The Impact of Competitive Scenarios on Individual and Team Behaviour

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Abstract

In this thesis, we study the impact of competitive scenarios on individual and team behaviour. In chapter one, we study experimentally the role of leadership in teams facing a game with a complex strategy space. Teams of three members face an instance of a team dispatching problem, in which the members jointly devise then separately implement a plan to visit a set of locations on a map. Some teams have one member designated as a "leader", although this role does not confer any distinct responsibility or capability in the game. We compare the performance of teams with elected leaders, appointed leaders, and no leaders. We find that teams with leaders perform better than those without, while teams with elected leaders and teams with appointed leaders perform similarly. Our results indicate that electing a leader serves as a device to coordinate team activity, and is valuable primarily when a team needs to be able to deliver well immediately. We find that teams with leaders are more confident than those without, but this additional confidence is in line with those teams' superior performance.

In chapter two, we study experimentally the effects of individual skill in a real-performance task and the responsiveness of individual skill to various incentive schemes. Participants faced instances of the Truck Dispatch Problem, in which they devised three journeys which visit a set of locations on a map. Some participants were remunerated under a rank order tournament incentive scheme, some participants were informed of their performance ranking and were given a fixed rate whilst some participants were remunerated under a fixed rate incentive scheme. We find evidence for individual skill differences in the task, but that the distribution of these differences does not depend on the incentive treatment.

In chapter three, we study empirically the effects of domestic and international football tournaments on domestic abuse in England and Wales and how these effects vary with people's expectations of the football match outcomes. Previous studies on domestic abuse and football in England and Wales have focused primarily on international tournaments and have not taken into account the effects of expected match outcomes. This is surprising given the visibility of the English Premier League (EPL). We find in our analysis, that the existence of an EPL fixture is associated with a 1% percent increase in domestic violence while the existence of a FIFA World Cup fixture is associated with a 3% increase in domestic violence in England and Wales. Our results, also suggest that expected match outcomes have strong effects on domestic violence in England and Wales.

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Introduction

Competition as a situation in which at least two individuals (or groups) vie for the same goal which can only be attained one person (group) has vast applications in everyday life. These can range from encouraging higher levels of performance in a firm, to encouraging better sportsmanship in the sports field and even encouraging better scholarship in the colleges. These competitive settings, have been found to affect human behaviour in various ways. These effects can be good: competition can lead to improvements in productivity (Nalbantian et al., 1997) or lead to better team coordination (Bornstein et al., 2002; Riechmann and Weimann, 2008); or bad: competition can lead to a waste of effort expenditure (Sheremeta, 2018), increased likelihood of dishonest behaviour (Schwieren and Weichselbaumer, 2010), negative effects on well being (Brandts et al., 2006) particularly when rivalries run deep (Kilduff et al., 2012) and poorer performance of females relative to males in competitive environments (Gneezy et al., 2003; Gneezy and Rustichini, 2004).

In this thesis we approach competition from two broad perspectives. First, we consider competition as a motivator of performance and second, we consider competition as a source of emotional stimulus. As motivator of performance (Lazear and Rosen, 1981), the relative performance of individuals (groups) in a competition can serve as the standard against which their remuneration depends. This type of remuneration system is known the *rank order tournament* incentive scheme (system). In the first two chapters of this thesis, we use the rank order tournament incentive scheme to encourage the performance of teams and individuals in a *real-performance* task which we introduced to the experimental literature.

In chapter one, we focused primarily on how teams might perform in a competitive setting when they either have to self organise of have a named leader. In chapter two we study the responsiveness of individual performance, in a *real-performance* task, to various remuneration schemes. The tournament incentive scheme comprises of the idea that your payment is contingent on you ranking. It is possible that people might care about their ranking more than they care about their payment, or might care about their ranking before it determines their payments. In chapter two, we break the tournament incentive scheme into some of its components and study how the performance of individuals respond when payments are dependent on ranking and when rankings are known but payments are independent of ranking.

In chapter three, we consider competition experienced vicariously as an emotional stimulus. The outcome of competition, when experienced directly can affect emotions such that happiness can result from the satisfaction of winning and sadness can result from the pain of losing (Dohmen et al., 2011). Interestingly, the outcome of competition, even when experienced indirectly, can have strong effects on emotions i.e. the joy or sadness of a sports fan based on the performance of their supported team (Spaaij, 2014).

We explore this indirect effect of competition in chapter three, where we investigate the effects of the outcome of major sporting (football) tournaments on domestic abuse in England and Wales.

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Chapter 1

Leadership in Complex Games: A Laboratory Experiment

In this chapter, we study experimentally the role of leadership in teams facing a game with a complex strategy space. Teams of three members face an instance of a team dispatching problem, in which the members jointly devise then separately implement a plan to visit a set of locations on a map. Some teams have one member designated as a "leader", although this role does not confer any distinct responsibility or capability in the game. We compare the performance of teams with elected leaders, appointed leaders, and no leaders. We find that teams with leaders perform better than those without, while teams with elected leaders and teams with appointed leaders perform similarly. Our results indicate that electing a leader serves as a device to coordinate team activity, and is valuable primarily when a team needs to be able to deliver well immediately. We find that teams with leaders are more confident than those without, but this additional confidence is in line with those teams' superior performance.

1.1 Introduction

Many activities require coordination among a small team. Clubs, musical bands, and sporting teams are groups which act jointly to discover how best to organise an event, write a hit song, or win a championship. Firms often screen job candidates in part on their perceived ability to act effectively and take initiative within the context of teams. Managerial practice often encourages employees to develop leadership skills, through a combination of training and personal development, to support the effective operation of small teams. One motivation for this can be to "flatten" organisational hierarchy, so no individual need be named as leader or manager.

Meanwhile, in professional team sports such as soccer and rugby football, the identity of the player who is named "captain" is a topic of great interest among sports journalists and fans alike. Although the captain (often) does not have a functional role specified by the rules of the game, the naming or removal of a captain can create a greater furore than decisions about who is in or out of the squad, and therefore eligible to play. Although flat, non-hierarchical teams without formally identified leaders may hold some attraction for organisations, in the belief (or hope) that leaders will emerge naturally, experience from sports suggests people believe a named leader is important for team performance.

Experimental economics has extensively studied the effect of leadership on coordinating the activities of a group. Many laboratory studies have used coordination games, specifically those with multiple, Pareto-rankable equilibria, as the theoretical framework for defining the task facing a group of participants. Van Huyck et al. (1990) showed experimentally that play in a coordination game may converge to a Pareto-dominated equilibrium, and proposed strategic uncertainty as a reason for this coordination failure.[1] Cooper et al. (1990) proposed that strategic uncertainty could result from the existence of multiple plausible rules for selecting from a game's set of equilibria, including for example payoff dominance (Harsanyi and Selten, 1988), risk dominance (Van Huyck et al., 1990) and focal points (Schelling, 1980). Devetag and Ortmann (2007) have surveyed the types of games used to examine the reasons for these coordination failures.

Calvert (1992) posits that a group's recognition of the strategic uncertainty in a coordination problem underpins demand for leadership within the group. This idea has been developed further by Hellwig and Veldkamp (2009) and Dessein et al. (2016). Calvert (1992) further argues that leadership helps to satisfy this demand and reduce strategic uncertainty by imparting focal properties onto some equilibria which otherwise lack them. Leadership can bring this about by use of selective incentives (Olson, 1971), explicit communication (Dewan and Myatt, 2008), or by sending a signal (Wilson and Rhodes, 1997) which may can be costly (Hermalin, 1998; Majumdar and Mukand, 2004).

The experimental evidence on leadership and coordination largely supports the above arguments. Managers can use targeted changes in financial incentives to improve performance

[1] Although play may converge to an equilibrium, we will follow Van Huyck et al. in referring to a situation in which a group is stuck at a Pareto-inferior equilibrium as an instance of "coordination failure".

(Brandts and Cooper, 2006). However, communication from leaders can be equally or even more effective, even in the absence of the ability to target incentives (Brandts and Cooper, 2007).

The effectiveness of a leader depends on the group's perception of him or her. Wilson and Rhodes (1997) studied a setting in which a group's leader could send a signal to the group. In their experiment, there were two leader types: a good leader type who could send group-serving signals, and a bad leader type who could send self-serving signals at the group's expense. They found that if the leader type and by extension the leader's credibility was questionable, coordination suffered significantly. The legitimacy of a leader, that is, the process through which a person attains a named leadership role, also has been argued to affect the ability of a leader to influence group performance. Brandts et al. (2014) compared the efficacy of appointed leaders and elected leaders to bring about coordinated change in the turnaround game, and found that groups with elected leaders performed better.

The importance of credibility and legitimacy is also identified in the social psychology literature. Legitimacy is seen as set of complex attitudes held by followers towards the person of the leader as well as the process that named the leader (Hollander and Julian, 1969; Read, 1974; Bass and Stogdill, 1990). Within this body of literature there is evidence that the process of assigning leaders matters for the efficacy of leadership (Goldman and Fraas, 1965). Election often leads to stronger legitimacy and thus better leader-follower relations as investments in and expectations of the leader are higher, especially when compared to leadership named by random appointment (Ben-Yoav et al., 1983).

Timing also plays a role in the usefulness and effectiveness of leadership. Bolton and Farrell (1990) argue that leadership, defined as a central authority or planner, is more efficient when the group must take a decision under time pressure, and/or when members of the group do not hold private information relevant to determining the best decision. Calvert (1992) notes that leadership is more efficient for coordination when the group lacks a long social history, for example, if it is newly-formed or if membership in the group is transient.

By using coordination games with relatively small strategy spaces (typically under 10 choices), the experimental economics literature has focused on leadership as a way to address strategic uncertainty arising from competing equilibrium selection rules. However, many groups operate in complex environments, in which identifying candidate solutions in the first place is an important part of the decision-making process. When the strategy space is sufficiently large, cognitive constraints imply group members will be able to consider only a small subset of alternatives, and likewise may not conceive fully of the outcomes associated with the alternatives they do consider.

In this chapter, we address the hypothesis that leadership can have additional value in complex environments by shaping the process the group uses to identify the options to give fuller consideration to. Teams with three members are assigned to one of three leadership treatments: some teams have no named leader, some have a named leader who is appointed, and some a named leader who is elected by the team members. The teams are presented with combinatoric routing problems, and given financial incentives to propose the most efficient routing they can find. In our experiment, leadership is only a label which does not confer any additional information or capability to the leader. We find that having a named leader significantly improves the quality of the routes teams propose. However, the process of naming the leader does not have an effect: teams with elected leaders and those with appointed leaders propose routes of similar quality.

The chapter proceeds as follows. In Section 1.2 we introduce the team dispatching problem, a combinatoric optimisation problem well-suited to address our research questions. Section 1.3 describes our implementation of the team dispatching problem as a laboratory experiment. Section 1.4 lists our main research hypotheses. Section 1.5 presents our analysis of our results. Section 1.6 concludes with a discussion.

1.2 The Team Dispatching Problem

We introduce to the literature in experimental economics a new group decision-making task, the *team dispatching problem* (TDP), as a setting to study group dynamics and the role of leadership when the set of feasible strategies is large. To the best of our knowledge, ours is the first study to explore how human subjects perform in the TDP. The TDP is a variation on the well-known Traveling Salesman Problem (TSP) in combinatorial optimisation. In the TSP, a decision-maker is presented with a number of locations on a map. A feasible solution (i.e. a strategy) for the decision-maker is a route which starts at a home location, visits each other location once, and then returns to the home location. The decision-maker's objective is to find the feasible route which involves traveling the shortest distance.

The TSP is an example of a combinatorial optimisation problem. It it classified as an NP-hard problem. There is no known algorithm which can solve an NP-hard problem in time proportional to a polynomial function of the problem size. In principle only exhaustive enumeration of all possible feasible routes ensures that the optimal one will be found. If there are N locations to be visited, the number of feasible routes is proportional to $N!$. There do exist heuristic algorithms for identifying "good" but not necessarily optimal solutions. These do not result in a guarantee of finding the optimal route because making local improvements to a route, such as swapping the order in which two locations are visited, is not guaranteed to converge monotonically to the optimum.

There is a limited literature in psychology studying human performance in the TSP. MacGregor and Ormerod (1996) studied the performance of subjects in the laboratory on TSPs with 10 locations and with 20 locations. They found that with maps of this size, human performance was comparable to that of heuristic algorithms. Therefore, although the task is sufficiently challenging that people do not frequently find the optimal solution, nevertheless it is possible for them to make useful progress on finding a reasonably good one. MacGregor and Ormerod did not find significant variation in performance across subjects, in that a subject who submitted a close-to-optimal solution for one map was not more likely to submit a close-to-optimal solution on another map.

The TDP modifies the TSP by having a group of several agents who jointly must visit all of the locations on the map. The TDP was first formulated by Dantzig and Ramser (1959) as the Truck Dispatching Problem. Each member of the group can make one *journey*, which starts at the home location, visits no more than $n < N$ other locations, and then returns to the home location. A feasible route is therefore a collection of journeys, one for each member of the group, in which each locations is visited exactly once by exactly one member of the group, and no member of the group visits more than n locations. Like the TSP, the objective is to find the feasible route which minimises the total distance traveled, and the TDP is likewise an NP-hard problem.

Dantzig and Ramser (1959) pose the TDP as an optimisation problem with a central planner who defines and coordinates the routes. We use it as the basis for a coordination game with pre-play communication. Instead of having a central planner, in our TDP the members of a group choose their respective journeys. Put in game-theoretic terms, a journey is a strategy for a group member. If group members choose their journeys simultaneously, they face a Pareto-coordination problem. First, members want to coordinate by choosing journeys which, put together, form a feasible route. In addition, among those feasible routes, members would prefer to coordinate on one with a shorter total distance than a route with a longer total distance.

As the number of valid journeys a member can select from is very large, successful coordination requires the members to have some form of guidance *regarding how best to divide up the N locations among the group members* before making their choices. In our experiment, the members of a group engage in pre-play communication in the form of a free-text chat. Cooper et al. (1992) reported an experiment in which communication between the two players in a coordination game led to the play of the Pareto-superior equilibrium. Similarly, Blume and Ortmann (2007) reported an experiment in which costless pre-play communication led to increased coordination in games with two or more players. In their experiment, participants played a coordination game for 8 rounds, where strategies were numbered 1 through 7. Prior to each round, participants were allowed to send a message taken from the set 1 through 7; the distribution of these messages was made known to the players before they made their strategy decision in the round. Brandts and Cooper (2007) reported an experiment in which two-way communication between subjects, labeled as managers and employees, led to better coordination in the turnaround game.

