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Does watching football increase the chance of getting in a car accident?

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Introduction

In Great Britain, an estimated amount of 23,529 people was seriously injured in traffic accidents in the year 2020 only. Out of all these people, 1,460 people lost their lives due to the accident. Almost half of these casualties are among men between the ages of 25-59. Younger people of ages between 17-24 years old make around 15% of the total casualties. This number is even lower than usual, since this period includes 4 months of national lockdown due to the corona virus pandemic (Department for Transport, 2021). According to Statista (2022), a fatal accident resulted on average in around two million British pounds in prevention costs. These costs are significantly lower for serious and slight accidents, with costs of around 250,000 and 20,000 pounds, but these are still large amounts of money that the tax payer has to bear.

Policy makers are interested in what causes dangerous driving behaviour that leads to traffic accidents, which is a serious problem as sketched above. What causes these accidents? It might be that dangerous driving behaviour is a conscious decision, which is rationally taken by drivers after weighing the costs and benefits. An alternative explanation is that reckless driving tends not to be premeditated, but is instead caused by certain unexpected emotional cues. Both of these explanations have been studied and modelled by Card and Dahl (2011), to explain the effect of American football matches on family violence. The same principle would apply to football matches and car crashes. To shed some light on which of these competing explanations is most plausible, this thesis will examine how the outcomes of football matches - a source of emotional shocks - may affect the occurrence of car accidents.

Literature review

In former research, Hu et al. (2013) found via a survey and an experiment that negative emotions significantly elevate a driver´s risk perception, but that it does not lead to a suiting driving attitude. This leads to more dangerous driving behaviour by drivers that experience negative emotions. They also found the same results when the experiment tested for the mood of drivers. The opposite effect was found for happy people, but this positive effect was much smaller than the negative effect. This study is very relevant for this paper, since football matches tend to evoke both strong positive and negative emotions among supporters, which may affect their driving attitudes.

In research by the University of Leicester, it has however also been found that positive emotions lead to bad driving behaviour. They conducted an experiment where people would listen to football commentary on the radio while driving a simulated car, and they found that when the team the driver supported attacked, the driver would tend to drive faster, and vice versa for when the team is in defence. They also found that drivers would tend to let go of the steering wheel more often and would not pay as much attention to the road as usual, which might lead to dangerous situations (Pont, 2009).[1]

There have also been various other papers that have researched topics that relate to the topic of car accidents and football matches, but they all differ on certain points. Redelmeier and Stewart (2003) found a 41% relative increase in the average number of casualties after the telecast on Super Bowl Sunday. This effect also existed for non-fatal accidents and was absent during or before the telecast. They also found that the effect was larger in states that originated the losing team, compared to neutral and winning states.

Yam et al. (2020a) and Yam et al. (2020b) both study the effect of watching football matches on car accidents. The first paper studies the effect of football matches on the car accidents among cab drivers in Singapore and among the whole population of Taiwan, where the second paper is an extension on the study among cab drivers in Singapore. They found that when a big football match was played in Europe, the amount of car accidents in Asia rises significantly the next day. They argue this is because of the time difference between Asia and Europe, which results in people staying up all night to watch football. This would result in approximately 41,000 car accidents among Taiwanese people and around 400 car accidents among taxi drivers in Singapore annually.

Another big sport that tends to increase car crashes is the formula 1. Fischer et al. (1986) found that the number of high road deathly accidents in South Australia significantly rose in the last two months of 1985, right after the first Australian Formula 1 Grand Prix of Adelaide occurred. This might indicate that football is not the only sport that evokes strong emotional cues. The Grand Prix might have made fans overconfident with their own driving skills and made that fans wanted to copy Formula 1 drivers. These cues then lead to a significant increase in road traffic accidents and fatal traffic accidents.

Another research that studies sports matches and emotional cues is done by Card and Dahl (2011). They researched the effect of unexpected emotional cues caused by American Football matches on domestic violence. They found a significant rise in reported violence when the supported team suffered an upset loss, which is a loss when a win was predicted. They also found that this rise in violence only occurs after the game, and not before or during. Card and Dahl also found that this effect exists for emotionally salient games and for games against a traditional rival team. A similar effect was found by Deakin et al. (2007). They researched the effect that the 2006 World Cup had on

[1] Unfortunately this paper could not be found. This reference refers to a press release from the University of Leicester, regarding to the content of the paper.

ambulance car profiles and volumes in the area of Winchester. They found that on the day of the first match of the World Cup, ambulance call volume was 50% higher than on typical Saturdays. These calls also peaked right before and after the match. The call profiles consisted of mostly alcohol related emergencies, such as assault and road traffic accidents. The increase of assaults was mostly located after the match and increased again late into the evening, which is similar to the findings of the Card and Dahl (2011) paper.

A more recent study by Hughes et al. (2018) researched the effect of major sporting events on emergency department attendances. They particularly used the Euro 2016 football championship as their sporting event. They did however not find a significant impact of matchdays on emergency department attendances levels. What they did find however, was that in a four-hour pre-match period and during a match the attendances were significantly lower. They did not find a significant effect after matches, which is unexpected regarding the findings of the Card and Dahl (2011) and the Deakin et al. (2007) paper. The absence of this effect might however be the case since low-stakes matches were also included in the analysis, so the emotional cues evoked by these matches were not as high. This might be concluded since in France, whose national team lost the finals during that particular European Championship, the number of emergency department attendances did significantly increase in the four-hour period after the final. This indicates that there only might only be an effect on emergency department attendances when the stakes of a match are so high that the emotional cues that are evoked are much stronger than in more ordinary football matches.

Sport matches might also influence road traffic accidents via the alcohol consumption that occurs among many fans during the games. Vingilis et al. (1992) found that after the introduction of legal beer sales in Canadian sports stadiums, the proportion of alcohol related road traffic accidents are greater in postgame time than in pregame or control times. This proportion was however not significantly different than before the introduction of beer sales in stadiums. According to the authors, this suggests that consuming alcohol during a sports match was already commonly done before the legal introduction of it. Even though this paper did not find a significant effect, it did find that the proportion of drink driving accidents is larger after matches than before matches or in control times. This indicates that sports matches do have an effect on road traffic accidents, not only via emotional cues, but also via alcohol consumption.

