D > N \geq 0$ and thus $(N)^{n-1} < (D)^{n-1}$. Therefore, if the other *n*-1 drivers have not pitted, Driver *n* would prefer to pit, which contradicts no one pitting being a subgame perfect equilibrium. □

<Insert Figure 1 Here>

**Estimating Model Parameters for NASCAR Sprint Cup Series**

The 2009 NASCAR Sprint Cup series involved 36 races in total. For most races we have lap-by lap position data captured through a computer program that monitored NASCAR's website in real-time during a race as positions were being updated.[7] This constitutes our primary data source. For all but one race, we also have video recordings which were sometimes used to clarify and confirm the lap-by-lap data.[8] Of the races for which data are available, we eliminate races on road courses races. Road course races have non-standard shapes with more turns and smaller road widths and are likely to have distinct optimal pitting strategies. We also restrict our data set to races in which the race was completed instead of being forced to end early due to rain. Finally, we restrict attention to races in which a caution occurred within the final pit window. The pit window is defined as the number of laps that a car can complete on a single tank of gas, which varies with lap length and road conditions.[9] Table 1 summarizes our sample.

<Insert Table 1 Here>

We restrict our focus to the decisions of drivers on the lead lap during the final caution. Other drivers are not allowed to pit on the same caution laps as the "leaders" and restart behind the leaders regardless of pitting decisions. Further, these racers essentially have no chance of winning the race given how far behind they are and their probabilities of passing other cars are likely different from those cars that are on the lead lap because they have been lapped. Table 2 gives detailed information for each of the analyzed restarts.

For each race identified in Table 2, we know the order when the pit road opened under the final caution, each driver's decision to pit or not[10], the order at the restart, and the order at the end of the race. We then compare the restart position and the finishing position to see if any particular driver has successfully passed. There are three types of passes: a car that pitted passing another car that pitted (P→P), a car that pitted passing a car that did not pit (P→N), and a car that did not pit passing another car that did not pit (N→N). As described in the model section, we begin with the second place car and determine if he was able to pass the leader. We then evaluate the third place car and so on. As an example with $n$ = 5 racers, if the observed path through the game is {N,N,P,P,N}, then only the third and fourth place drivers before the caution pitted. Let (1,2,3,4,5) denote the ordered set of five drivers before the decision to pit. In this example, the restart order would be (1,2,5,3,4). We would first look at the attempted pass of Driver 1 by Driver 2. Suppose the final order at the end of the race was (2,1,4,5,3). Since Driver 2 finishes before Driver 1, this pass attempt was a successful N→N resulting in the order (2,1,5,3,4). We would then consider Driver 5's attempt to pass Driver 1, which, according to the final order, was an unsuccessful N→N attempt leaving the order at (2,1,5,3,4). Fourth place on the restart was Driver 3, which was unsuccessful in passing Driver 5, the car that restarted ahead of it, and thus was an unsuccessful P→N attempt. The order would remain (2,1,5,3,4). Finally, we consider last place at the restart. Driver 4 passed Driver 3, a successful P→P resulting in the order (2,1,5,4,3). Driver 4 then successfully passed Driver 5, a successful P→N, but failed to pass Driver 1, an unsuccessful P→N, resulting in the final ordering (2,1,4,5,3).

<Insert Table 2 Here>

The number of successful and unsuccessful passing attempts by type for the analyzed races are shown in Table 3. The raw numbers confirm the intuition that pitting enhances car performance because cars that pit have more success passing cars that do not pit than cars that did not pit have passing other cars that did not pit (i.e. 76% > 64%). Also, cars that pit have more difficulty passing cars that pitted than passing cars that did not pit (i.e. 70% < 76%).