Within this framework of a group playing a Pareto-coordination game with pre-play communication, in some treatments a group has one member designated as a “leader”. Viewed entirely from a standard game-theoretic perspective, a group’s leader plays the same role functionally as any other member of the group. The leader is able to participate in the pre-play discussion, and then chooses his or her own, and only his or her own, journey as part of the play of the game. The leader role is therefore just a label, which is observed by the group members within the pre-play communication.

Leaders therefore do not have a central command power as assumed in Dantzig and Ramser (1959). Instead, our groups have a flat (non-hierarchical) structure, in which some decision-making ability is vested in each group member. In social psychology, Salas et al. (2005) argue that within flat teams, communication is one of the major coordinating mechanisms, and leadership emerges organically as a result of this working of the group. Pearce et al. (2008) propose a theory of shared leadership, in which leadership roles within teams are shared, or shift among team members depending on the task and the capability of each member.

In contrast, most designs in experimental economics impose a functionally distinct role for the leader. Leaders may have some private information not available to the group as a whole (Komai et al., 2011). Communication may be restricted, such that communication between the leader and group members is possible, but direct communication among the group is prohibited. (Brandts et al., 2014) Leaders may make the decisions at a different time than other group members, for example, moving first as a potential exemplar for the rest of the group (Sahin et al., 2015). The role and efficacy of leadership may be quite different in these more hierarchical structures than within a flat team (Burke et al., 2006).

1.3 Experimental Design

In each session, we invited 18 participants selected randomly from the standing participant pool at the Laboratory for Economic and Decision Research (LEDR) at University of East Anglia. All interaction was mediated via computer, with a program written using zTree (Fischbacher, 2007). Our design consisted of two blocks. In the first block, participants completed seven instances of the TDP individually, designing all three journeys as in the original optimisation problem of Dantzig and Ramser (1959). Prior to the second block, our software formed six teams of three participants each. These teams completed an additional seven instances of the TDP in the second block.[2] In these instances, team members had an opportunity to communicate first, and then each member simultaneously completed one of the team's three journeys.

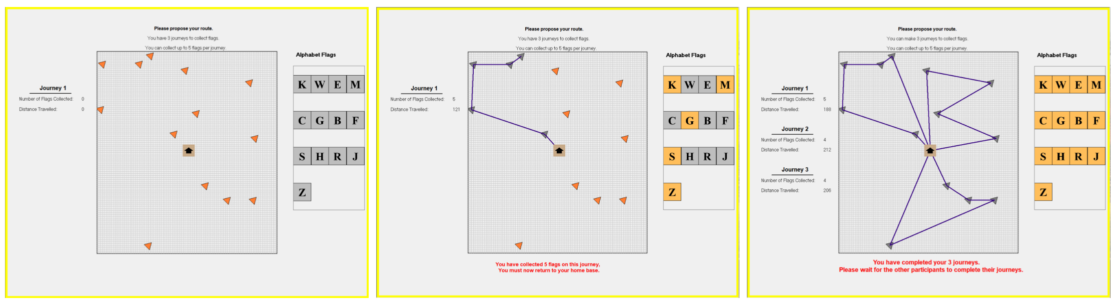
1.3.1 Block One: Individual Solutions

Block One consisted of seven rounds. In each round, participants proposed routes for an instance of a TDP with 13 locations, which were called *checkpoints*. Each round began with a *decision screen*, which displayed the 13 checkpoints as orange triangles on a map 100 units high by 100 units wide, as in Figure 1.1(a). The starting and ending point for all journeys was the home base, located in the centre of the map and indicated by an icon of a house. To start

[2]We selected the 14 TDP instances via a series of pilot exercises. We started with 200 randomly-generated maps, and selected the 14 which generated the most heterogeneity in proposed solutions. That is, we tried to pick maps on which reasonable people would disagree as to what the best solution would be.

a journey, a participant clicked on one of the orange triangles to indicate the first checkpoint to be visited. A line was drawn from the home base to this checkpoint, and the checkpoint's colour changed from orange to grey, indicating that it had been visited. Each checkpoint was associated with a different letter of the alphabet.[3] At the right of the screen was an *alphabet flag box* listing all of these letters. Initially all of these letters were grey; a letter changed colour to orange when the participant visited the corresponding checkpoint.

Figure 1.1: Interacting with the decision screen



(a) At the start of a period (b) Drawing a route (c) After all journeys completed

To continue a journey, the participant then clicked on another orange triangle to visit another checkpoint. As each checkpoint was visited, the clicked triangle turned grey, the line indicating the path of the journey was extended, and the corresponding letter turned orange.[4] At the left of the screen, a box displayed, for each journey, the number of checkpoints visited on that journey and the corresponding distance traveled. Distances were computed as the straight-line distance between successive checkpoints. Figure 1.1(b) shows what the decision screen looked like in the middle of the process of inputting a route.

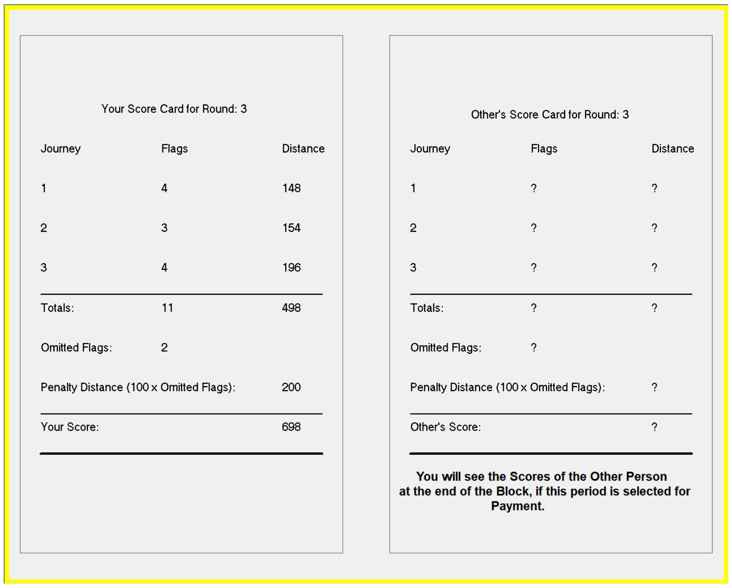
The participant could visit at most five locations on a single journey. The participant could end a journey at any time by clicking on the home icon. Once the participant had visited five checkpoints on the current journey, a reminder message appeared at the bottom of the screen, and the decision screen would only accept a click on the home icon as the next location to visit, and complete the journey. Figure 1.1(c) shows a typical decision screen after the completion of all three journeys.

After completing all three journeys in a round, participants saw a *score card screen* as shown in Figure 1.2. This screen provided two score cards. At the left was the score card for the route the participant selected for the current instance of the TDP. This listed, for each journey, the number of locations visited on that journey, and the distance traveled on the journey. We rounded the distance for each journey to the nearest integer, and computed the total distance for the route as the sum of these three rounded distances. The decision screen did not enforce

[3]The role of assigning letters to each of the locations was to facilitate communication in the team discussions in Block Two, as will be seen presently.

[4]We frame this task as being as if the participant is making the journey from checkpoint to checkpoint. Therefore there was no mechanism to undo a checkpoint visit once the triangle was clicked. We designed all maps so that checkpoints were sufficiently far apart that accidental clicks on an unintended triangle should not occur.

Figure 1.2: The score card as shown at the end of a round in Block One. The left card details the route selected by the participant. The right card is blank, because information on the performance of the other participant was revealed only at the end of the block.



that the participant provide a feasible route visiting all 13 locations. The score card reported the number of locations not included in the route, if any, and the total penalty distance of 100 units per omitted location. The total score was computed as the sum of the distances traveled on the three journeys, plus any penalty distance for omitted locations.

At the right of the screen was a score card labeled *Other's Score Card for Round j*. This score card had the same structure as the participant's score card, except all entries contained question marks. This was to remind participants they were matched with one other participant, and the comparison of their score against this other participant's score would determine their earnings for Block One. However, they would only learn about the routes chosen by the other participant after all seven rounds of Block One were completed.

After all seven rounds in Block One were completed, one of the rounds was chosen at random to be the round which would determine earnings for the Block. This was done by placing seven balls, numbered one through seven, in an opaque bag; the experimenter asked a participant to reach into the bag and pull out one of the balls. The number on the selected ball determined the round which was paid.

After the payment round was drawn, the participant saw a summary table as in Figure 1.3. This table listed, for each round, the participant's score, and the score of the other participant with whom they were matched. The round selected for payment was highlighted with an orange background. If the participant's score was lower than the other's score in that round, the participant earned £10 for Block One; if their score was higher, the participant earned £5 for Block One. In the event of a tie, the participant earned £7.50 for the block. This calculation was summarised at the bottom of the results screen.

Block One concluded with a screen re-visiting the score cards for the round selected for

Figure 1.3: Summary screen at the end of Block One. The round selected for payment is highlighted in orange. The earnings calculation for the Block is summarised at the bottom.

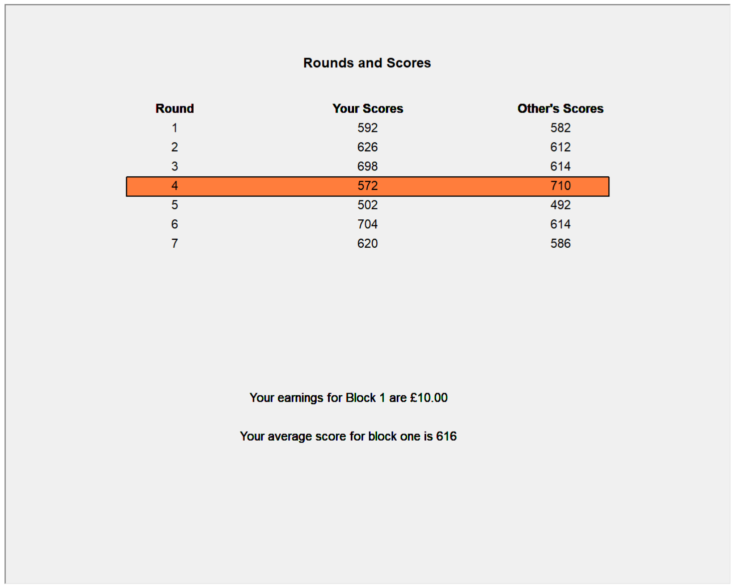
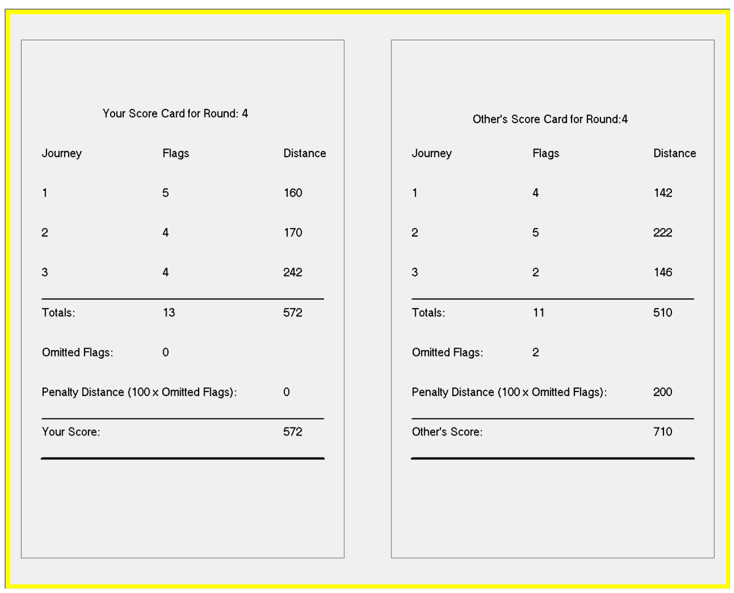


Figure 1.4: The score card as shown at the end of Block One, including the details of the route selected by the other participant.



payment, as in Figure 2.4. This recapped the same information on the participant's route in the given round as they saw it at the end of that round, and adds the details for the other participant's route as well.

1.3.2 Block Two: Team solutions

Block Two followed the same general structure as Block One, in that there were seven instances of the TDP, which participants completed in sequence without information on the performance of others. In Block Two, however, participants were formed into teams of three, who jointly completed one instance of the TDP in each round.

We used the performance of participants in Block One to assign the participants into teams. The 18 participants in a session were grouped into two cohorts of nine based on the desk at which they were seated. Within each cohort, we ranked the nine participants in order of their average score across the seven rounds of Block One. Participants were then assigned to teams using the schema outlined in Table 1.1. For example, participants of rank 1, 2, 3, 4, 5, and 6 were allocated to team 1, 2, 3, 3, 2, and 1 respectively. This "serpentine" system attempts roughly to equalise the average skill of participants across teams, as measured by their relative performances in Block One, such that no team is comprised of only high ranked or low ranked participants.

Table 1.1: Schema for assigning participants to teams based on their Block One performances.

Member ID	Team 1	Team 2	Team 3
Purple	Rank 1	Rank 2	Rank 3
Yellow	Rank 6	Rank 5	Rank 4
Indigo	Rank 7	Rank 8	Rank 9

At this point, teams were assigned to one of the three treatments: elected leader (**EL**), appointed leader (**AL**), or no leader (**NL**). We rotated which team number, as given by Table 1.1, was assigned to which treatment, according to Table 1.2. There were equal numbers of cohort types **EAN**, **ANE**, and **NEA**.

Table 1.2: Schema for allocation of teams to treatment, by cohort type.