What stands out from the current literature, is that all studies were done at a large scale. This thesis will be conducted on a micro-level, and will only take areas into account where the residents are likely to support a certain club. Furthermore, this thesis will only make use of EFL Championship matches, which are supported vastly, but more in local areas than over countries or the whole world.

This thesis will also take match outcomes into account, just like in the Card and Dahl (2011) paper. This has been done for American football matches, but not for European football games. Lastly, this thesis covers a period of three calendar years, which is much longer than in previous literature. All matches in these three years will be taken into account, which means that not only big matches will be analysed, like often happened in previous literature. This thesis will therefore be a contribution to the current literature.

This leads us to the research and sub questions of this paper:

- What is the effect of unexpected positive and negative emotional cues caused by football matches in the English Championship on the occurrence of car accidents in the areas of support of the playing clubs?
    - What is the effect of derby matches in the English Championship on the occurrence of car accidents in the areas of support of the playing clubs?

The answers on these questions will give us more understanding of why car accidents happen. Since this research has never been conducted for English football matches, it might lead to new policies that can prevent such car accidents after football matches, given that there will be found an effect. When this effect is likely to be caused by rationally taken decisions, as discussed above in the introduction, it might be necessary to launch big information campaigns which properly inform people of the real costs of dangerous driving. This will educate people better, which will make sure that the costs of dangerous driving in their own cost-benefits analysis will be higher. However, when the effect is likely to be caused by emotional cues, information campaigns will not be effective. The focus should then switch to other policies, like traffic calming infrastructure and more efficient public conveyance availabilities.
This thesis does not find a positive relation between football matches and car crashes, like the papers of Card and Dahl (2011) and Hu et al. (2013) would predict. It does however find that whenever a team achieves an unexpected win or suffers a normal loss, the number of car crashes after the match drop slightly. These findings are similar to the findings of Hughes et al. (2018), who did not find a significant rise in emergency department levels during the Euro 2016. They did find that there is a significant effect for highly salient games, which might also be the case for this thesis. This is however something that could be studied in further research.
The remainder of this thesis starts with describing the data that will be used for the analysis. Then will be continued with describing the variables and the methodology that will be used for the analysis. Then the results from the analysis will be discussed, and this thesis will finish with a discussion and conclusion regarding the results that were found.

Data construction

The data that will be used in this paper is drawn from two separate databases. The first database contains data on football matches and is accessed from Bet Brain[2], the second database contains data on road traffic accidents and is drawn from the Department for Transport[3]. The Bet Brain data contains information about football matches from the English Championship, with for example the match date, home and away teams and home and away goals. It also contains various match statistics, such as shots made, shots on target, cards given, etc. and betting odds data, which is drawn from several bookmakers. We use data from the Championship instead of the Premier League, since Championship club supporters tend to be more locally concentrated, which makes it easier to attribute an accident to a certain club's area of support. An overview of all the clubs that were active in the Championship during the relevant period is presented in appendix A. When a square is marked blue, this means that this club was active in the Championship during that particular season. This totals to 39 clubs that are included in the dataset, with 24 clubs that play in the Championship per season. The total amount of clubs is larger than the number of clubs per season, since the English Football League works with a promotion and relegation system, which makes that clubs can play in a different league the following season.

The accident data contains information on the date of the accident, the severity of the accident, several descriptives about the location of the accident and area specific fixed effects. The data consists of three different data sets, containing the accident data for the years 2010, 2011 and 2012. These datasets have been combined into one set, which then contains accident information on the 01-01-2010 – 31-12-2012 period.

The period of which the data is available are three full years. This poses a problem, since the Championship season starts in August and ends in May. This means the competition does not follow calendar years and the period on which we have data starts and ends mid-season. To overcome this problem, the matches in the first half of the 2009/10 season and in the second half of the 2012/13 season will be excluded from the dataset. This way both the accident and the football data cover the same time period.

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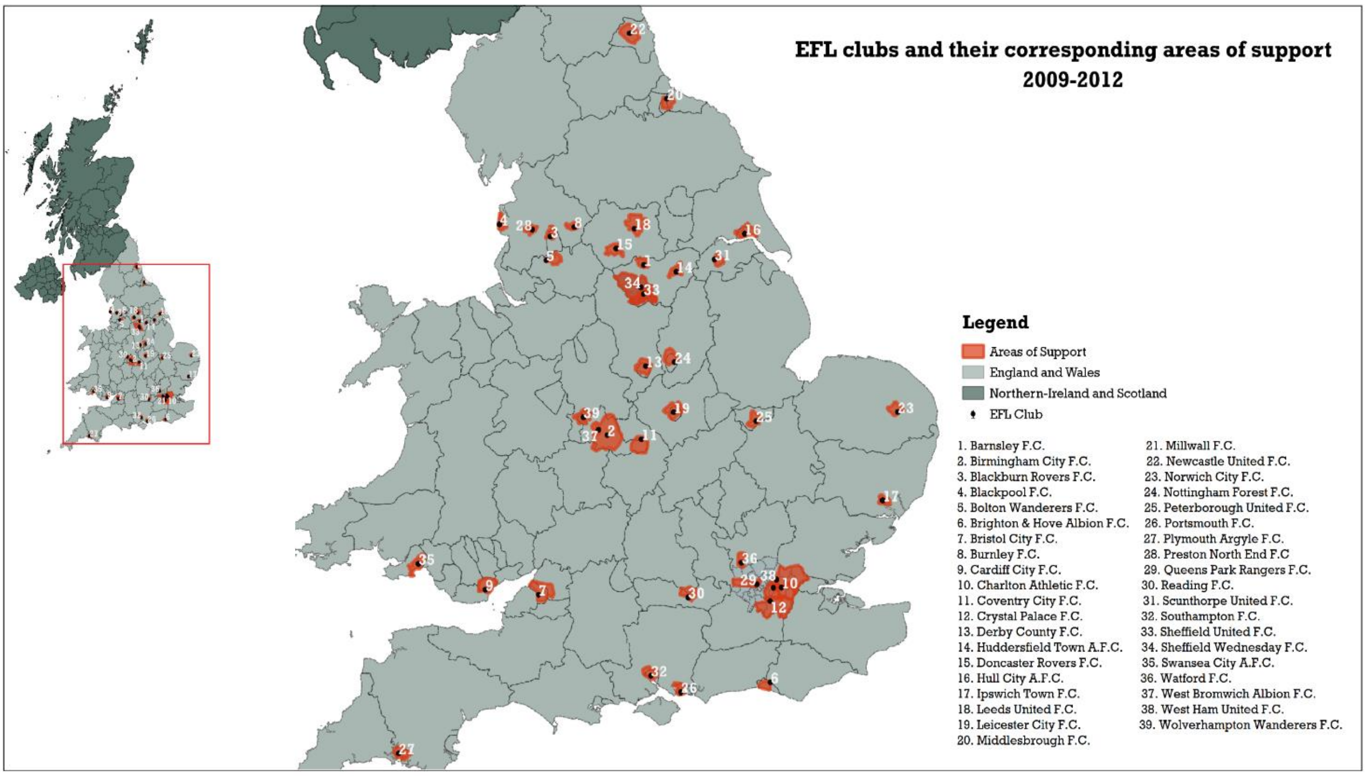
[2] Data may be accessed from the following website: https://www.betbrain.com/football-odds