<Insert Table 3>

Of course, the probability of a successful pass depends on a variety of factors. While we cannot control for all possible influences, we do know the number of laps remaining in the race at the restart and the lap length, both of which affect the number of passing opportunities that a driver will have. As our goal is to estimate the probability that each type of pass is successful so that we can evaluate driver strategy, we pool the data across races and use a separate probit estimation for each type of passing attempt. For the estimation, the dependent variable equals 1 if the attempted pass was success and 0 if it was not. We control for both “LapLength” (i.e. the distance in miles of a single lap) and “Laps2Go” (i.e., the number of laps remaining when the caution is over). To allow for the fact that track structure and thus speeds differ with track length, we also include “Miles2Go”, which is the interaction of “LapLength” and “Laps2Go”. Table 4 provides the estimation results for the three types of passing attempts, while Table 5 gives the estimated probabilities for each type of passing attempt by race. From Table 4, it appears that all three types of passing attempts are more likely to be successful the larger the size of a lap and the more laps that are left.

<Insert Table 4 Here>

Insert Table 5 Here>

**Analysis of Driver Strategy**

Analyzing each driver’s decision amounts to constructing the appropriate extensive form game for each race, similar to Figure 1, and then comparing observed behavior to subgame perfect behavior at each node along the realized path. That is, each driver is evaluated in comparison to the optimal choice at his realized decision node assuming subsequent drivers will respond optionally regardless of the optimality of any preceding driver. The game trees become prohibitively large quickly, involving $2^n$ possible paths and payoffs and $\sum_{d=1}^{n} 2^{d-1}$ individual decision nodes all of which must be considered. Due to computational constraints, we limit our attention to races where $n \leq 20$ resulting in 210 total driver decisions in 12 races.[11]

Before looking at actual driver decisions we first consider equilibrium behavior. Rather than recreating the extensive form game trees for each race considered, Table 6 provides the subgame perfect equilibrium path for each race. In none of the races analyzed in Table 6 should everyone pit. In three races (March 8th in Atlanta, July 11th in Chicago, and October 11th in Fontana) no one should pit. In all three of these races, there are only two or three laps left at the restart and thus a car does not have much of an opportunity to pass so maintaining track position is relatively more important. This is reflected in Table 5 as N is slightly greater than D for these three races. None of the other races that are evaluated have this relationship and in each case at least one driver should pit, consistent with our proposition. It is worth noting that none of the subgame perfect equilibrium paths are where no one pits up to a point and then everyone else does, excluding the three trivial cases discussed above where no one should pit. It is also interesting that in no case analyzed should a driver in the leading half of the group pit.

<Insert Table 6 Here>

We now turn to the actual behavior of the drivers. Table 6 indicates the optimal choice of each driver up until the point some driver deviates, but once a driver makes a sub-optimal choice taking the group off of the subgame perfect equilibrium path, the optimal response for others may differ from what is shown in Table 6.

Table 7 provides the observed behavior at each realized decision node. Entries in Table 7 marked with a * indicate that the driver made the optimal decision at that point in the game tree given the choices of the preceding drivers. Overall, half of the decisions were optimal. However, there is considerable variation in optimal behavior from race to race. In the October 11th race at Fontana, no one should pit and no one did resulting in the subgame perfect equilibrium outcome. In three races, no driver made the optimal decision (March 8th in Atlanta, April 5th in Texas, and October 4th in Kansas). In all three of these cases one should not pit if doing so would result in restarting in first place, but everyone chose to pit. In all of the other races considered, some drivers pitted and some did not. From the table, it appears that mistakes are more likely to occur in the later positions, when backwards induction should be easier. These mistakes are often due to people pitting when they should not. In fact, every race in Table 7 follows the pattern that once the first driver chooses to pit, everyone behind him pits too. This suggests that drivers are generally following the car ahead of them rather than engaging in backwards induction. In fact, of the 198 decisions by drivers who were not the race leader, only 4% did not follow the preceding driver.

<Insert Table 7 Here>

We anticipated estimating a Probit model where the pitting decision was the dependent variable and the independent variables included the conditionally optimal choice and the decision of the preceding car. However, the correlation of one's pitting choice and the decision of the preceding car is so high (approximately 0.93) that the model is recognized as having "quasi-complete separation."[12] Further, the correlation between the optimal choice and the observed decisions is very low (approximately -0.15). We take this as sufficiently convincing evidence that drivers are simply following the car ahead of them rather than reacting optimally.