	EAN cohort	ANE cohort	NEA cohort
Team 1	EL	AL	NL
Team 2	AL	NL	EL
Team 3	NL	EL	AL

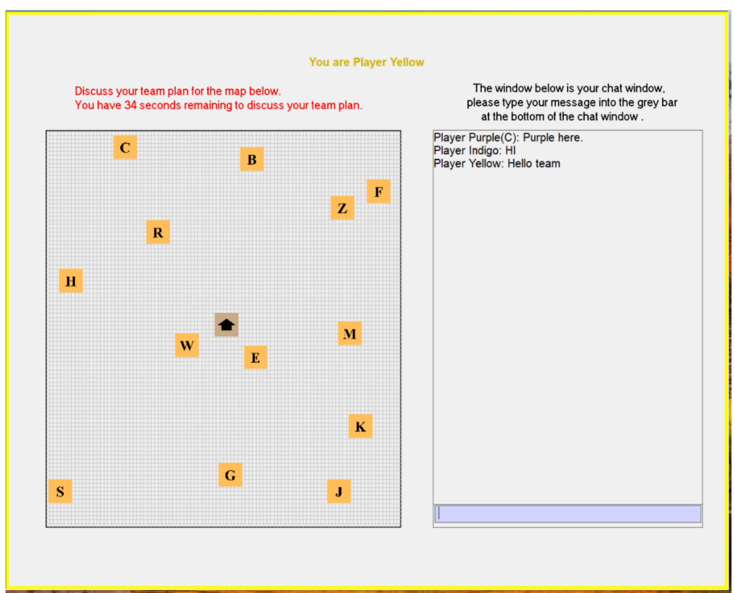
Before the start of Block Two, the experimenter read aloud instructions introducing the rules of the team version of the TDP. Block Two began with a series of three screens. The content of the three screens varied based upon the treatment the participant's team was assigned to. The verbal instructions made no mention of a team captain; therefore participants were unaware of the existence of other treatments within the same session.

After the instructions, the first screen of Block Two introduced the organisation of the team, including that each member of the team would receive a colour name as their identity for the duration of Block Two. Teams assigned to the elected leader (EL) treatment additionally saw a message that on the subsequent screen, they would have an opportunity to select a "team captain". Teams assigned to the appointed leader (AL) treatment saw a message that a captain would be appointed for their team. It was explained that the team captain's role would be to click a button to start each round.

On the second screen of Block Two, players learned their colour names, assigned per the schema in Table 1.1, and also observed the average scores of all three members of their team in Block One. The best-performing member of each team, as measured by Block One performance, was Player Purple; the second-best performing member Player Yellow, and the worst-performing member Player Indigo. Teams assigned to the elected leader (EL) treatment additionally had a pair of radio buttons at the bottom of the screen, captioned "Please vote for your team captain." There were two candidate, Player Purple and Player Yellow, which the candidate receiving the majority of votes to be named as captain.[5]

On the third screen of Block Two, teams in EL learned which candidate had been selected as the captain. Each cohort included exactly one EL and one AL team. The third screen of Block Two also revealed the captain to the AL team. The AL captain was always selected to be the same colour as the successful candidate for the EL team in the same cohort. In this way, the distribution of the relative performance of the team captain in Block One is comparable between EL and AL.

Figure 1.5: A chat in progress, for Player Yellow. This team has a captain, Player Purple, indicated by the (C) label in the chat window.



Following the three preliminary screens, each team completed seven instances of the TDP. Each round began with a chat stage, as in Figure 1.5. At the left of the screen was the map. Checkpoints on the map were displayed as rectangles labeled with letters of the alphabet.[6] At

[5]By restricting to two candidates, we ensure that ties were not possible. Brandts et al. (2014) used a voting mechanism in which all members of 6-member groups could vote for any member, including themselves; ties were broken at random. In Levy et al. (2011) group members (in a 4-member group) could vote for other participants only; they reported that ties did not occur.

[6]We used letters to label the checkpoints to offer a convenient shorthand for participants to exchange possible allocations quickly, e.g. "I'll take RCHW." Indeed we found participants often did communicate in this way; see

the right was a chat window. Messages entered into the chat box were sent immediately to the other two members of the team. For teams in the EL and AL treatments, the member designated as the team captain was indicated with a (C) notation, e.g. "Player Purple(C)" or "Player Yellow(C)". The chat phase lasted 90 seconds; a countdown on the screen indicated how much time was remaining in this phase.

The Decision Screen followed the chat phase. The Decision Screen followed the same structure as the Decision Screen from Block One, except each participant could input only one journey. The three team members entered their journeys simultaneously, without knowing what journeys the other members of their team were making. The alphabet labels were removed from the checkpoints in the Decision Screen. So, if teams did use the labels to discuss possible journey allocations, participants had to commit to memory which labels corresponded to which checkpoints before passing from the chat phase to the Decision Screen. A typical Decision Screen with a route input is shown in Figure 1.6(a).

After all three team members completed their journeys, the next screen displayed the composite route consisting of the three journeys of the team members, as in Figure 1.6(b). As in the individual TDP Decision Screen, the number of checkpoints visited on each journey and each journey's distance were tabulated at left. In addition, the number of omitted checkpoints was presented.

After the composite route was shown, the team's Score Card for the round was displayed. This Score Card was identical in structure to the individual TDP Score Card from Block One (Figure 1.2). It likewise included question marks for the results of the other team, as the performance of the other team was only revealed at the end of the Block.

After completing the seventh and final round, but before seeing the results of the Block, participants completed some questions which captures (over)confidence.

1.4 Hypotheses

Hypothesis 1. *Teams with a named leader (elected or appointed) will perform better, as measured by task scores, than teams without a named leader.*

Recall from our discussion in Section 1.1 that leadership has the capacity of aiding effective navigation through strategic uncertainty, as well as the capacity of imparting focal qualities on equilibria or solutions which would otherwise lack them. We anticipate that teams with named leaders (elected or appointed) will navigate the strategy space of the TDP more effectively and thus, perform better than teams without leaders.

Hypothesis 2. *Teams with an elected leader will perform better, as measured by task scores, than teams with an appointed leader.*

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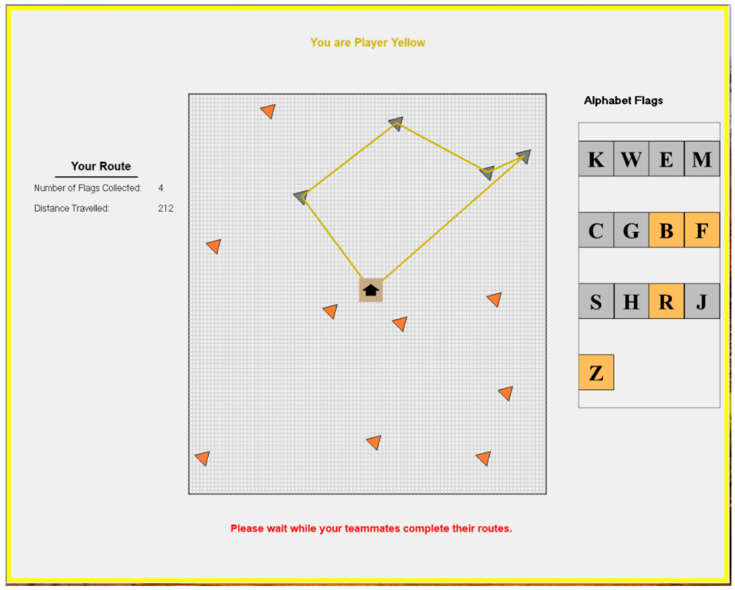
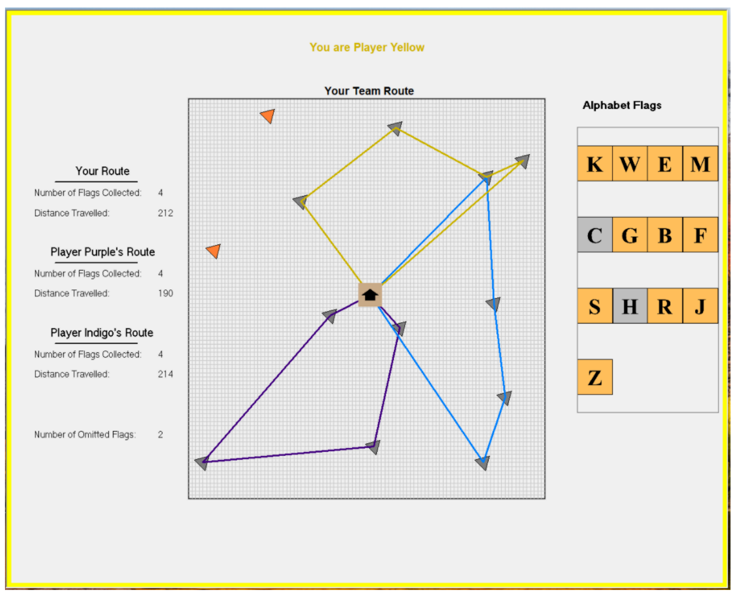
the Results for more details.

Figure 1.6: The Decision Screen for the team TDP.



(a) A typical Decision Screen for Player Yellow.



(b) A team's completed route, with the journeys of all three players.

Since the effectiveness of a leader depends on their legitimacy and how they are perceived by their group. We anticipate, because the process of election is associated with stronger legitimacy, that teams with elected leaders will perform better than teams with appointed leaders.

Hypothesis 3. *Teams with named leaders will be (more) overconfident about the performance of their team.*

As a group's recognition of strategic uncertainty in a coordination problem underpins demands for leadership, it is possible that in the presence of a leader a group might feel (over) optimistic about the group's ability to navigate strategic uncertainty and perform well on a task.

Hypothesis 4. *The solutions proposed by teams will be better than those proposed by individuals on their own.*

Drawing from the experimental literature which argues that teams perform better than individuals in experimental tasks (Cooper and Kagel, 2005; Maciejovsky et al., 2010), we anticipate that solutions proposed by teams will be better than solutions proposed by individuals in the TDP.

Hypothesis 5. *In the chat phase, teams with leaders will have fewer journey (or route) proposals than teams without leaders.*

Drawing from Hypothesis 1, we anticipate that teams with leaders will be more effective than teams without leaders and therefore more organised. More organised teams will require fewer journey (or route) proposals than less organised teams when deciding on a team solution to each instance of the TDP.

1.5 Results

We conducted a total of 15 experimental sessions with 18 participants each, for a total of 270 participants. These participants were grouped in total into 90 teams in Block Two, 30 teams assigned to each of the treatments NL, AL, and EL.

Let $i = 1, \ldots, 90$ index teams, and $T : \{1, \ldots, 90\} \to \{NL, AL, EL\}$ be the function mapping each team into its leadership treatment. Let $m = 1, \ldots, 7$ index the seven maps, in the order in which they were presented to the teams. Let S_{im} be the score of team i on map m, which is the total distance traveled by team i on its three journeys, plus any penalties for omitted flags.

Let i denote a team, t and t' denote treatments with $t \neq t'$, and m a map. The winning percentage of team i on map m, against opponents of type t' is

$$W_m(i, t') = \frac{1}{|t'|} \sum_{j \in t', j \neq i} \mathbf{1}(S_{im} < S_{jm}) + \frac{1}{2} \cdot \mathbf{1}(S_{im} = S_{jm}), \tag{1.1}$$

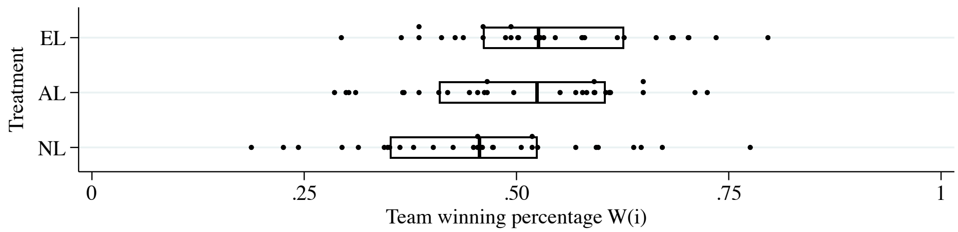
where $\mathbf{1}(b)$ is the indicator function equal to 1 when the boolean condition b is true and 0 otherwise. The overall winning percentage of team i against treatment t' is $W(i, t') = \frac{1}{7} \sum_{m=1}^{7} W_m(i)$, and team i's winning percentage overall is $W(i) = \frac{1}{3} \sum_{t \in \{EL, AL, NL\}} W(i)$.

Given these, we can compute the winning percentage $V_m(t, t')$ of teams in treatment t against those in treatment t' in map m as $V_m(t, t') = \frac{1}{|t|} \sum_{i \in t} W_m(i)$, and the overall winning percentage of teams in treatment t against those in t' as $V(t, t') = \frac{1}{|t|} \sum_{i \in t} W(i)$.

Result 1. *Teams with leaders perform better overall than teams without leaders.*

Support. Overall, teams with elected leaders outperform those with appointed leaders, who in turn outperform those with no leaders. Specifically, $V(EL, NL) = .581$, $V(EL, AL) =$

Figure 1.7: Distribution of team winning percentages $W(i)$ by treatment. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.



.536, and $V(AL, NL) = .551$. To test this more formally, Figure 1.7 plots the distribution of team winning percentages $V(i)$ by treatment. The median of team winning percentages in NL is .456, as compared to .524 for AL and .526 for EL. We use the Mann-Whitney-Wilcoxon (MWW)[7] test over the ordinal ranking of teams generated by $W(i)$[8] to compare the distribution of teams without leaders versus those with leaders. We reject the null hypothesis that winning percentages without and with leaders come from the same distribution (p-value .026). The effect size, the chance or probability that a randomly-selected team without a leader outperforms a randomly-selected team with a leader is $r = .356$.[9]

Result 2. *Teams with elected leaders perform only slightly better overall than teams with appointed leaders.*

Support. Figure 1.7 suggests that, among teams with leaders, there is little difference between those whose leaders were elected versus those who were appointed. The upper and lower quartiles are lower for AL than for EL, but medians are very close. The MWW test comparing teams with appointed leaders to teams with elected leaders is not significant ($p = .438$, $r = .442$).

Result 3. *Overall teams exhibit overconfidence. Teams with leaders do report more optimistic assessments of their performance; however, this additional optimism is roughly in line with those teams' superior actual performance.*

Support. At the end of the experimental session, we asked each participant, "How many rounds do you think your team won?" Each participant answered this independently of other team members, prior to knowing the outcomes of Block Two. For each team, we construct a measure

[7]The Mann-Whitney-Wilcoxon (MWW) test also known as the Mann-Whitney two sample statistic or the Wilcoxon Ranksum test is a nonparametric test statistic which tests the hypothesis that two independent samples, say A and B are from populations within the same distribution. The null hypothesis H_0 is that A and B have the same distribution and the alternative hypothesis H_1 is that A and B have different distributions. In conducting the MWW the observations in both samples are ranked in order of increasing size and ties are averaged. The sum of ranks for each sample are obtained and compared (Moffatt, 2015; Siegel and Castellan, 1988).

[8]Note that the calculation of $W(i)$ does not use information about which treatment team i is assigned to. Therefore, it is suitable to use this ranking as the data for an MWW test.