[3] Data may be accessed from the following website: https://www.gov.uk/government/statistical-data-sets/reported-road-accidents-vehicles-and-casualties-tables-for-great-britain

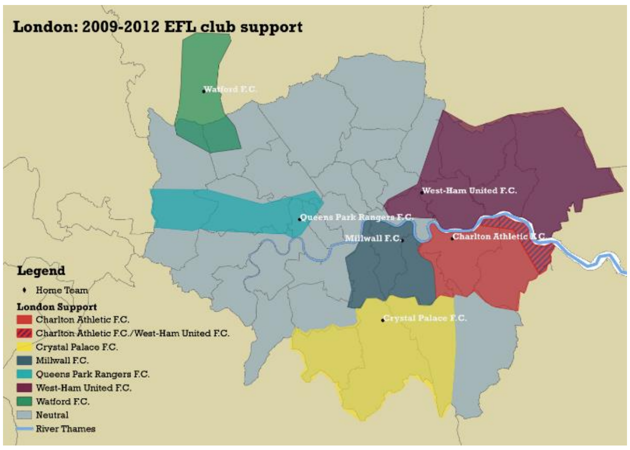
The accident data provides the raw data of number of accidents as well as the location of the accidents. Since the location of each accident is given, all the accidents can be attributed to a football club's area of support (AOS). These areas of support are areas in which residents are likely to support the club that is located in that area. Each of the 39 Championship clubs that have been active in the Championship in the 2010-2012 period have been designated an AOS. Since the Championship has a much more local impact than the Premier League, most of the fanbase is likely to be local. The AOSs of Championship teams are therefore constructed to contain the area within their home cities or town's administrative borders. This does however pose a problem, since there are 5 clubs located in London and 2 clubs located in Sheffield. These clubs cannot have overlapping AOSs, so these cities have been divided in various AOSs, so that each club still has its own AOS. An overview of all AOSs can be found in figure 1. An overview of how London and Sheffield have been divided in different AOSs can be found in figures 2.1 and 2.2.

FIGURE. 1. Championship clubs and their corresponding areas of support (2009-2012).



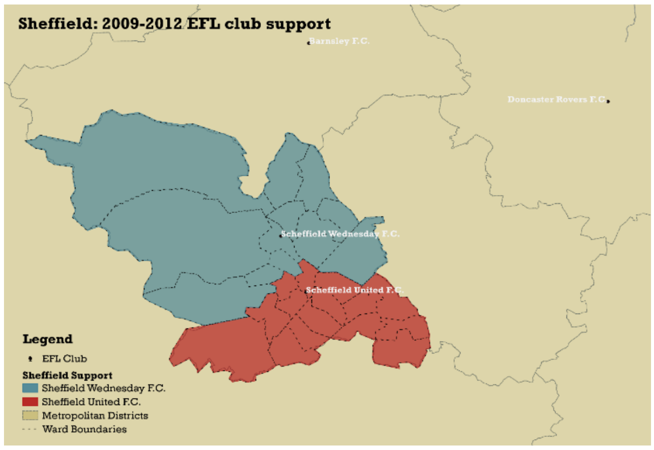
Orange areas show areas of support for Championship teams. The numbers in the area correspond to the teams mentioned in the

FIGURE 2.1 London: 2009-2012 Championship club support



The colours on the map represent different areas of support within London. These colours correspond to the teams as mentioned in the legend.

FIGURE 2.2 Sheffield: 2009-2012 Championship club support



The colours on the map represent different areas of support within Sheffield. These colours correspond to the teams as mentioned in the legend.

Key variables

The analysis makes use of a few different variables. The first variable is the dummy variable matchday. This variable indicates whether a match is played on a certain day. When this is the case, the variable will take the value of 1, otherwise it will be 0. The dataset contains a total of 3,346 matchdays, which will all be taken into account for the analysis.

Other variables needed to be constructed from the available data. Firstly, we have an upset loss, which will take the value of 1 when a team suffers an upset loss, and value 0 otherwise. An upset loss is defined as a loss when the probability that the team would win is larger than 55%, according to the corresponding betting odds. Since all the betting odds are available in the data, we can create the variable upsetloss for match results that match the definition. Creating this variable gives us a total of 67 matches in which a club suffered an upset loss.

Furthermore, we have the variable upset win. This is defined as a win when the probability that the team would win is smaller than 30%, according to the corresponding betting odds. As mentioned before, this variable can be created using the betting odds data that we already have. This results in a total of 191 matches in which a team achieved an upset win.