**Concluding Remarks**

Concepts from game theory are used to analyze a wide array of strategic situations. Recently, several scholars have analyzed various sporting events in order to test basic game theoretic predictions. The intent of these projects is not so much to test the athlete's ability to conform to the theoretical predictions, but rather to ascertain the degree to which theory predicts behavior. While the results generally indicate that the theory successfully predicts behavior, this work has been largely limited to simultaneous play games such as penalty kicks in soccer and serves in tennis.

This paper uses a sports setting to evaluate the predictive power of game theory in sequential games requiring players to backwards induct. Specially, we look at the sequential pitting decisions of NASCAR Sprint Cup drivers under caution late in a race. The Sprint Cup series is the highest level of professional stock car driving where race purses can exceed $1 million dollars. Under a caution, drivers cannot pass each other, but they can enter the pit area to enhance their car's performance while risking track position depending upon the decisions of the drivers behind them. We collected data from the 2009 racing season and estimated the likelihood of successfully passing another car based upon the remaining distance in the race and the decision to pit. Our estimation results indicate that passing attempts are more likely to be successful at larger tracks and less likely to be successful when the race is nearly complete.

Based upon our estimated likelihood of a pass being successful, we are able to construct an extensive form game for each race and compare the observed behavior with the optimal behavior at each decision node that is reached. Due to computational limits we restrict our attention to races with twenty or fewer drivers on the lead lap. Far from implementing backwards induction and making optimal decisions, it appears that drivers use a simple heuristic of following the preceding driver.

As with any attempt to use field data to test a theoretical model, we have made several assumptions about the game. For one, we assume that drivers are attempting to maximize their chance of winning the race instead of their expected standings in the race or across the entire season. Another assumption that we make is that all driver decisions in a race are made independently. In reality, one owner may have multiple cars in the race, thus enabling those drivers to coordinate their decisions. While accommodating either of these alternatives would change the subgame perfect equilibrium path, it is unlikely such changes would yield the observed follow the proceeding driver strategy as optimal.

**Notes**

1. As quoted in 4wide.com interview after Hamlin won the April 2010 Martinsville Sprint Cup race.

2. While Levitt, et al. (2011) look at the behavior of professional chess players, they do so in simple stylized games rather than chess.

3. With this type of money on the table, it is not surprising that cheating is also a major concern in NASCAR (see Baucus, et al. 2008)

4. Levitt, et al. (2011) find that professional chess players do backwards induct in “pure backward induction games” as opposed to centipede games.

5. Maximum speed and track width vary widely depending on the length of a lap around the track.

6. There is some justification for this assumption in that cars are not allowed to pass when a race resumes until they pass the start-finish line which denotes where laps begin and end. Thus the second place car comes up to speed before the third place car, and so on.

7. This data collection process did not begin until the fourth race of the season. Some of the later races were not captured because the race was delayed while the computer program ran at the originally scheduled race time. Other races were not captured because the race was on a road course.

8. Videos were provided on the official NASCAR website www.nascar.com.

9. Data on estimated pit windows are available at http://www.racegoodyear.com/cfmx/web/racing/.

10. The decision variable is determined by a combination of the lap-by-lap data and the video data. These data are unambiguous for 14 of the analyzed races. However, in 7 of the races we had to infer the actions of at least some of the drivers. This is caused by a variety of factors such as the caution occurring during a commercial break. Also, the lap-by-lap data can be misleading because the start finish line crosses pit road at some tracks and sometimes cars are in the wrong order and have to be reset by NASCAR officials before the race is restarted. When inferences are made as to the pitting decision, the guiding rules were that a car that moved back in the field pitted since that car could not be passed on the track during a caution and a car restarting behind a car that pitted also pitted since otherwise it would have moved ahead of

the pitting car in the restart order.  The results remain substantively unchanged if the races for which the pitting decision had to be inferred are omitted.