[9]We report this effect size (probability) for all MWW tests. We express all MWW tests as population A versus population B, and the effect size is in the sense of a random member of population A being higher than a random member of population B.

Figure 1.8: Team predicted performance versus actual performance. Each point represents one team. The line plots the linear fit on actual performance as a function of predicted.

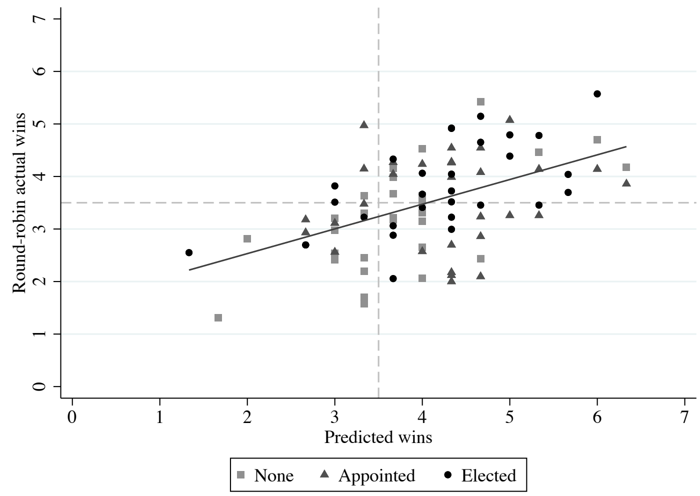


Figure 1.9: Distribution of predicted wins by treatment. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.

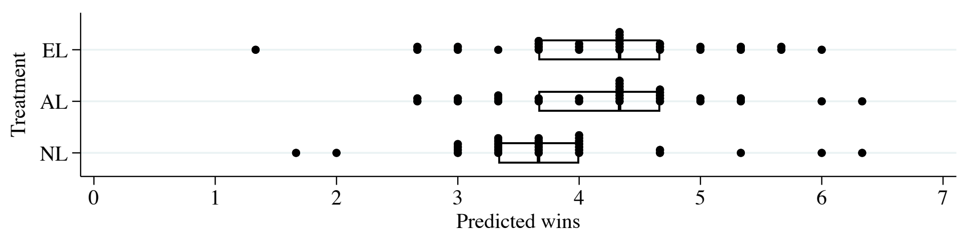
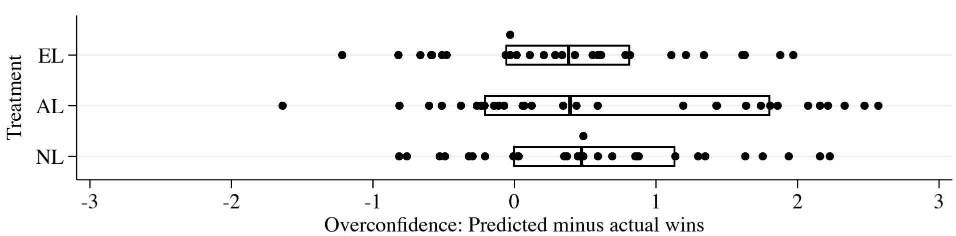


Figure 1.10: Distribution of overconfidence (predicted minus actual wins) by treatment. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.



of a team's assessment of their own performance by averaging the three responses of each team's members. We can compare this to the team's actual performance $W(i)$. Figure 1.8 plots each team's predicted versus actual performance. Overall, teams expected to win 4.06 out of the 7 rounds, giving a mean overconfidence of 0.56 wins.[10] Overconfidence aside, there is a positive correlation between a team's predicted performance and their actual performance. A

[10]This is consistent with standard results on overconfidence, e.g. Oskamp (1965); Lichtenstein et al. (1977); Camerer and Lovallo (1999).

Table 1.3: Predicted and actual team performance, by treatment. All cells are averages over all teams, measured in wins per 7 rounds.

		Wins		
Treatment	N	Predicted	Actual	Overconfidence
NL	30	3.76	3.19	0.57
AL	30	4.26	3.54	0.72
EL	30	4.17	3.78	0.39
Total	90	4.06	3.50	0.56

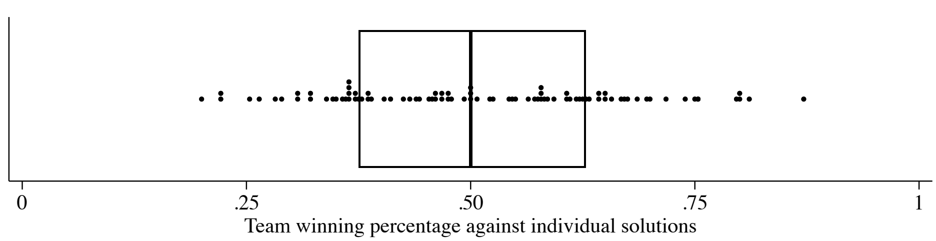
simple linear regression of actual performance on predicted performance gives

$$\text{actual performance} = 1.592 + 0.470 \times \text{predicted performance}, \tag{1.2}$$

with an adjusted $R^2 = .24$. Although teams do not get feedback on their performance relative to that of any other teams, nevertheless teams which actually do well tend to believe they did well, and vice versa.

Teams without a leader predicted on average 3.76 wins out of the 7 rounds. Teams with a leader predicted 4.21 wins on average. Figure 1.9 plots the distribution of predicted wins by treatment. Teams without a leader predict fewer wins than those with a leader (MWW $p = .0095$, $r = .333$). There is no difference in predicted wins between teams with appointed or elected leaders (MWW $p = .81$, $r = .482$). However, the more optimistic assessments offered by the teams with leaders, are in line with actual performance differences. The last column of Table 1.8 reports the mean overconfidence by treatment, computed as the difference between the predicted performance and the actual performance. Figure 1.10 plots the distribution of this overconfidence measure by treatment. The overconfidence of teams without leaders and with leaders is not different (MWW $p = .77$, $r = .519$). Likewise, teams with appointed leaders do not differ from those with elected leaders (MWW $p = .38$, $r = .434$).[11]

Figure 1.11: Distribution of team performance against individual solutions.



Result 4. *Over the seven maps, the scores of solutions proposed by teams are not systematically different than those proposed by individuals.*

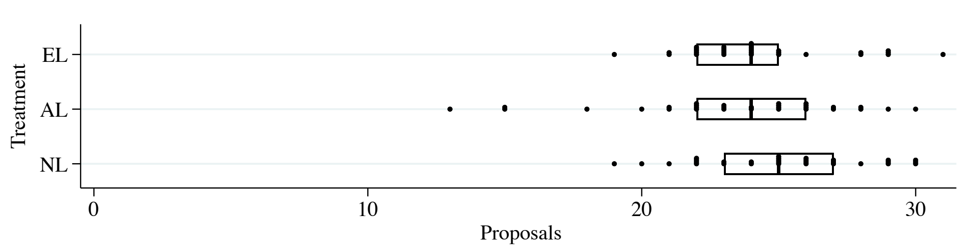
[11] Alternatively, a Kruskal-Wallis test does not reject the null hypothesis that all three treatments have the same distribution of overconfidence ($p = .60$).

Support. We selected the maps used in the sessions based on a series of pilot experiments. In the pilot experiments, participants completed two blocks of seven maps each, as in Block One of these experiments, and were incentivised using the same system as in Block One. In the pilot experiments, we used a wider range of maps. We used the pilot data to select the 14 maps in our experiment, by choosing maps which generated the largest dispersion of submitted routes in the individual experiments, with the goal of posing instances of the TDP to teams in which individual judgments as to what constituted a good solution differed, and therefore it would be more likely that teams would need to choose among different proposals offered by different members.

For each map in Block Two, in addition to the 90 observations of team solutions, we have 20 observations of individuals proposing routes on those same maps. We can therefore benchmark the performance of a team i by comparing, for each map m, its performance against the 20 solutions proposed by individuals. A team's overall performance is given by its average performance over the seven maps. We plot these team-versus-individual winning percentages in Figure 1.11. The median team-versus-individual winning percentage is exactly .5; the lower quartile is .375 and upper quartile .629, meaning the distribution is close to being symmetric around .5. Therefore there is no evidence overall that teams perform better or worse than individuals.

We now turn to the chat transcripts to look for ways in which having a leader might affect the decision-making process of the team. There are (at least) two coordinated approaches a team might take in organising the process of identifying and agreeing a plan. In a centralised approach, one team member can act as a central planner and allocate or propose a journey to each member of the team. Alternatively, a team may adopt a more decentralised, bottom-up approach, in which each member of the team makes proposals sequentially for their own (intended) journey. Either model would result in a total of three journey proposals, while attempting to use a mix of the models or members making proposals simultaneously would lead to overlapping journeys or missed flags, requiring the proposal of revised journeys. This suggests using the number of proposals per chat period as a measure of team organisation.

Figure 1.12: Distribution of proposals by treatment. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.



Result 5. *In the chat phase, teams with leaders have fewer journey or route proposals than teams without leaders.*

Table 1.4: Number of proposals per team, across all rounds.

		Proposals	
Treatment	N	Mean	Std. Dev.
NL	30	25.23	3.05
AL	30	23.37	4.11
EL	30	24.30	2.81
Overall	90	24.30	3.42

Support. Table 1.4 shows the average number of proposals by treatment, and Figure 1.12 plots the distribution of proposals by treatment. Teams in EL have the lowest number of proposals and teams in NL the highest number. Teams with no leaders (NL) have significantly higher numbers of proposals than teams with named leaders (EL and AL) (MWW, $p = 0.0752$, $r = 0.615$). Teams in EL and AL have similar numbers of proposals (MWW, $p = 0.7258$, $r = 0.473$).

1.6 Discussion

We investigate the role of leadership in flat teams facing a complex decision task with a large number of possible options. Our decision task, drawn from a problem in combinatoric optimisation, has several features found in the problems faced by real-world teams such as clubs, musical bands and sporting teams. Teams do not have the time to consider and rank every feasible option, and face a coordination problem both in agreeing on which option to implement, and then in actually carrying it out. Similar to results in experimental economics on coordination games, we find that having a named leader (elected or appointed) improves the quality of teams' decisions. We strengthen this finding because our experiment does not introduce any functional or asymmetric role for the named leader. In contrast to theories from social psychology, although our design allows teams to self-organise, teams with named leaders outperform those without; self-organisation is not a complete solution for teams in our environment.

The captaincy of a sports team might be a frequent topic of discussion because people may misperceive that having a named leader improves the performance of a team. A feature of our experimental design is that we are able to look for evidence that having a named leader affects the (over)confidence of a team, because we have a measure of team performance in a controlled environment. As is usual, we do find that participants are on average overconfident in their team's performance, and that participants on teams with leaders are more confident than those on teams without. However we do not find additional overconfidence among those teams with leaders. Higher reported confidence correlates positively with actual performance; the optimism of our teams with named leaders is not a misperception but is grounded in the team's performance. Sports journalists and bloggers opining on captain controversies therefore may not be merely filling column inches and dead airtime.

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Appendices

1.A Instructions

1.A.1 Block One: Individual Solutions

Introduction

Welcome and thank you for taking part in this experiment.

This is an experiment of decision-making. If you follow the instructions and make appropriate decisions, you can earn an appreciable amount of money. You will receive your earnings for today's session in cash before you leave the laboratory.

It is important that you remain silent and do not look at other people's work. If you have any questions, or need any assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, e.t.c., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

Today's session consists of two blocks. Your earnings in each block depend only on the decisions made in that block.

We will now describe the session in more detail. Please follow along with these instructions as they are read aloud.

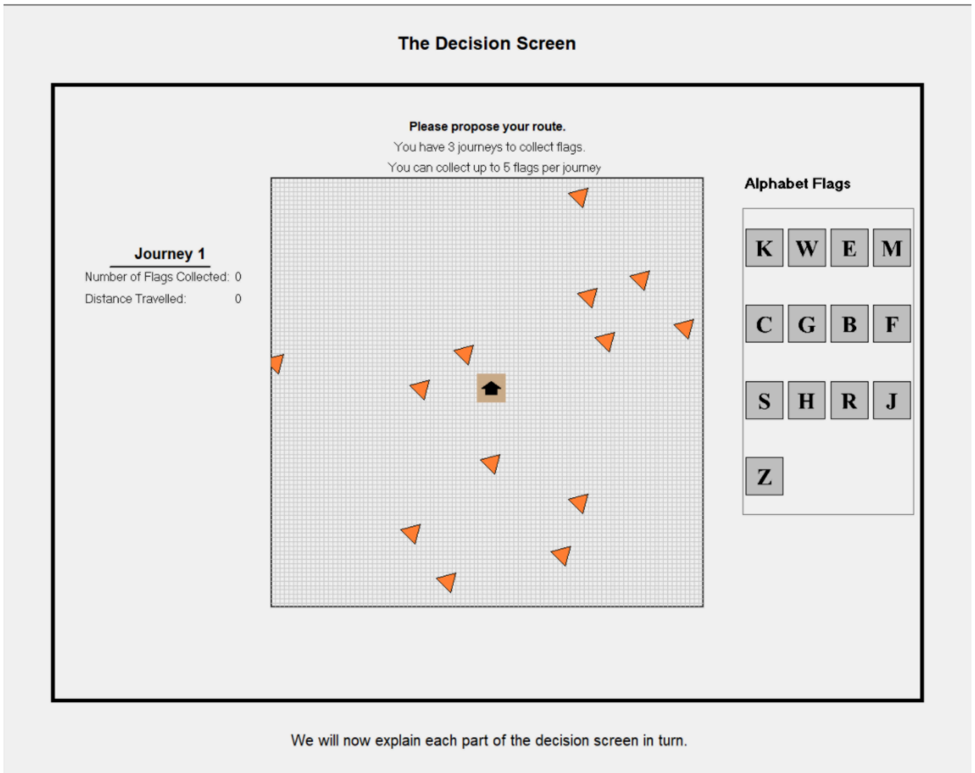
Block 1

In Block 1, you will be matched randomly and anonymously with one other participant in today's session. You will not know the identity of the participant with whom you are matched, nor will that participant know your identity, either during or after the session.

Your earnings for Block 1 will be determined by your choices and the choices made by the other participant with whom you are matched.

In Block 1, there will be seven (7) decision rounds. In each round you will propose a route which visits checkpoints laid out on a map. Each checkpoint is associated with a letter of the alphabet. We will now show you what your screen will look like during a decision round.