Teams can naturally also suffer other losses or wins than upset ones. These are taken into account with the variables close loss and close win. These variables are defined as a loss when the probability that the team would win is between 55% and 35%, according to the corresponding betting odds and a win when the probability that the team would win is between 30% and 55%, according to the corresponding betting odds. All other wins and losses will be taken into account as a normal win or a normal loss. This results in a total of 516 close losses, 793 close wins, 649 normal losses and 248 normal wins. The 882 remaining matches have all been ended with a draw. The definitions of these variables can also be found in table 1.

Table 1. Created variable names and their definitions.

Variable name	Definition
Upset loss	A loss when the probability that the team would win is larger than 55%, according to the corresponding betting odds.
Upset win	A win when the probability that the team would win is smaller than 30%, according to the corresponding betting odds.
Close loss	A loss when the probability that the team would win is between 55% and 35%, according to the corresponding betting odds.
Close win	A win when the probability that the team would win is between 30% and 55%, according to the corresponding betting odds.
Normal loss	All other losses.
Normal win	All other wins.

The next variable is the variable rival match. This variable takes the value of 1 when a match is played between two rival teams, and will take 0 otherwise. In order to indicate which matches can be denoted as rival matches, information has been pulled from SportBible (2019). They posted an article in which they explain and present the results of a research called *'The League Of Love And Hate'*. This is an annual survey carried out by tens of thousands of supporters from Premier League, Championship, League One and League Two teams. These fans all make a top five of most hated rival teams in the English football pyramid. For this thesis, only the top two of each team has been taken into account as the biggest rivals and deemed relevant for this thesis. This is done because we want to research the extra effect that a real rival match has on road traffic accidents, and most teams do not have five fierce rivals. If all these rivals would be taken into account, the effect would be likely to be much smaller, since the difference in suspense and excitement between the number one rival and number five rival is very likely to be very significant. This is also visible in the results *of 'The League Of Love And Hate'*, since the number one rivals often have been mentioned by up to 90% of the supporters, where the number five rivals often not have been mentioned by more than 30%.

Each team in the dataset has as beforementioned been assigned two rivals. When these teams have mentioned each other in their top two rivals, these matches will be indicated as rival matches. This approach brings us to a total of 16 potential rival matches, which are listed below in table 2.

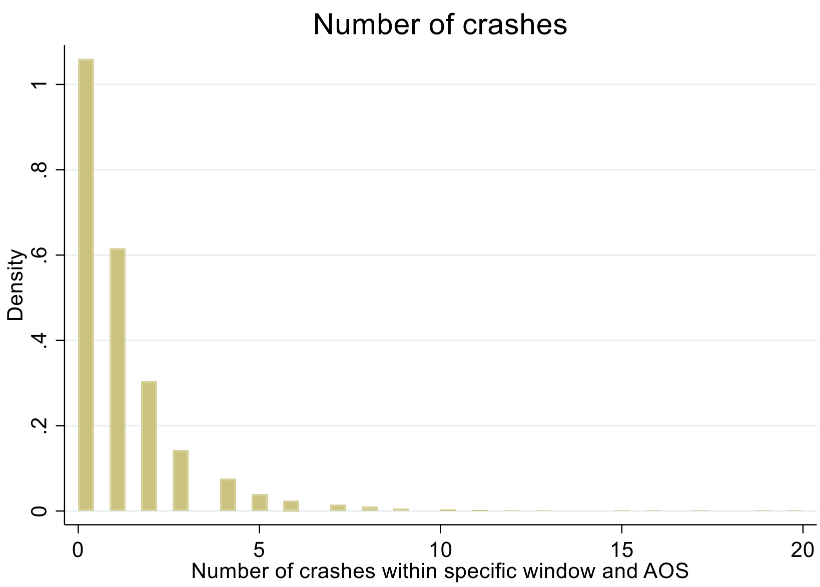
#	Team 1	Team 2	Number of times played during the three year period
1	Blackburn Rovers F.C.	Burnley F.C.	2
2	Blackburn Rovers F.C.	Preston North End F.C.	0
3	Blackpool F.C.	Preston North End F.C.	2
4	Brighton & Hove Albion F.C.	Crystal Palace F.C.	6
5	Brighton & Hove Albion F.C.	Portsmouth F.C.	4
6	Bristol City F.C.	Cardiff City F.C.	12
7	Crystal Palace F.C.	Millwall F.C.	10
8	Derby County F.C.	Nottingham Forest F.C.	12
9	Derby County F.C.	Leicester City F.C.	12
10	Ipswich Town F.C.	Norwich City F.C.	4
11	Leicester City F.C	Nottingham Forest F.C.	12
12	Middlesbrough F.C.	Newcastle United F.C.	2
13	Millwall F.C.	West Ham United F.C.	4
14	Portsmouth F.C.	Southampton F.C.	4
15	Sheffield United F.C.	Sheffield Wednesday F.C.	2
16	West Bromwich Albion F.C.	Wolverhampton Wanderers F.C.	0
		Total	88

Table 2: overview of rival matches 2010 - 2013. This table shows matches that are considered a rival match. Both home and away matches are taken into account. The last column refers to the number of matches that are played between the teams in the relevant time period.

Of these matches, number two Blackburn Rovers F.C. – Preston North End F.C. and number 16 West Bromwich Albion F.C. – Wolverhampton Wanderers F.C. have unfortunately not taken place in the relevant period for this thesis, since these teams have not played in the Championship during the same years. This leaves us with a total of 14 matches that have been indicated as rival matches and will be taken into account as such in the analysis. Over 3 three years of observations, these matches have been played 88 times, which leaves us with 88 observations for the rival match variable.
Lastly, the dependent variable that is important to this paper is the number of road traffic accidents that are reported in area *j* in time period *t*. This will be denoted as RTA_{jt} in the econometric model. This variable is obtained by counting the number of RTAs in each club's area of support on a gameday after the match ended until 6.00 AM the next day. This is because actual start and finish times of games are unfortunately not available. The assumption is that football matches will have an effect after the match ended, when the teams have suffered either a (unexpected) win or a (unexpected) loss. Since the actual kick-off times are not known, it is assumed that 15.00 is the earliest time at which a match might finish. Therefore, all RTAs in a club's AOS are deemed relevant from 15.00 until 6.00 and will be counted towards the dependent variable. Using this definition of the number of crashes, we have 46,032 observations, which consists of each day of the three observed years, per AOS. The average number of crashes per day is equal to 1.13, with a standard deviation of 1.60. The minimum number of crashes on a day in a certain AOS was 0, whereas the maximum was a number of 20 crashes on one day. The distribution of the number of crashes can be found in figure 3. It is

notable that zero crashes is by far the most common volume of crashes. This decreases quickly and days with more than ten crashes are almost non occurrent in the dataset.