11. With *n* = 20, the computation time was approximately a week.

12. This message is from the statistical package EViews.

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Figure 1. Extensive Form of Pitting Game with *n* = 2 Players

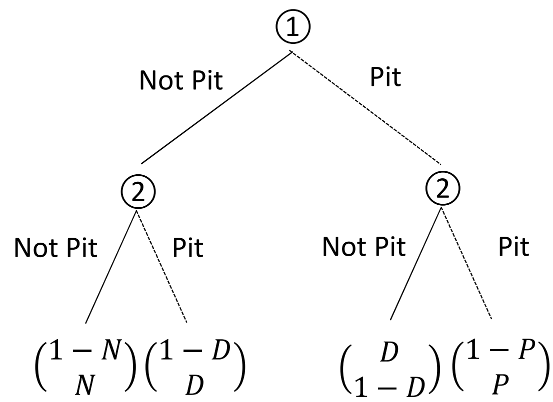


TABLE 1. 2009 Races Included in Sample

| Date | Location | Name[a] | Data[b] |
|---|---|---|---|
| 2/15 | Daytona | Daytona 500 | NL |
| 2/22 | Fontana | Auto Club 500 | NL |
| 3/1 | Las Vegas | Shelby 427 | NL |
| 3/8 | Atlanta | Kobalt 500 | |
| 3/22 | Bristol | Food City 500 | |
| 3/29 | Martinsville | Goody's 500 | |
| 4/5 | Texas | Samsung 500 | |
| 4/18 | Phoenix | Subway 500 | NL |
| 4/26 | Talladega | Aaron's 499 | |
| 5/2 | Richmond | Friedman 400 | |
| 5/9 | Darlington | Southern 500 | |
| 5/25 | Charlotte | Coca-Cola 600 | NL |
| 5/31 | Dover | Autism 400 | |
| 6/7 | Pocono | Pocono 500 | |
| 6/14 | Michigan | LifeLock 400 | OW |
| 6/21 | Sonoma | SaveMart 350 | RC |
| 6/28 | Loudon | Lenox 301 | R |
| 7/4 | Daytona | Coke Zero 400 | NL |
| 7/11 | Chicago | LifeLock 400 | |
| 7/26 | Indianapolis | Allstate 400 | |
| 8/3 | Pocono | PA 500 | NL |
| 8/10 | Watkins Glen | Heluva Good! | NL |
| 8/16 | Michigan | Carfax 400 | |
| 8/22 | Bristol | Sharpie 500 | |
| 9/6 | Atlanta | Pep Boys 500 | |
| 9/12 | Richmond | Chevy 400 | |
| 9/20 | Loudon | Sylvania 300 | NL |
| 9/27 | Dover | AAA 400 | |
| 10/4 | Kansas | Price 400 | |
| 10/11 | Fontana | Pepsi 500 | |
| 10/17 | Charlotte | Banking 500 | |
| 10/25 | Martinsville | Tums 500 | |
| 11/1 | Talladega | Amp 500 | |
| 11/8 | Texas | Dickies 500 | OW |
| 11/15 | Phoenix | Checker 500 | NL |
| 11/22 | Homestead | Ford 400 | NL |

a. Some names have been condensed for space. The number in a name sometimes refers to the total distance of the race and sometimes refers to the number of laps completed during the race.
b. NL denotes that the race was excluded because lap-by-lap data was not captured. R denotes that the race was shortened due to rain and therefore excluded. RC denotes a road course that was excluded from the sample. OW denotes that the race was excluded because the last caution was outside the final pit window.