Figure 1.13: Example of the Decision Screen

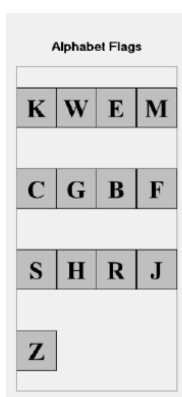


Alphabet Flags

In each round there will be 13 checkpoints for you to visit. When you visit a checkpoint, you will automatically collect a flag with that checkpoint's letter.

The box of 'Alphabet Flags' at the right of the screen keeps track of the lettered flags you have collected so far. When you collect a flag, the corresponding letter box will change from grey to orange.

Figure 1.14: Box of Alphabet Flags

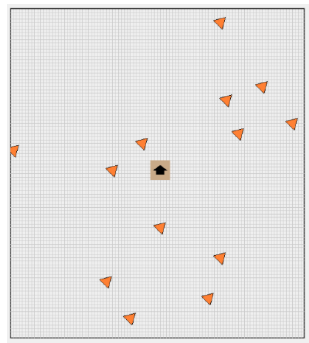


The Map

The checkpoints in each round are laid out on a map like the one below, which will be shown in the middle of your screen. In each round, all participants will see the same map.

The map is 100 units top to bottom and 100 units left to right. In the centre of the map is your home base, indicated by the picture of a house. On the map are the 13 checkpoints, each indicated by a triangle. Each checkpoint has a corresponding alphabet flag.

Figure 1.15: Example of a Map



Choosing Your Route

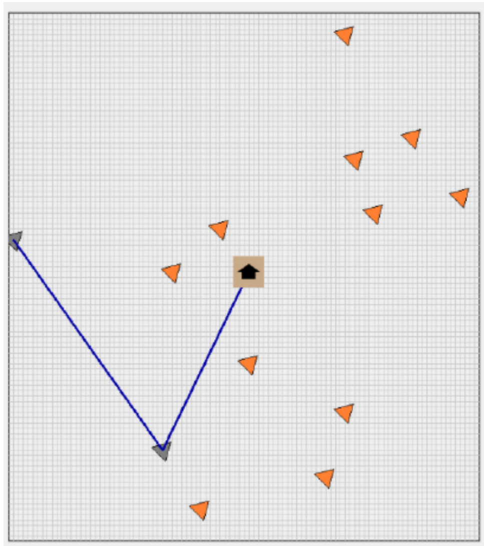
You can make three journeys to collect flags. You begin each journey at your home base. From there, you can visit a checkpoint by clicking on the corresponding triangle. When you visit a checkpoint, you will automatically collect a flag with that checkpoint's letter. That checkpoint's triangle will change colour from orange to grey, and in the Alphabet Flags box the checkpoint's letter will change colour from grey to orange.

You can visit checkpoints in any order while on a journey. However, you can carry no more than five flags at a time. Once you have visited five checkpoints and therefore collected five flags, you must complete the journey by returning to your home base. You may choose to complete a journey at anytime, even if you have not yet collected five flags. But, remember that you have only three journeys in which to visit the 13 checkpoints and collect the corresponding 13 flags.

As you make your journeys, the computer will draw the route you have taken. Your route will be represented by straight lines between checkpoints. Checkpoints which you have already visited will be shown as grey triangles; the checkpoints you have yet to visit will be shown as orange triangles.

Once you collect a flag from a checkpoint you cannot return it. So plan ahead for your journey before setting out.

Figure 1.16: Routes are represented as straight lines between checkpoints



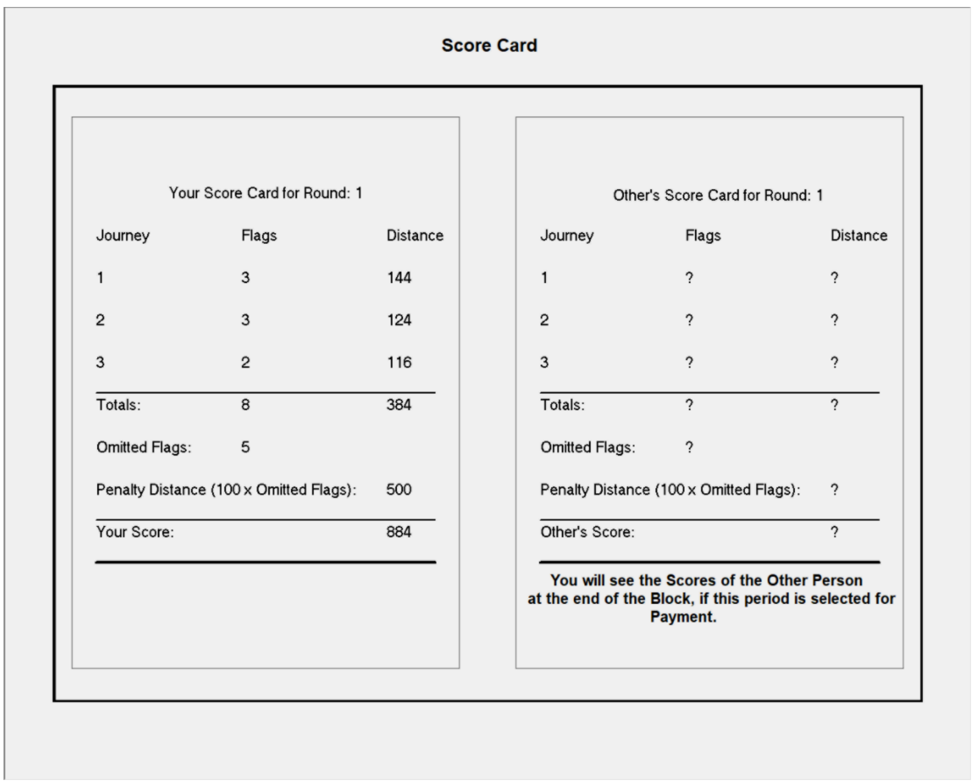
Your Score

Your score for a round is given by the total straight-line distance you travel along the routes you choose for your three journeys. Lower scores are better; therefore in choosing your journeys your aim is to minimise the total distance travelled.

In the event you do not collect all of the flags on your three journeys, an additional penalty distance of 100 will be added to your score for each flag you did not collect. Because the grid is 100 units high and 100 units wide, you can always get a lower score by visiting all checkpoints rather than missing some out.

You will complete seven rounds, with a new map in each round. At the end of each round, you will see a Score Card showing a detailed breakdown of how your score was determined for that round. You will also see a Score Card for the person with whom you are match in Block 1. Their score card will contain question marks, as you will only find out their score for that round at the end of the block. The next screen shows a sample Score Card.

Figure 1.17: Example of a Score Card



Summary Screen

At the end of Block 1, one of the seven rounds in the block will be selected at random. Each round has an equal chance of being select. In each pair the participant who had the lower score in the selected round will earn £10, and the participants who had the higher score in the selected round will earn £5. In the event both participants in a pair have the exact same score (i.e., a tie), both participants will earn £7.50. Because you will not know in advance which round will be selected, you should complete each round as if it will be the one chosen to determine payment for the block.

After the round for payment is determined for Block 1, you will see a summary like the one below. This table will show your score and the score of the other person with whom you are matched for each of the seven rounds. The round which is selected for payment will be highlighted.

Figure 1.18: Example of the Summary Screen

Round	Your Scores	Other's Scores
1	849	850
2	800	701
3	850	701
4	701	700
5	700	849
6	849	850
7	850	1300

1.A.2 Block Two: Team Solutions

Introduction

As you were told earlier, today's session consists of two blocks. Your earnings in each block depend only on the decisions made in that block. You have just completed Block 1. We will now begin Block 2. We will describe the block in more detail. Please follow along with these instructions as they are read aloud.

Block 2

Block 2 has exactly the same structure as Block 1. You will see a new series of seven maps, 100 units wide by 100 units high, with a home base in the middle and 13 checkpoints. You have three journeys to collect the flags, and on each journey you can collect at most five flags.

In Block 2 your will be matched anonymously with two other participants in today's session to form teams of three. You will never find out the identities of those with whom you are matched, nor will they find out yours. for identification purposes, one member of the team will be known as Indigo, one member as Yellow, and one member as Purple. At the start of the block, when your team is organised, you will learn your colour identities. The composition of the team and the identifying colours, will remain the same throughout Block 2.

Each team will then be matched randomly and anonymously with one other team. Your team will not know the identity of the members of the team with which your team is matched, nor will be members of the other team know your identity, either during or after the experiment.

Your earnings for Block 2 will be determined by your team's choices and the choices made by the other team with which your team is matched.

Choosing your route

Your team will make a total of three journeys to collect flags. Each member of the team will make exactly one journey. Each journey begins at your home base. From there, you can visit a checkpoint by clicking on the corresponding triangle. When you visit a checkpoint, you will automatically collect a flag with that checkpoint's letter. That checkpoint's triangle will change colour from orange to grey, and in the Alphabet Flags box the checkpoint's letter will change colour from grey to orange.

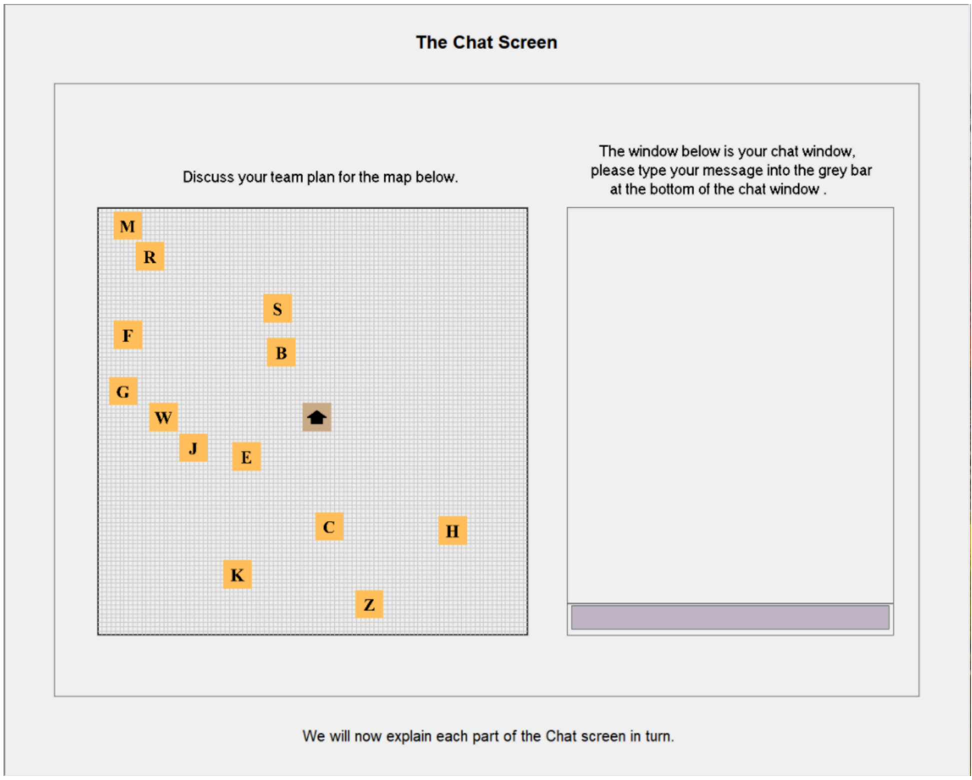
You can visit checkpoints in any order while on a journey. However, you can carry no more than five flags at a time. Once you have visited five checkpoints on a journey and therefore have collected five flags, you must complete the journey by returning to your home base. You may choose to complete a journey at any time, even if you have not yet collected five flags. Remember that your team has only three journeys in order to collect all 13 flags.

You and the other two members of your team will make your journeys individually. You will not see which checkpoints the other members of your team are visiting while you are making your journey.

Prior to making your journey, your team will have the opportunity to discuss a plan of action in text-based chat which we will now discuss.

The chat screen

Figure 1.19: Example of the Chat Screen



To the left of the chat screen will be the map for that round. The label on each checkpoint corresponds to the alphabet labels on the alphabet flags panel of your decision screen. To the right is the chat window. Any message you type in this chat window will be seen by the other two members of your team and vice versa. These messages will not be seen by the members of other teams. Your team will have 90 seconds to discuss your plan of action. During this time your team is free to discuss the plan any way you wish, with the following restrictions:

1. You may not identify yourself or pass along any information that could be used to identify you (for example, age, race, background, seat number and so forth).

2. You may not use obscene or offensive language.

After the 90 seconds are over, you will be taken to the decision screen where each member of the team will make their own journey.

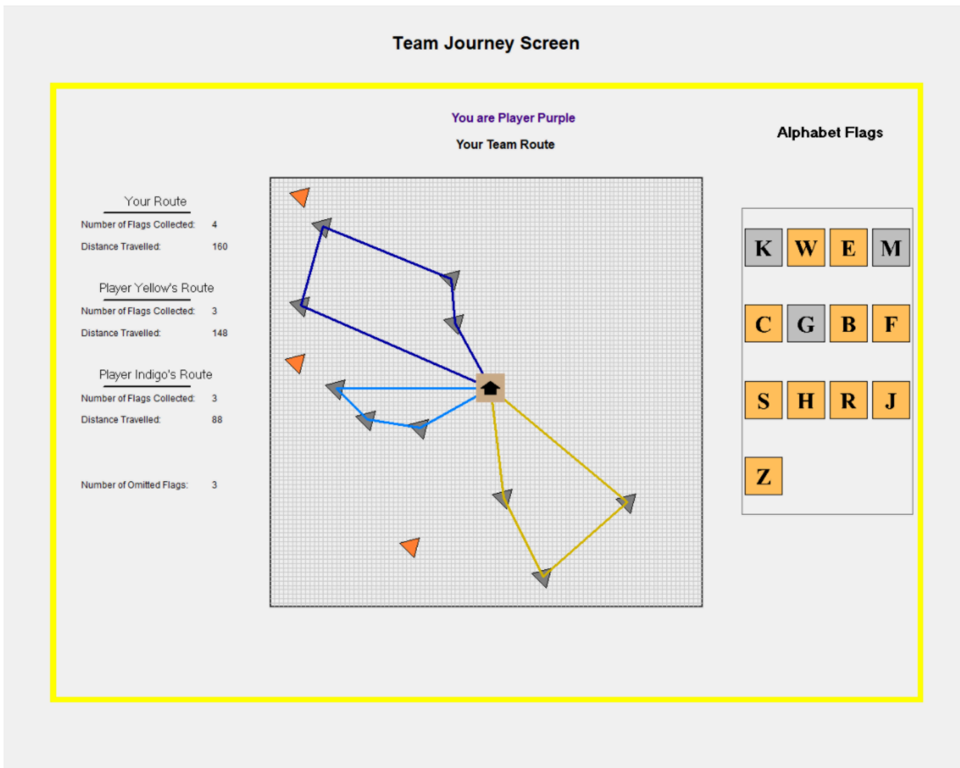
Choosing your route

Your will make your journeys individually. You will only see the journeys of your team mates, after your own journey has been completed. As you make your journeys, the computer will draw the route you have taken. Your route will be represented by straight lines between checkpoints. Checkpoints which you have already visited will be shown as grey triangles; the checkpoints you have yet to visit will be shown as orange triangles.