Figure 3: Distribution of the number of crashes within a specific time window and AOS



The descriptive statistics for the key variables can also be found in table 3. The variables number of crashes and AOS win probability are the only continuous variables. The variable number of crashes has been described above, whereas the variable AOS win probability only has observations for matchdays, since it makes no sense to have a construct the probability that the team will win when the team does not play a game. This also goes for all the other variables that are included in the analysis. The mean of the AOS win probability is 38.91, which means that the average chance that a team from the AOS would win is 38.91%. Furthermore, the standard deviation is 12.78 and the minimum and maximum win probabilities are 10.21% and 76.92%. All other variables that will be used in the analysis are categorical variables. The means of the variables close win, close loss, upset win, upset loss, normal win, normal loss and draw all relate to the ending of a match. The means here are the proportion of the total matches that ended in a certain result, which is reflected by the variables. Thus, all these proportions add up to 1 and can be seen as the percentage of matches that ended in a certain result. The mean of rival match should be interpreted slightly different, since this variable does not reflect to a certain game outcome, but to a type of game. The proportion of 0.03 means then that 3% of the matches played can be seen as a match between rivals.

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Number of crashes	46,032	1.134884	1.603378	0	20
Aos win probability	3,346	38.91009	12.77886	10.2145	76.92308
Game day	46,032	0.0726886	0.2596274	0	1
Rival match	3,346	0.0263001	0.1600501	0	1
Close win	3,346	0.2369994	0.4253055	0	1
Close loss	3,346	0.154214	0.3612077	0	1
Upset win	3,346	0.0570831	0.232036	0	1
Upset loss	3,346	0.0200239	0.1401029	0	1
Normal win	3,346	0.0741184	0.2620025	0	1
Normal loss	3,346	0.1939629	0.3954593	0	1
Draw	3,346	0.2635983	0.4406498	0	1

Table 3. Descriptive statistics for all key variables. These statistics include the number of observations, the mean values, the standard deviations, the minimum values and the maximum values.

Methodology

In order to analyse the data for this thesis, the analysis will make use of several OLS regressions. This type of regression comes with three assumptions. Firstly, all observations must be independent. Secondly, the variance must be homogeneous and thirdly, the residuals must follow a normal distribution. These assumptions will result in omitting the game day variable from the regressions, since all other variables only contain a value when a game is played. These observations are then not independent, so this cannot be included in the regression model.

An OLS regression model minimizes the sum of the squares of the differences between the dependent variable and the independent variables. This way, one can predict a coefficient which can indicate the direction and magnitude of the effect that an independent variable might have on a dependent variable. This coefficient represents the causal relationship between variables, when the error term in the regression is equal to zero. This way all the variation in the dependent variable is caused by the independent variable. The problem with an OLS regression is that one can never be sure whether the error term is zero. That is where an instrumental variable comes in use. An instrumental variable is a variable that has no correlation with the error term and the dependent variable, but does have a correlation with the independent variable. When an analysis using an OLS regression then results in finding an effect from the instrumental variable on the dependent variable, this effect must be directed through the independent variable, since the instrumental variable and the dependent variable are not correlated. This way one can conclude that there is a causal relationship between the dependent and independent variable. This thesis uses football matches as an instrumental variable. These football matches have no effect on car crashes whatsoever, but do have an effect on unexpected emotional cues. When this thesis finds an effect of football matches on car crashes, this would mean that this effect comes through the unexpected emotional cues, which then results in finding a causal relationship. In order to test this, this thesis will make use of a few different sets of regressions.

The first regression that will be done using the following formula:

$$\mathrm{RTAjt} = \theta\mathrm{j} + \beta 1 * \mathrm{game\ day\ /\ rivalmatch} + \varepsilon$$

Where RTA_{jt} represents the number of road traffic accidents reported in area of support *j* in time period *t* from 15.00 until 6.00 the next day, θj represents a set of fixed effects, existing of the AOS a game was played in, the date a game was played on, and the day of the week a game was played on. The variables game day and rival match indicate what the effect of having a game on a certain day has on the number of crashes on that day. These regressions will be done three times for the rival match variable, one for all games and one for only home or only away games. This strategy can however not be used with the game day variable, since there always is a game day if a team plays at home or away. This bring up the problem of multicollinearity, so the variable number of crashes will be regressed on whether a team plays at home or away. The value that this variable takes is 0 for an away game and 1 for a home game. The difference between the effect of home and away matches on car crashes can be analysed this way.

The next set of regressions will be done without fixed effects, and will be a single regression for each variable on RTA_{jt}. This way one can see the effect that different match outcomes have on the car crashes after that match. This means that these regressions do not analyse whether football matches have an effect on the number of car crashes, but whether different results within a football match have different effects on the number of crashes after that match. The regression formulas will then be:

$$RTAjt = \beta 1 * match\ outcome\ variable + \varepsilon$$

This regression will be done for all match outcome variables. Lastly, these regressions will be repeated but with an extra control for match odds, so:

$$RTAjt = \beta 1 * match\ outcome\ variable + \beta 2 * AOS\ win\ probability + \varepsilon$$

Using these regression formulas will show what the difference is between a match ending in a draw and a match ending in another result, since draw will be the reference category. This way the analysis will show what the effects of certain match outcomes are on the number of car crashes after a game.

Results

Graphical results

This section presents various histograms in order to better understand the data. These histograms are displayed in figures 4.1, 4.2, 5.1 and 5.2.

Figures 4.1 and 4.2 show the distribution of the number of car crashes within a specific time window and AOS for game days and for non-game days. It is notable that the non-game days distribution has a longer tail than the game days distribution, which indicates that there were more days with a lot of crashes on non-game days than on game days.