TABLE 2. Details of Analyzed Races

| Date | Location | Lap Length (Miles) | Laps to Go on Restart | Pit Window | Number of Racers on Lead Lap | Number of Leaders who Pit |
|---|---|---|---|---|---|---|
| 3/8/2009 | Atlanta | 1.54 | 2 | 50-54 | 12 | 12 |
| 3/22/2009 | Bristol | 0.533 | 2 | 130-140 | 16 | 4 |
| 3/29/2009 | Martinsville | 0.526 | 23 | 125-135 | 18 | 2 |
| 4/5/2009 | Texas | 1.5 | 26 | 50-55 | 16 | 16 |
| 4/26/2009 | Talladega | 2.66 | 4 | 34-36 | 23 | 6 |
| 5/2/2009 | Richmond | 0.75 | 39 | 100-110 | 25 | 10 |
| 5/9/2009 | Darlington | 1.366 | 21 | 60-65 | 24 | 6 |
| 5/31/2009 | Dover | 1 | 27 | 75-80 | 19 | 1 |
| 6/7/2009 | Pocono | 2.5 | 35 | 35-37 | 28 | 28 |
| 7/11/2009 | Chicago | 1.5 | 2 | 50-55 | 18 | 5 |
| 7/26/2009 | Indianapolis | 2.5 | 24 | 32-35 | 24 | 7 |
| 8/16/2009 | Michigan | 2 | 38 | 40-44 | 33 | 20 |
| 8/22/2009 | Bristol | 0.533 | 4 | 130-140 | 22 | 0 |
| 9/6/2009 | Atlanta | 1.54 | 12 | 50-54 | 17 | 17 |
| 9/12/2009 | Richmond | 0.75 | 14 | 90-100 | 24 | 24 |
| 9/27/2009 | Dover | 1 | 28 | 75-80 | 19 | 11 |
| 10/4/2009 | Kansas | 1.5 | 27 | 50-55 | 16 | 16 |
| 10/11/2009 | Fontana | 2 | 3 | 42-45 | 20 | 20 |
| 10/17/2009 | Charlotte | 1.5 | 17 | 50-55 | 20 | 6 |
| 10/25/2009 | Martinsville | 0.526 | 2 | 125-135 | 19 | 2 |
| 11/1/2009 | Talladega | 2.66 | 2 | 34-36 | 29 | 0 |

TABLE 3: Passing Attempt by Type

| Passing Type | Attempts | Failures | Successes | Percentage Successful |
|---|---|---|---|---|
| N→N | 646 | 231 | 415 | 64% |
| P→N | 306 | 74 | 232 | 76% |
| P→P | 437 | 129 | 308 | 70% |

TABLE 4: Probit Estimation Results for Each Type of Passing Attempt

| | P→P | N→N | P→N |
|---|---|---|---|
| Constant | -1.78 | -1.31 | -1.03 |
| | (0.59***) | (0.20***) | (0.53*) |
| Laps2Go | 0.07 | 0.05 | 0.05 |
| | (0.02***) | (0.01***) | (0.02***) |
| LapLength | 0.95 | 0.82 | 0.59 |
| | (0.39**) | (0.09***) | (0.24**) |
| Miles2Go | -0.02 | -0.03 | -0.02 |
| | (0.01*) | (0.01***) | (0.01*) |
| Log Likelihood | -236.71 | -376.95 | -161.87 |
| # of Observations | 437 | 646 | 306 |

Standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

TABLE 5: Estimated Probability of Passing by Type of Attempt

| Date | Location | P | N | D |
|---|---|---|---|---|
| 3/8/2009 | Atlanta | 40.3% | 49.3% | 47.4% |
| 3/22/2009 | Bristol | 12.3% | 21.4% | 26.5% |
| 3/29/2009 | Martinsville | 49.2% | 50.1% | 60.0% |
| 4/5/2009 | Texas | 69.2% | 60.2% | 71.4% |
| 4/26/2009 | Talladega | 78.4% | 79.0% | 71.9% |
| 5/2/2009 | Richmond | 80.8% | 71.6% | 82.3% |
| 5/9/2009 | Darlington | 60.8% | 56.2% | 65.3% |
| 5/31/2009 | Dover | 64.1% | 58.4% | 69.3% |
| 6/7/2009 | Pocono | 83.1% | 61.1% | 80.6% |
| 7/11/2009 | Chicago | 38.9% | 48.0% | 46.5% |
| 7/26/2009 | Indianapolis | 80.1% | 66.5% | 76.8% |
| 8/16/2009 | Michigan | 82.6% | 62.8% | 81.5% |
| 8/22/2009 | Bristol | 14.6% | 23.7% | 29.3% |
| 9/6/2009 | Atlanta | 52.9% | 53.9% | 57.9% |
| 9/12/2009 | Richmond | 35.6% | 40.6% | 48.3% |
| 9/27/2009 | Dover | 65.7% | 59.4% | 70.5% |
| 10/4/2009 | Kansas | 70.3% | 60.6% | 72.3% |
| 10/11/2009 | Fontana | 57.7% | 63.1% | 58.3% |
| 10/17/2009 | Charlotte | 58.2% | 55.7% | 62.5% |
| 10/25/2009 | Martinsville | 12.2% | 21.2% | 26.3% |
| 11/1/2009 | Talladega | 78.0% | 80.0% | 71.2% |