Once you collect a flag from a checkpoint you cannot return it. So plan ahead for your journey before setting out. When all journeys have been completed, you will see a screen which shows the map with the journeys made by all three members of your team.

Team Journey Screen

Figure 1.20: Example of the Team Journey Screen

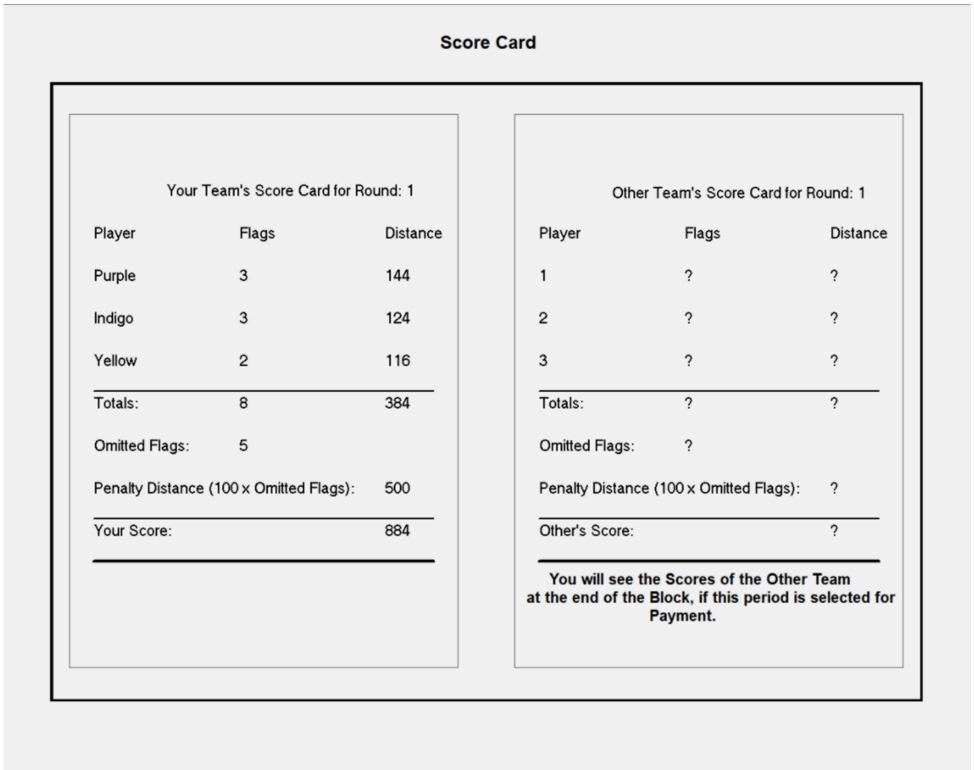


Your Score

Your team's score for a round is given by the total distance the members of the team travel along the routes you choose for your three journeys. Lower scores are better; therefore in choosing your journeys your team's aim is to minimise the total distance travelled. In the event your tea does not collect all of the flags on your three journeys, an additional penalty distance of 100 will be added to your score for each flag your team did not collect. Because the grid is 100 units high and 100 units wide, your team can always get a lower score by visiting all locations rather than missing some out.

You will complete seven rounds, with a new map in each round. At the end of each round, you will see score card showing a detailed breakdown of how your team's score was determined for that round. You will also see a score card for the team with which your team is matched in the block. Their score card will contain question marks, as you will only find out their score for the round at the end of the block. The next screen shows a sample score card.

Figure 1.21: Example of the Team Score Card



Summary Screen

Recall that your team will be matched with one other team for Bock 2, at the end of Block 2, one of the seven rounds in the block will be selected at random. Each round has an equal chance of being selected. If your team had the lower score in the selected round, all participants in your team will earn £10 each, and if your team had the higher score, all the participants in your team will earn £5 each. In the event both teams have the exact same score (i.e., a tie), all members in your team will earn £7.50 each. Because you will not know in advance which round will be selected, you and your team should complete each round as if it will be the one chosen to determine payment for the block.

After the round for payment is determined for Block 2, you will see a summary like the one below. The table will show your team's score and the score of the other team with which your team is matched for each of the seven rounds. The round which is selected for payment will be highlighted.

Figure 1.22: Example of the Team Summary Screen

Round	Your Team's Scores	Other Team's Scores
1	849	849
2	800	701
3	850	700
4	701	700
5	700	850
6	849	850
7	851	1300

Chapter 2

Individual Skill and Incentives in a Laboratory Experiment

In this chapter, we study experimentally the effects of individual skill in a real-performance task and the responsiveness of individual skill to various incentive schemes. Participants faced instances of the Truck Dispatch Problem, in which they devised three journeys which visit a set of locations on a map. Some participants were remunerated under a rank order tournament incentive scheme, some participants were informed of their performance ranking and were given a fixed rate whilst some participants were remunerated under a fixed rate incentive scheme. We find evidence for individual skill differences in the task, but that the distribution of these differences does not depend on the incentive treatment.

2.1 Introduction

Economics experiments ask participants to make a variety of decisions, usually guided by financial or other incentives. Within this framework, the types of decisions that participants make can vary substantially depending upon the objectives of the experiment. Many studies in the experimental literature make use of tasks which we will refer to as *stated effort* tasks. For example, in the turn-around game (Brandts et al., 2014), each participant chooses a number, for example, from the set $\{1, 2, 3, 4, 5, 6\}$. Each number is interpreted as a level of effort. Higher numbers correspond to higher levels of effort, and come at a higher cost to the participant, which is represented by a financial cost in the experiment. Stated effort tasks have the advantage of controlling for individual characteristics such as ability and experience, when those characteristics are not of primary interest to the research question.

However, stated effort tasks have been criticized on the grounds that they are unrealistic and lack external validity (Levitt and List, 2007). *Real effort* tasks, which involve participants performing a tangible action, such as accurately positioning slider bars on a computer screen or stuffing envelopes, have become increasingly popular in the experimental literature (Brüggen and Strobel, 2007; Charness and Kuhn, 2011; Corgnet et al., 2015; Gächter et al., 2016). These tasks trade off the benefit of realism against a loss of some degree of control over the idiosyncratic effects of ability and experience. For example, if effort is believed to come at a cost to participants, as is often assumed in economic models (Falk and Fehr, 2003), in a real effort task this cost of effort is unknown to the experimenter.

In the experiment in Chapter One, teams of three participants produced solutions to instances of the Truck Dispatching Problem (TDP).[1] Similar to a real-effort task, the TDP involves executing a tangible action, namely, drawing a route around a map. Unlike most real effort tasks, which are simple and repetitive, the TDP is a complex problem, and it is the problem-solving aspect of the TDP that makes it an interesting task to use in Chapter One to investigate the role of leadership.

Therefore, the TDP has some features of stated effort tasks and some features of real effort tasks. Carrying out the task is important for the experiment, but it is not per se the effort in carrying out the task that is of direct experimental interest. We propose to refer to this type of task as a *real performance* task. We coin the term real performance task to refer to tasks which have the quality of being a tangible task with a cost of effort function that can be controlled and known by the experimenter.

As a tangible task, performance in the TDP might be affected by individual characteristics such as ability, experience, or the subjective utility derived from performing such tasks (Brüggen and Strobel, 2007). We designed the experiment in Chapter One to construct teams based on their performance in an initial set of TDP instances, in such a way that teams within a session would be of comparable overall skill. Nevertheless, because we constructed the teams from

[1] In Chapter One, we referred to this as the Team Dispatching Problem as teams had to jointly participate on the task.

cohorts of nine participants, if participants do vary significantly in their performance on the task, the teams we constructed might likewise vary significantly in their capacity to produce good solutions to the TDP.

The TDP is a generalisation of the Travelling Salesman Problem (TSP). The TSP and TDP are demonstrably difficult optimisation problems for which efficient solution algorithms are not known. The psychology literature has studied he ability of people to produce approximations to the optimal solution in the TSP, and has found mixed evidence of individual differences in skill. Experimental designs in that literature focus more on the processes or heuristics people use to produce approximate solutions, as opposed to the quality of the solutions themselves. Our experiment focuses on the quality of the approximation solutions produced, and how the quality is affected by the use (or absence) of performance-contingent incentives, and the type of feedback participants receive.

2.2 Related Literature

The Truck Dispatching Problem (TDP) (Dantzig and Ramser, 1959) is a generalisation of the Traveling Salesman Problem (TSP). In an instance of a TSP, the objective is to find the route passing once through each of N locations on a map, which has the shortest distance (MacGregor and Ormerod, 1996; Laporte, 2010). In our formulation of the Truck Dispatching Problem, the route must begin from a given "home" location. A route is comprised of several journeys. On each journey, no more than m of the other $N-1$ locations may be visited. If $m = N-1$ this is equivalent to the TSP; if $m < N-1$, as in our experiment, multiple journeys are required to visit all locations. The objective is to find the route, which satisfies this constraint, which has the shortest distance.

The TSP and the TDP is easy to state and understand. Nevertheless, it is remarkably computationally difficult to find the shortest distance in many instances. Computationally, these problems are classified as NP-hard. There are no known algorithms which can provide solutions to NP-hard problems, in which the running time increases as a polynomial function of the size N of the problem.[2] There do exist heuristic algorithms which are not guaranteed to find the optimal route, but usually find "good" routes, the length of which is not much longer than the length of the optimal route. It is the combination of the ease of description and the challenge of solution which made the TDP suitable for the experiment in Chapter One.

There exists a body of experimental literature in psychology which studies human performance on instances of the TSP (MacGregor and Ormerod, 1996; Vickers et al., 2001; Chronicle et al., 2008). From the evidence, it is not clear whether people are systematically different in their ability to produce good routes. One set of studies consistently finds evidence in favour of individual differences (Vickers et al., 2001, 2003, 2004; Burns et al., 2006). People who

[2]Such an algorithm, or a proof that no such algorithm exists, would fetch a $1,000,000 prize from the Clay Mathematical Institute (Applegate et al., 2006).

produce better routes for the TSP also tend to perform better on other tasks, as well as scoring more highly on intelligence measures such as Raven's Advanced Progressive Matrices (Vickers et al., 2001). Within instances of the TSP itself, Vickers et al. (2001) compared performance on TSP problems with 10, 25, and 40 nodes, and found within-subject rank-order correlations of $0.81 \leq \rho \leq 0.87$.

On the other hand, another set of studies consistently finds no evidence that individual skill is important in TSP performance. This strand of the literature argues that when presented as a set of points on a two-dimensional map, people produce routes using the human perceptual system, instead of using explicit cognitive reasoning (MacGregor and Ormerod, 1996; MacGregor et al., 1999, 2006). MacGregor and Ormerod (1996) compared performance on TSP problems with 10 and 20 nodes, and found within-subject rank-order correlations of $0.02 \leq \rho \leq 0.06$.

In an attempt to reconcile this stark difference, Chronicle et al. (2008) argued that the cause of the discrepancies might be differences in experimental practices. For example, Vickers and coauthors use TSP instances with larger numbers of nodes, which participants completed on a computer. MacGregor and colleagues, on the other hand, use TSP instances with relatively few nodes, which participants completed using paper and pencil. Chronicle et al. reported an experiment in which TSP instances used by Vickers and colleagues were presented to participants using the paper and pencil method from MacGregor and colleagues. They compared performance on TSP problems with 30 and 40 nodes, and found within-subject rank-order correlations of $0.20 \leq \rho \leq 0.30$. These correlation are higher that those obtained by MacGregor and Ormerod (1996) but smaller than those obtained by Vickers et al. (2001). They interpreted their results as evidence that individual differences in performance on the TSP become more apparent as TSP problems become more complex, arguing that more complex problems require a shift from basic perceptual mechanisms to higher-order cognitive or analytic mechanisms.

In the studies discussed above, participants were paid a flat fee for their participation, which did not depend on the routes they chose. This is the usual practice in psychology experiments, which psychologists defend by arguing that participants are intrinsically motivated to do well, and therefore payment contingent on performance is not beneficial (Deci, 1971; Deci et al., 1999). In experimental economics, on the other hand, it is standard practice to pay participants contingent on the choices they make or their performance on a task. Experimental economists argue that such incentives give the experimenter greater control over the preferences of the participants in the context of the decision-making environment of the experiment. Monetary incentives are argued to be more uniformly valued across experimental participants, compared to e.g. course credits or the satisfaction of doing well, and therefore support the replicability of experiments (Smith, 1976; Hertwig and Ortmann, 2001; Croson, 2005).

Economists maintain that financial incentives improve performance and reduce variance in experimental data (Smith and Walker, 1993; Camerer and Hogarth, 1999; Hertwig and Ortmann, 2001; Read, 2005). Smith and Walker (1993) argue that financial incentives improve the performance of experimental participants by compensating for the cost of mental effort. They presented a theoretical model in which mental effort, much like physical effort, imposes a cost upon the economic agents. In order to encourage higher effort levels, agents need to be offered a monetary compensation which offsets the mental cost of decision making. From their meta-analysis of 31 experimental studies, which include bilateral bargaining, Cournot oligopoly, binary choice prediction, and double auction market experiments, they found that when experiments are incentivised the central tendencies of performance are closer to the predictions of normative models, and that the variance of errors around optimal decisions is reduced. The effects of incentives are more pronounced when participants are offered larger monetary incentives.