What also stands out is that the density of lower values is higher for the game days than for the non-game days, which indicates that the volume of crashes for game days were lower than for non-game days. For instance, the number of "zero crash" days is far higher for game days than non-game days.

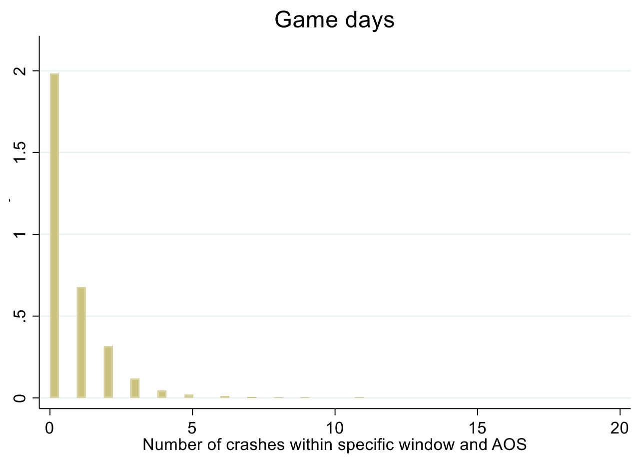


Figure 4.1: Distribution of the number of crashes within a specific time window and AOS on game days

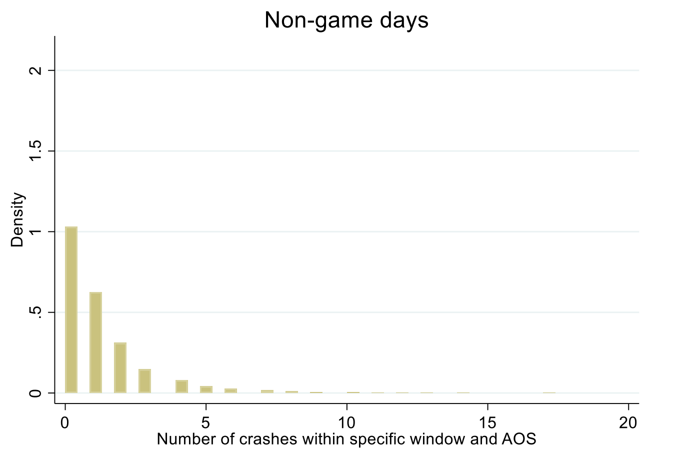


Figure 4.2: Distribution of the number of crashes within a specific time window and AOS on non-game days

Figures 5.1 and 5.2 show the distribution of the number of car crashes within a specific time window and AOS for game days on which the team in the AOS won and for game days on which the team in the AOS lost. The histogram of won games has a longer tail than the histogram of the lost games. This indicates that there were more games with a lot of crashes on days that the team won than on days that the team lost, furthermore, the density of lower values is higher for the lost games, which indicates that the volume of crashes for lost games were lower than for won games.

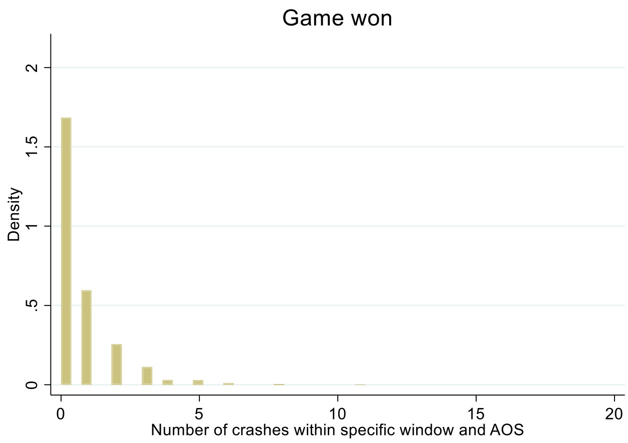


Figure 5.1: Distribution of number of crashes within a specific time window and AOS for won games

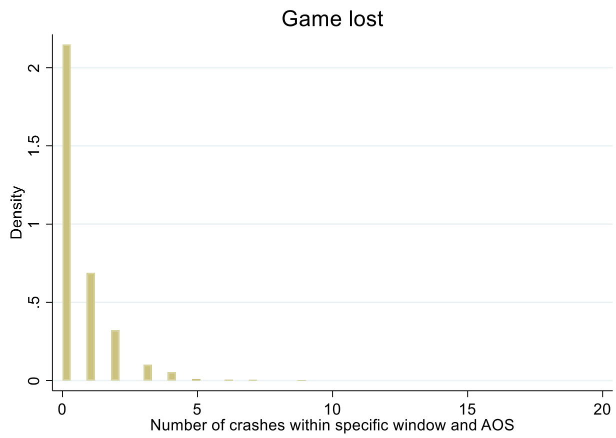


Figure 5.2: Distribution of number of crashes within a specific time window and AOS for lost games

Regression results

To further investigate the effect of football matches on road traffic accidents, there have also been done several regressions. The first five regressions can be found in table 4. These regressions show the effect that a game day have on the number of crashes on that day, compared to non-game days. They also show the extra effect that rival matches and home or away matches have on the number of crashes. The first regression is a regression of only game day on the number of crashes. The regression does contain fixed effects, like the AOS a game was played in, the date a game was played on, and the day of the week a game was played on. The regression has 46,032 observations, which is every day in the dataset for each AOS. The value of the game day coefficient is -0.457. This must be interpreted as that the number of crashes on a game day is on average 0.457 lower than on a non-game day. This value is significant at a 95% significance level. The second regression shows whether there is a difference between home and away games. The value of -0.0109 should be interpreted as the average decrease in number of crashes when a team plays at home, compared to when playing away. This value is however not significant. The last three regressions show the extra effect that rival matches have on the number of car crashes, for both all matches and for only away (regression 4) and home (regression 5) matches. These coefficients are however not significant, so the playing of a rival match does not significantly change the number of crashes compared to not playing a common match.

Table 4: Regressions with fixed effects for the AOS a game was played in, the date a game was played on, and the day of the week a game was played on. These regressions show the effect of having a match day or a rival match on the number of car crashes on that day, compared to a non-match day or non-rival match.