Table 6. Subgame Perfect Equilibrium Behavior at Nodes Reached on the Equilibrium Path

| Date | Location | Equilibrium Path |
|---|---|---|
| 3/8/2009 | Atlanta | {N,N,N,N,N,N,N,N,N,N,N,N} |
| 3/22/2009 | Bristol | {N,N,N,N,N,N,N,N,N,N,N,N,N,P,N,P} |
| 3/29/2009 | Martinsville | {N,N,N,N,N,N,N,N,N,N,N,P,N,P,P,P,N,P} |
| 4/5/2009 | Texas | {N,N,N,N,N,N,N,N,P,P,N,P,N,P,N,P} |
| 5/31/2009 | Dover | {N,N,N,N,N,N,N,N,N,P,N,P,N,P,N,P,N,P,P} |
| 7/11/2009 | Chicago | {N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N} |
| 9/6/2009 | Atlanta | {N,N,N,N,N,N,N,N,N,N,N,N,N,N,P,N,P} |
| 9/27/2009 | Dover | {N,N,N,N,N,N,N,N,N,P,N,P,N,P,N,P,P,N,P} |
| 10/4/2009 | Kansas | {N,N,N,N,N,N,N,P,P,N,P,N,P,N,P,P} |
| 10/11/2009 | Fontana | {N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N,N} |
| 10/17/2009 | Charlotte | {N,N,N,N,N,N,N,N,N,N,N,N,N,P,N,P,N,P,N,P} |
| 10/25/2009 | Martinsville | {N,N,N,N,N,N,N,N,N,N,N,N,P,N,N,P,P,P,P} |

Table 7. Observed Driver Behavior

| Date | Location | Observed Sequential Pitting Decisions | Percent Optimal |
|---|---|---|---|
| 3/8/2009 | Atlanta | {P,P,P,P,P,P,P,P,P,P,P,P} | 0% |
| 3/22/2009 | Bristol | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,P,P,P,P} | 75% |
| 3/29/2009 | Martinsville | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,<br>*N,N,N,N,N,N,*P,*P} | 72% |
| 4/5/2009 | Texas | {P,P,P,P,P,P,P,P,P,P,P,P,P,P,P,P} | 0% |
| 5/31/2009 | Dover | {*N,*N,*N,*N,*N,*N,*N,*N,*N,N,<br>N,N,N,N,N,N,N,N,*P} | 53% |
| 7/11/2009 | Chicago | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,<br>*N,*N,*N,P,P,P,P,P} | 72% |
| 9/6/2009 | Atlanta | {P,P,P,P,P,P,P,P,P,P,P,P,P,P,P,P,P} | 0% |
| 9/27/2009 | Dover | {*N,*N,*N,*N,*N,*N,*N,*N,P,P,P,P,P,P,P,P,P,P,P} | 42% |
| 10/4/2009 | Kansas | {P,P,P,P,P,P,P,P,P,P,P,P,P,P,P,P} | 0% |
| 10/11/2009 | Fontana | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,<br>*N,*N,*N,*N,*N,*N,*N,*N,*N,*N} | 100% |
| 10/17/2009 | Charlotte | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,<br>*N,*N,*N,N,*P,*P,P,P,P,P} | 75% |
| 10/25/2009 | Martinsville | {*N,*N,*N,*N,*N,*N,*N,*N,*N,*N,<br>*N,*N,N,N,N,N,N,*P,*P} | 74% |