Camerer and Hogarth (1999) study the effects of incentives on performance in experiments by conducting a meta-analysis of 74 studies published in the *American Economic Review*, *Econometrica*, *Journal of Political Economy* and *Quarterly Journal of Economics* between 1990 and 1998. They find evidence for a more nuanced picture of the relationship among tasks, incentives and performance. Over all tasks, they find that financial incentives lead to a reduction in variance of performance, which is consistent with the results of Smith and Walker (1993). The results for levels of performance are mixed. Using task complexity as proxy for the skill demanded by a task, they find financial incentives have a stronger effect on performance levels when the task is simple. For example, financial incentives tend to result in higher performance in judgement tasks, such as memory or recall tasks, or clerical tasks which are mundane and require close attention to perform well. Tasks such as these do not require much skill; they are within the capacity of most (if not all) experimental participants, so performance depends primarily on a willingness to exert some kind of effort. In contrast, more complex tasks typically require skill. For some participants, skill (for example, cognitive capital or lack thereof) becomes a binding constraint on performance; for these participants more effort does not lead to more performance, so incentives for effort are not relevant for them. Camerer and Hogarth argue that variation in performance on complex tasks therefore depends more on individual characteristics than on the amount of effort participants are willing to give. This is consistent with the model in Smith (1976), in which financial incentives will not lead to increased performance when the agent's ability is bounded.

Bonner et al. (2000) conduct a meta-analysis of 131 studies in which they take into account both the complexity of the task, and characteristics of the incentive scheme. They likewise find that the more complex the task, the less participants' performance depends on monetary incentives. They provide a ranking of types of tasks ordered by increasing complexity: vigilance and detection tasks; memory tasks; production and simple clerical tasks; judgement and choice tasks and problem solving; reasoning and game playing tasks. They divide the incentive schemes used in their sample into four categories, given some quantified measure of participants' performance. In *fixed-rate schemes*, participants are paid a fixed amount irrespective of performance. In *quota schemes*, participants are paid a fixed amount irrespective of performance until a given level of performance is attained; beyond this level participants receive a bonus. A *tournament scheme* compares the participants' performance measures, and pays participants using a schedule depending only on the relative ranking of their performance. When, in addition, the measure of the participants' performance is on a cardinal scale, so the performance scale has meaningful units, a *piece-rate scheme* pays participants a fixed amount per each unit achieved on that scale. Bonner et al. find that quota schemes are the most effective in producing higher performance – and therefore presumably more effort – followed by piece-rate schemes, tournament schemes and fixed-rate schemes.

The foregoing has focused on outcomes as the measure of performance; for example, in the TSP, performance is measured by the length of the route the participant constructs. Other measures of behaviour, such as the time participants spend completing the task, could be useful in understanding the processes participants use. Vickers et al. (2001) report on a TSP experiment with two treatments. In one treatment, the Optimisation Group, participants were instructed to draw a route which was " as short as possible"; in the other, the Gestalt Group, participants were instructed to draw the route which looked "most natural, attractive and aesthetically pleasing". They found that participants in the Gesalt Group completed the task more quickly on average than participants in the Optimization Group; however, the average route length did not differ significantly between the groups. They interpret the difference in response times as arising from different psychological processes: the wording of the Optimisation Group prompt triggered the use of higher-order cognitive mechanisms, while the working of the Gestalt Group led to reliance on the basic human perceptual system.

Within economics, the argument that cognitive processes should lead to longer response times also in decisions and games was advanced by Rubinstein (2007). He analyses "several thousand" observations of response times of over 5000 students on classic experimental economics games, including matrix games, the traveller's dilemma (Basu, 1994), the p-beauty contest (Nagel, 1995), the centipede game (Rosenthal, 1981; Binmore, 1987), the ultimatum game (Güth et al., 1982), and the Kahneman and Tversky (1979) version of the Allais Paradox, collected via the gametheory.tau.ac.il website. He argues that participants who make decisions consistent with models of strategic sophistication, generally take longer to make their response. Arad and Rubinstein (2012) study decisions and response times in a Colonel Blotto game, and find that participants who take longer to submit their decision are more likely to win the game.

2.3 Experimental Design

In our experiment, participants completed 14 instances of the TDP, designing all three journeys as in the original optimisation problem of Dantzig and Ramser (1959). Each session consisted of two blocks. Seven instances of the TDP were completed in Block One and another seven instance were completed in Block Two.[3] We used the same maps in the same sequence in all

[3]We selected the 14 TDP instances via a series of pilot exercises. We started with 200 randomly-generated maps. We gave these to some of our colleagues, and eliminated maps for which most people gave the same

sessions. Each map was referred to as a "round" in the experimental instructions.

Within each block, participants completed the seven instances successively without any feedback about the performance of others. We conducted three treatments, across participants and across sessions, in which we varied the information at the end of each block, and its consequences for the participants' earnings. One of the seven rounds (call it m) in the block was drawn at random.

- In Treatment Contingent Tournament (CT), each participant saw their own score in round m and the score of another participant in the session in the same round.[4] If their score was better than the score of the other participant, they earned £10 for that block. If their score was worse than other participant's score, they earned £5 for that block. In the event of a tie, both participants earned £7.50.

- In Treatment Non-contingent Tournament (NT), each participant saw their own score in round m and the score of another participant in the session in the same round. However, their earnings did not depend on the comparison of the scores; both participants earned £7.50 for completing the block.

- In Treatment Non-contingent Non-tournament (NN), each participant saw their own score in round m, and also the score from the optimal route. No participant received any information about the scores of other participants. All participants earned £7.50 for completing the block.

Each participant's earnings were determined by adding their earnings from the two blocks. In the next section, we describe the TDP task.

2.3.1 The TDP task

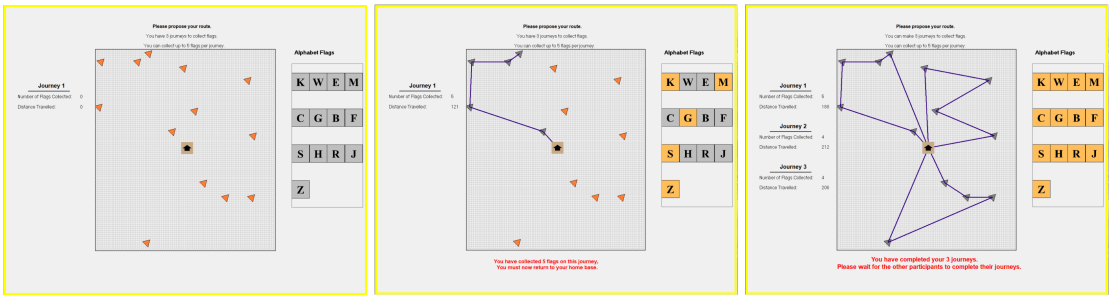
In each round, participants proposed routes for an instance of a TDP with 13 locations, which were called *checkpoints*. Each round began with a *decision screen*, which displayed the 13 checkpoints as orange triangles on a map 100 units high by 100 units wide, as in Figure 2.1(a). The starting and ending point for all journeys was the home base, located in the centre of the map and indicated by an icon of a house. To start a journey, a participant clicked on one of the orange triangles to indicate the first checkpoint to be visited. A line was drawn from the home base to this checkpoint, and the checkpoint's colour changed from orange to grey, indicating that it had been visited. Each checkpoint was associated with a different letter of the alphabet. At the right of the screen was an *alphabet flag box* listing all of these letters. Initially all

solution. We then conducted an additional pilot exercise with student participants, and used the same criterion to settle on the final selection of 14 maps.

[4] Another possible scheme for giving incentives would be a piece-rate scheme, in the spirit of e.g. Lazear and Rosen (1981) and Nalebuff and Stiglitz (1983). Such a scheme would reward participants proportionally to the distance saved by producing a shorter route. In early pilots we experimented with such a scheme; however, because there are many "good" routes with similar distances, this produces very flat incentives.

of these letters were grey; a letter changed colour to orange when the participant visited the corresponding checkpoint.

Figure 2.1: Interacting with the decision screen



(a) At the start of a period (b) Drawing a route (c) After all journeys completed

To continue a journey, the participant then clicked on another orange triangle to visit another checkpoint. As each checkpoint was visited, the clicked triangle turned grey, the line indicating the path of the journey was extended, and the corresponding letter turned orange.[5] At the left of the screen, a box displayed, for each journey, the number of checkpoints visited on that journey and the corresponding distance traveled. Distances were computed as the straight-line distance between successive checkpoints. Figure 2.1(b) shows what the decision screen looked like in the middle of the process of inputting a route.

The participant could visit at most five locations on a single journey. The participant could end a journey at any time by clicking on the home icon. Once the participant had visited five checkpoints on the current journey, a reminder message appeared at the bottom of the screen, and the decision screen would only accept a click on the home icon as the next location to visit, and complete the journey. Figure 2.1(c) shows a typical decision screen after the completion of all three journeys.

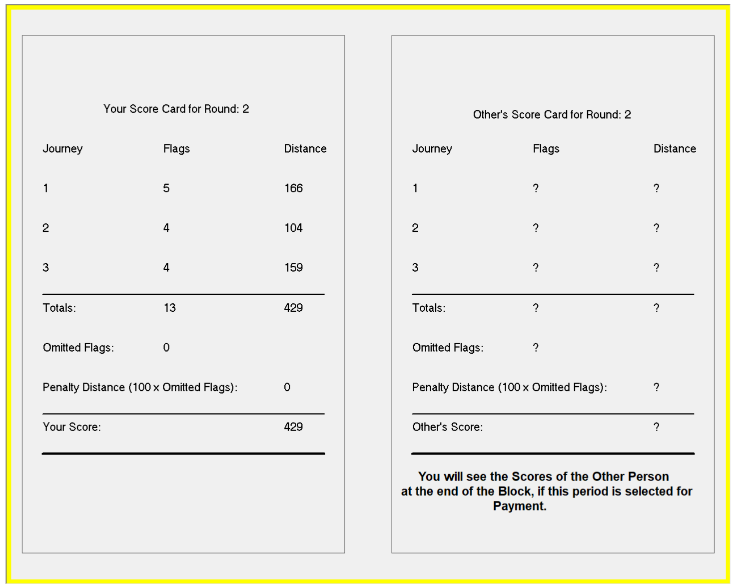
After completing all three journeys in a round, participants saw a *score card screen* as shown in Figure 2.2. This screen provided two score cards. At the left was the score card for the route the participant selected for the current instance of the TDP. This listed, for each journey, the number of locations visited on that journey, and the distance traveled on the journey.

We rounded the distance for each journey to the nearest integer, and computed the total distance for the route as the sum of these three rounded distances. The decision screen did not enforce that the participant provide a feasible route visiting all 13 locations. The score card reported the number of locations not included in the route, if any, and the total penalty distance of 100 units per omitted location. The total score was computed as the sum of the distances traveled on the three journeys, plus any penalty distance for omitted locations.

At the right of the screen was a score card labeled *Other's Score Card for Round j* (for CT and NT) or *Optimal Score Card for Round j* (for NN). This score card had the same structure

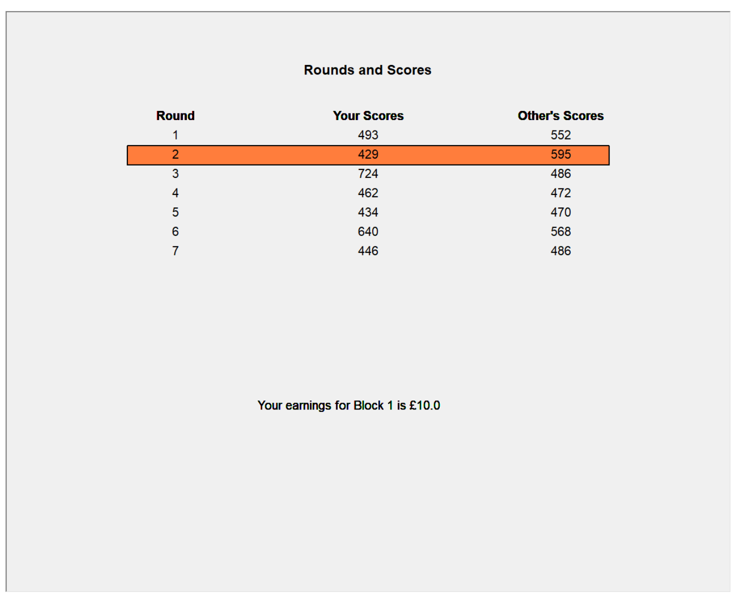
[5]We frame this task as being as if the participant is making the journey from checkpoint to checkpoint. Therefore there was no mechanism to undo a checkpoint visit once the triangle was clicked. We designed all maps so that checkpoints were sufficiently far apart that accidental clicks on an unintended triangle should not occur.

Figure 2.2: The score card as shown at the end of a round in Block One. The left card details the route selected by the participant. The right card varies by treatment. In this example, the right card is blank, because information on the performance of the other participant was revealed only at the end of the block.



as the participant's score card, except all entries contained question marks. Details of this score card would be revealed after all seven rounds of the block were completed.

Figure 2.3: Summary screen at the end of Block One. The round selected for payment is highlighted in orange. The earnings calculation for the Block is summarised at the bottom.



After all seven rounds in the block were completed, one of the rounds was chosen at random to be the round which would be revealed in detail (and determine earnings in CT) for the Block. This was done by placing seven ping-pong balls, numbered one through seven, in an opaque bag; the experimenter asked a participant to reach into the bag and pull out one of the balls. The number on the selected ball determined the round which was displayed (paid).

After the round to be displayed (paid) was drawn, the participant saw a summary table as in Figure 2.3. This table listed, for each round, the participant's score, and the score of the other participant with whom they were matched (or the optimal score in NN). The round selected for payment was highlighted with an orange background.

Figure 2.4: The score card as shown at the end of Block One, including the details of the route selected by the other participant.

Your Score Card for Round: 2

Journey	Flags	Distance
1	5	166
2	4	104
3	4	159
Totals:	13	429
Omitted Flags:	0	
Penalty Distance (100 x Omitted Flags):		0
Your Score:		429

Other's Score Card for Round:2

Journey	Flags	Distance
1	5	170
2	3	121
3	3	104
Totals:	11	395
Omitted Flags:	2	
Penalty Distance (100 x Omitted Flags):		200
Other's Score:		595

The block concluded with a screen re-visiting the score cards for the round selected for payment, as in Figure 2.4. This recapped the same information on the participant's route in the given round as they saw it at the end of that round, and adds the details for the other participant's (or the optimal) route as well.

2.4 Hypotheses

Hypothesis 6. *The average performance of participants in the TDP will not vary by treatment.*

Because the task of finding the shortest route in a TDP is NP-hard, we argue that the task in our experiment is complex. Based on previous results, we expect that the incentive scheme should not affect the level of performance.