	(1) RTA's	(2) RTA's	(3) RTA's	(4) RTA's	(5) RTA's
Game day	-0.457**				
	(0.194)				
Home/away game		-0.0109			
		(0.0242)			
Rival match			0.0995	0.0394	0.167
			(0.0768)	(0.116)	(0.111)
_cons	1.168***	0.674***	0.655***	0.654***	0.629***
	(0.0141)	(0.0363)	(0.00202)	(0.00265)	(0.00256)
N	46032	3346	3346	1568	1568

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The next set of regressions that were done can be found in table 5. In this table, all the variables of interest have been regressed on the number of crashes. These regressions can be found in the first seven columns of the table. Each regression, another variable has been regressed on the number of crashes. This way, we can analyse the effect that different match outcomes have on the number of crashes, and we leave non-match days out of the equation.

Table 5: Regressions of just one variable on the number of crashes. Lastly, a regression with al variables combined. These regressions show what effect different outcomes of games have on the number of crashes

	(1) RTA's	(2) RTA's	(3) RTA's	(4) RTA's	(5) RTA's	(6) RTA's	(7) RTA's	(8) RTA's
Close loss	-0.0147							-0.0759
	(0.0532)							(0.0614)
Close win		0.0651						-0.0139
		(0.0451)						(0.0543)
Upset win			-0.181**					-0.234***
			(0.0827)					(0.0885)
Upset loss				0.0598				-0.00466
				(0.137)				(0.140)
Normal win					0.0647			-0.00339
					(0.0733)			(0.0797)
Normal loss						-0.143***		-0.179***
						(0.0485)		(0.0573)
Rival match							-0.0337	-0.0368
							(0.120)	(0.120)
_cons	0.660***	0.642***	0.668***	0.657***	0.653***	0.686***	0.659***	0.722***
	(0.0209)	(0.0220)	(0.0198)	(0.0194)	(0.0199)	(0.0214)	(0.0195)	(0.0375)
N	3346	3346	3346	3346	3346	3346	3346	3346

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Most of the variables in table 5 are not significant at a 95% level, excluding upset win and normal loss. If a team achieves an upset win, the number of crashes after the game drop on average with 0.181, compared to when the match ends in a draw. When a team suffers a normal loss the number of crashes drop with on average 0.143 compared to when the match ends in a draw.

The last regression combines all the variables of interest. Just like in the regression in columns 1 to 7, the reference category here is the resulting of a match in a draw. The coefficients in regression 8 must therefore be interpreted as the difference in number of crashes between the match outcome variable and a draw. Only the variables upset win and normal loss differ significantly from the draw outcome, with a drop of 0.234 car crashes when a team achieves an upset win and a drop of 0.179 when a team suffers a normal loss, compared to when a team draws.

The last set of regressions is a copy of the second set, only now every variable gets controlled for the win probability of the team from the AOS. These can be found in table 6. It is notable that the win probabilities for the team from the AOS is almost always significant at a 99% level. This is only not the case in the regression with normal loss, where the win probability is only significant at a 90% level. The win probability variable should be interpreted as the change in the number of car crashes when the probability that the team will win rises with one percent. Furthermore, there are no variables that have a significantly different effect on the number of car crashes, compared to when a match ends in a draw. In the last regression, where all the variable are included and draw is the reference category, there are two significant variables. When a match ends in an upset win for the team from the specific AOS, there will be on average 0.195 car crashes less than when the match would have ended in a draw. When a match ends in a normal loss for the team from the specific AOS, there will be on average 0.142 less car crashes than when the match would have ended in a draw. All the other variable that are specified in the table do not have a significant effect that differs them from the reference category.

Table 6: The same set of regressions as in table 5, only now controlled for win probabilities

	(1) RTA's	(2) RTA's	(3) RTA's	(4) RTA's	(5) RTA's	(6) RTA's	(7) RTA's	(8) RTA's
Close loss	-0.0358							-0.0858
	(0.0535)							(0.0620)
Close win		0.0447						-0.0232
		(0.0456)						(0.0549)
Upset win			-0.118					-0.195**
			(0.0860)					(0.0947)
Upset loss				-0.0464				-0.0625
				(0.141)				(0.149)
Normal win					-0.0645			-0.0634
					(0.0839)			(0.0953)
Normal loss						-0.0867		-0.142**
						(0.0567)		(0.0655)
Rival match							-0.0332	-0.0358
							(0.120)	(0.120)
Win prob	0.00489***	0.00454***	0.00417***	0.00489***	0.00541***	0.00337*	0.00476***	0.00271
	(0.00151)	(0.00152)	(0.00156)	(0.00154)	(0.00172)	(0.00175)	(0.00150)	(0.00236)
_cons	0.473***	0.470***	0.502***	0.469***	0.452***	0.543***	0.473***	0.617***
	(0.0615)	(0.0615)	(0.0651)	(0.0625)	(0.0669)	(0.0769)	(0.0615)	(0.0991)
N	3346	3346	3346	3346	3346	3346	3346	3346

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Conclusion and discussion

In order to test whether unexpected emotional cues have an effect on car crashes, this thesis studied the relationship between football matches and car crashes. Football matches are a source of emotional cues, so when one understands the relationship between football matches and car crashes, one can extend this conclusion to the relationship between car crashes and unexpected emotional cues.

This thesis used data on car crashes and all football matches from the English Championship from the period 01-01-2010 – 31-12-2012 to study this relationship. To identify different emotional cues, this thesis has categorized different match outcomes into different variables used for the analysis. These variables and their definitions were upset loss (a loss when the probability that the team would win is larger than 55%, according to the corresponding betting odds), upset win (a win when the probability that the team would win is smaller than 30%, according to the corresponding betting odds), close loss (a loss when the probability that the team would win is between 55% and 35%, according to the corresponding betting odds), close win (a win when the probability that the team would win is between 30% and 55%), normal loss (all other losses) and normal win (all other wins). These variables are all referenced to when a match ended in a draw, which is the reference category in the regressions.

The results that were found are not as expected, given the current literature. A game day results in on average half a car crash less than on a non-game day. Furthermore, suffering or achieving an upset loss, a close loss, a close win, a normal win and playing rival matches never have a significant effect of the number of car crashes that occur after a game. Only achieving an upset win or suffering a normal loss affect the number of car crashes significantly, compared to when a match would have ended in a draw. These effects are however always negative and reduce car crashes after a match with a maximum of approximately 0.25 crashes, compared to the reference category.

These results are different than the current literature would suggest. Card and Dahl (2011) found that American football matches (also a cause of unexpected emotional cues) cause a significant rise in domestic violence. Since Hu et al. (2013) found that negative emotions lead to more dangerous driving behaviour, it would be expected that emotional cues would also have a significant upward effect on car crashes. The findings of this paper do however support the findings of Hughes et al. (2018), who found no significant effect in emergency department attendances levels at match days during the Euro 2016 football championship. They did find however that these attendances were significantly higher in France after their national team lost the cup final. This suggests that there might only be an effect by emotional cues caused by highly salient games. Even though the rival match variable did not lead to significant effects in this thesis, it might be the case that evoked emotional cues must be very strong to cause dangerous driving behaviour and car crashes. Because this thesis included all games played in the Championship during the studied period, it might lead to lower overall effects. It could however be the case that highly salient matches, such as cup finals, a championship match or a decisive match in the battle against relegation do evoke emotional cues that are strong enough to find significant, upwards effects. Another explanation for the decrease in number of car crashes on match days is that a football match causes a very big crowd to come together. These people all leave the stadium at roughly the same time, so the roads are very crowded on the way home. Accidents occur less when driving speeds are low, so that might also explain why the found effect is negative.

This thesis can not claim to have found a causal effect between unexpected emotional cues caused by football matches and the number of car crashes that occur after a match. As mentioned before, football matches might influence the number of crashes in other ways, like through the gathering of a large mass of people. We can thus not claim that the instrumental variable has no correlation with the error term in our econometric model, and can therefore not claim a causal relationship. This thesis can however claim that it has found a correlation between unexpected emotional cues caused by football matches and the number of car crashes that occur after a match. It is very unlikely that unexpected emotional cues cause people to watch football matches, while it is likely that emotional cues evoke different driving behaviour. This thesis can therefore safely claim that the effect that is found is directed in the way that unexpected emotional cues evoke unsafe driving behaviour, and not the other way around. However, this effect must be seen as a correlation and not a causal relationship, as mentioned before.

In reference to the possible policy implications, this thesis has proven that there is a correlation between unexpected emotional cues and dangerous driving behaviour. As mentioned in the introduction, it might be the case that dangerous driving is a rational decision that a driver takes. Another explanation might be that dangerous driving is caused by emotional cues, and that the driver does not rationally decide to drive more unsafe. The latter is what this thesis has researched. Since this thesis has only found no effects or decreasing effects of emotional cues on car crashes, it is not likely that dangerous driving is caused by emotional cues. This would mean that a large information campaign can influence the rational decisions of drivers, so that their mental costs of driving unsafe will increase. Changing infrastructure would be a less effective measure, since this does not affect the mental state of a driver and his rational consideration to drive unsafe.

As mentioned before, this thesis cannot claim to have found a causal correlation. This might be the case because the available dataset for this thesis was limited. Other variables that might influence driving behaviour, like weather conditions, were not available in the dataset. Another limitation might be that this thesis researches matches from the English Championship, which is a competition with less attraction and therefore less evoked emotions than in more important leagues. It might be the case that matches, in for example the Premier League, do evoke stronger emotions, which then do affect the driving behaviour of fans. It would therefore be recommended for future research to use a bigger league for the analysis, even though it is harder to define their areas of support. Furthermore, future research could focus more on the highly salient games, and extent the research into the effect of rival matches as has been done in this thesis. It is likely that emotions are stronger in those matches, since the stakes are higher. This might also influence the effect that can be found using the regressions as has been done in this thesis.

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Appendix

Appendix A: Overview of the football clubs playing in the Championship between 2010 and 2013

Overview of the football clubs playing in the Championship between 2010 and 2013						
			Season			
#	Team	2009/10	2010/11	2011/12	2012/13	City/Town
1	Barnsely F.C.					Barnsley
2	Birmingham City F.C.					Birmingham
3	Blackburn Rovers F.C.					Blackburn
4	Blackpool F.C.					Blackpool
5	Bolton Wanderers F.C.					Bolton
6	Brighton & Hove Albion F.C.					Brighton
7	Bristol City F.C.					Bristol
8	Burnley F.C.					Burnley
9	Cardiff City F.C.					Cardiff
10	Charlton Athletic F.C.					London
11	Coventry City F.C.					Coventry
12	Crystal Palace F.C.					London
13	Derby County F.C.					Derby
14	Doncaster Rovers F.C.					Doncaster
15	Huddersfield Town F.C.					Huddersfield
16	Hull City F.C.					Kingston upon Hull
17	Ipswich Town F.C.					Ipswich
18	Leeds United F.C.					Leeds
19	Leicester City F.C.					Leicester
20	Middlesbrough F.C.					Middlesbrough
21	Millwall F.C.					London
22	Newcastle United F.C.					Newcastle upon Tyne
23	Norwich City F.C.					Norwich
24	Nottingham Forest F.C.					Nottingham
25	Peterborough United F.C.					Peterborough
26	Portsmouth F.C.					Portsmouth
27	Plymouth Argyle F.C.					Plymouth
28	Preston North End F.C.					Preston
29	Queens Park Ragners F.C.					London
30	Reading F.C.					Reading
31	Scunthorpe United F.C.					Scunthorpe
32	Southampton F.C.					Southampton
33	Sheffield United F.C.					Sheffield
34	Sheffield Wednesday F.C.					Sheffield
35	Swansea City A.F.C.					Swansea
36	Watford F.C.					Watford
37	West Bromwich Albion F.C.					West Bromwich
38	West Ham United F.C.					London
39	Wolverhampton Wanderers F.C.					Wolverhampton
	Total	24	24	24	24	
	Team participated in the Championship this season					