Hypothesis 7. *The variance in participants' performance will be lower in the CT treatment.*

Although levels of performance may not vary, financial incentives have been argued to reduce variability in performance. Therefore, performance should be less variable when incentives contingent on performance are used.

Hypothesis 8. *Response times in CT will be longer.*

When payment is contingent on the performance outcome, participants are given financial incentives to apply cognitive reasoning processes to the task, rather than relying on instinctive responses or perceptual impressions. Therefore, the use of contingent incentives should result in longer response times.

Hypothesis 9. *Looking across instances of the TDP, participants will not differ systematically in the lengths of the routes they choose and performance within participants will not be positively correlated across rounds.*

The TDP instances participants face have 13 locations. Studies on the related TSP with similar problem sizes generally find that within-participant correlation of relative performance across instances is small. This implies that performance within participants will not be positively correlated across rounds and that good performance on one instance of the TDP will not imply good performance on subsequent instances of the TDP.

2.5 Results

The experiments were conducted at the Laboratory for Economic and Decision Research (LEDR) at the University of East Anglia. All interaction was mediated via computer, with a program written using z-Tree (Fischbacher, 2007). A total of 192 participants took part in the experiment; 66 participants in Treatment CT, 60 participants in Treatment NT and 66 participants in Treatment NN.

The average earnings per participant for the experiment was £15. We measure the quality of the routes chosen by the score obtained by each participant in each round. The optimal score in each round is different. To enable comparison in performance across rounds and across participants, we translate the scores into *winning percentages*. Let $i = 1, \ldots, 192$ index participants, and $T : \{1, \ldots, 192\} \to \{1, 2, 3\}$ be the function mapping each participant into the treatment they participated in. Let $m = 1, \ldots, 14$ index the fourteen maps, in the order in which they were presented to the participants. Let S_{im} be the score of participant i on map m, which is the total distance travelled by participant i on their three journeys, plus any penalties for omitted flags.

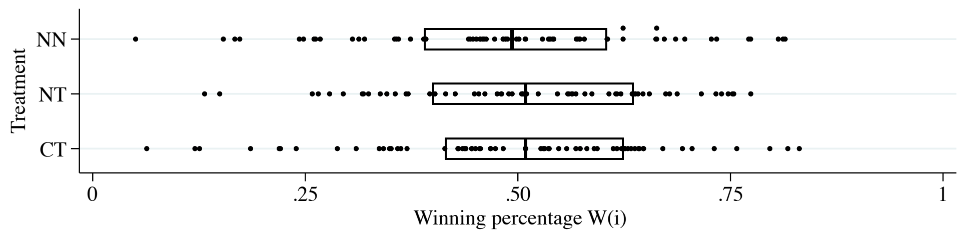
The winning percentage is computed as a round-robin comparison of each participant i's performance relative to the performance of others on the same map. The winning percentage of participant i on map m, measured against all opponents, is given by

$$W_m(i) = \frac{1}{|\{j \neq i\}|} \sum_{j \neq i} \left[\mathbf{1}(S_{im} < S_{jm}) + \frac{1}{2} \cdot \mathbf{1}(S_{im} = S_{jm}) \right], \tag{2.1}$$

where $\mathbf{1}(b)$ is the indicator function equal to 1 when the Boolean condition b is true and 0 otherwise. The overall winning percentage of participant i across the experiment is $W(i) = \frac{1}{14} \sum_{m=1}^{14} W_m(i)$.

Result 6. *The average performance of participants in the TDP as measured by winning percentages $W(i)$ do not vary by treatment.*

Figure 2.5: Distribution of participant winning percentages $W(i)$ by treatment. Each dot represents one participant. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.



Support. Figure 2.5 plots the distribution of winning percentages $W(i)$ by treatment. We use the Mann-Whitney-Wilcoxon (MWW) test to compare the distributions. From the MWW test, we obtain that the distribution of winning percentages in CT is not significantly different from the distribution of winning percentages in NT (MWW $p = 0.6514, r = .477$). The distrisbution of winning percentages in CT is not significantly different from the distribution of winning percentages in NN (MWW $p = 0.9166, r = .505$). The distribution of winning percentages in NT and NN are also not significantly different from one another (MWW $p = 0.4879, r = .536$).

This result is consistent with the arguments presented by Camerer and Hogarth (1999) and Bonner et al. (2000) that problem solving tasks are generally not responsive to financial incentives.

Result 7. *The variance in participant's performance, as measured by difference between participant's score and the optimal score, is not different across treatments.*

Support. We define the excess distance X_{im} for participant i on map m as the difference between the optimal score O_m on map m and the participant's actual score, $X_{im} = S_{im} - O_m$. The average excess distance X_i for participant i is then $X_i = \frac{1}{14}\sum_{m=1}^{14} X_{im}$. We plot the distribution of X_i for each treatment in Figure 2.6. Table 2.1 provides summary statistics of the distribution of X_i for each treatment.

Figure 2.6: Distribution of excess distance X_i by treatment. Each dot represents one participant. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.

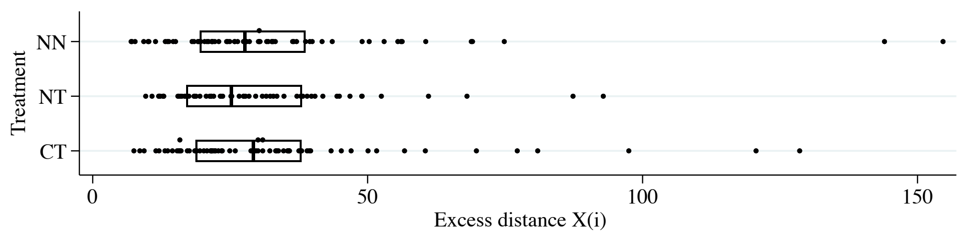


Table 2.1: Excess distance by treatment.

Treatment	N	Excess distance Mean	Std. Dev.
CT	66	33.7	23.9
NT	60	29.6	17.3
NN	66	33.4	25.9
Overall	192	32.3	22.8

We observe from Figure 2.6 that, despite the absence of contingent incentives in two of the three treatments, few participants choose routes which are exceptionally long consistently across all maps. The standard deviation of excess distance across participants is smaller in NT, but this is driven mainly by a few exceptional outliers in NN and CT. The quartiles of the distributions are similar.

We use the Mann-Whitney-Wilcoxon (MWW) test to compare the distributions. We find that the distribution of excess distance in NT is not significantly different from the distribution of excess distance in CT and NN (MWW $p = 0.4147, r = .537$). The distribution of excess distance in CT and NN are also not significantly different from one another (MWW $p = 0.8909, r = .493$).

Result 8. *Response times are fastest overall in NT.*

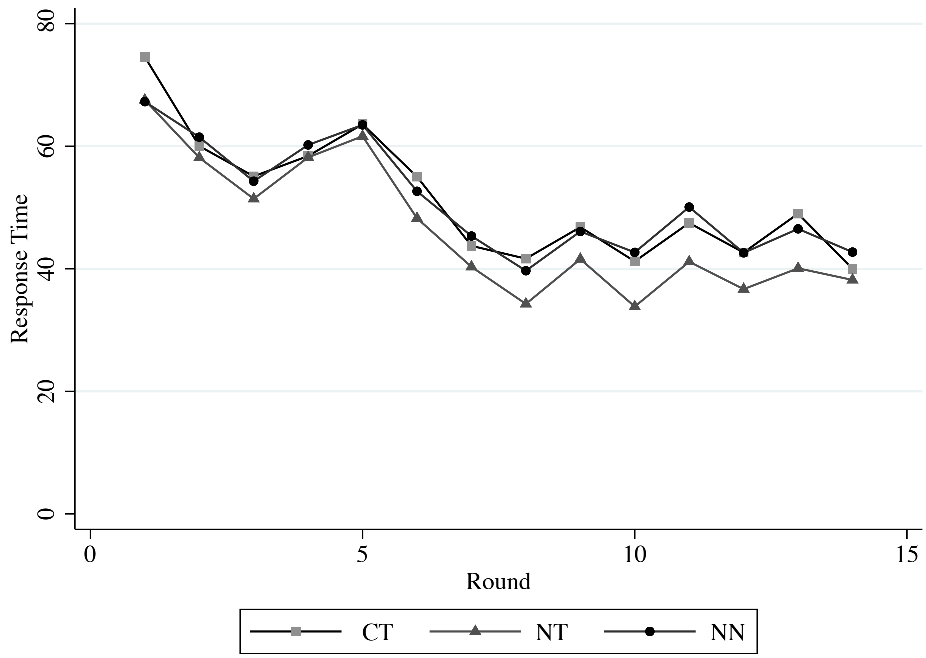
Table 2.2: Participant response times, in seconds, overall and for each journey.

Treatment	N	Response Time Mean	Std. Dev.	Min	Max
Journey 1	192	27.6	9.3	12.9	74.2
Journey 2	192	14.0	5.3	6.1	36.7
Journey 3	192	8.1	3.47	3.1	24.9
Overall	192	49.8	15.2	22.1	113.3

Support. Participants faced a “soft” time limit of 180 seconds per map. There was no countdown timer displayed on the screen. After 180 seconds elapsed, participants saw a message which encouraged them to complete the route. Few participants took 180 or more seconds on any map, and the average overall completion time was around 50 seconds. Figure 2.7 plots the average response time by round. Even in the first round, average response times are less than 80 seconds. Response times decrease through Block One, and are generally stable through Block Two.

Table 2.2 shows the summary statistics of average participant response times, in seconds. Response times are reported for the overall route, representing the time elapsed from the display of the map to the time where the participant completed the third journey. In addition, Table 2.2

Figure 2.7: Average response time by treatment over time.



breaks out the time spent on each of the three journeys. Completion time for the first journey is the longest, which is to be expected as this includes the time participants would spend looking at the map for the first time.

Table 2.3: Participant average response times over all maps, in seconds, by treatment

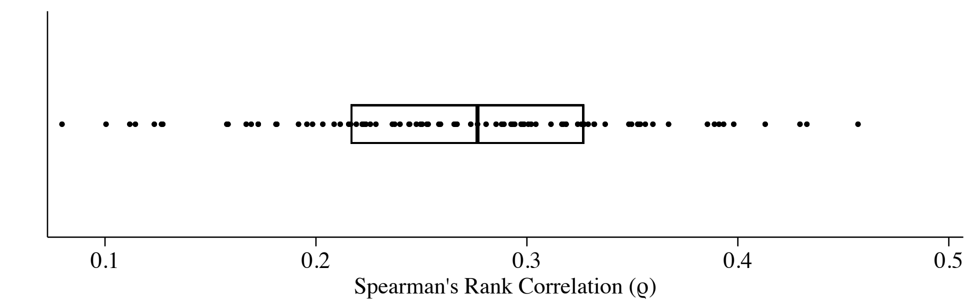
		Response Time	
Treatment	N	Mean	Std. Dev.
CT	66	51.4	13.5
NT	60	46.5	15.6
NN	66	51.1	16.3
Overall	192	49.8	15.2

Table 2.3 summarises participant response times by treatment. Response times in NT are lower than the other treatments (MWW, $p = 0.0370, r = 0.594$). Response times are not different between CT and NN (MWW, $p = 0.5113, r = 0.467$). Lower response times when the task is not rewarded by contingent incentives is plausible, as participants would not have financial incentives to spend more time reflecting on the problem. However, the comparable response times in CT and NN are surprising. A possible ex-post explanation for this result is that in NN, participants find out the best possible score rather than the actual score of another participant. Comparison against the optimal score may frame the task as one in which participants may be motivated to do as well as possible, rather than simply doing enough to beat a competitor. Bonner et al. (2000) suggest that having a clear performance benchmark is effective in encouraging

performance because the benchmark becomes salient.

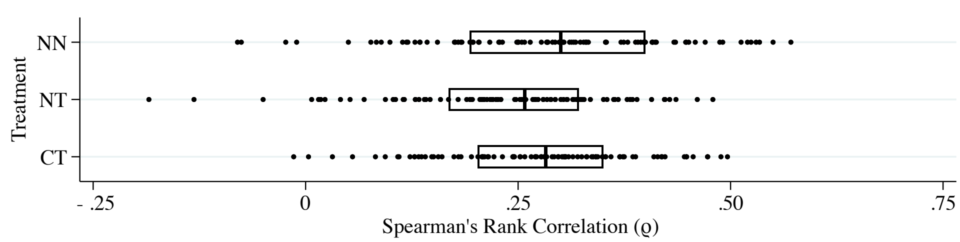
Result 9. *Performance within participant is positively correlated across rounds. Participant performance is more consistent than would be expected if all participants were identical.*

Figure 2.8: Distribution of Spearman's rank correlation coefficients for each pair of maps. Each dot represents the correlation between participant performances in one pair of maps. The boxes indicate the lower quartile, median, and upper quartile of the distributions for each treatment.



Support. Following e.g. MacGregor and Ormerod (1996) and Vickers et al. (2001), we take each pair of maps $m \neq n$ and calculate the Spearman's rank correlation coefficients ρ_{mn} of the scores S_{im} and S_{in} across all participants i. There are 91 such pairwise combinations. Figure 2.8 plots the distribution of these correlations, which range from 0.0796 to 0.4570 with a median value of 0.2766. This distribution is similar to the one obtained by Chronicle et al. (2008) ($0.25 \leq \rho \leq 0.35$), and provides evidence for a systematic difference in performance. In Figure 2.9 we repeat the same calculation restricting the sample to each treatment in turn. The median correlations are 0.2823 for CT, 0.2578 for NT and 0.3003 for NN, again placing each treatment within a range comparable to Chronicle et al. (2008).

Figure 2.9: Distribution of participant Spearman's rank correlation coefficient by treatment across all 14 rounds. The boxes indicate the lower quartile, median, and upper quartile of the distribution.



Another way to measure the persistence of individual differences across maps is to use the winning percentages $W(i)$ as plotted in Figure 2.5. When the differences in performance across participants are sustained over all maps, the standard deviation of the observed winning percentages will be large. We take as a benchmark the case in which the ranking of participants on a given map is random, assuming that each participant is equally likely to attain any rank, and the ranking of participants across any pair of maps is independent. We simulate 10000 draws of this benchmark and construct an empirical distribution of the standard deviation of winning percentages, and use this to conduct hypothesis tests. For the whole sample of 192 participants, we observe a standard deviation of .1646. Looking at each treatment separately, for CT, we observe a standard deviation of .1690; for NT, .1557; and for NN, .1700. All are significant at $p < .0001$.[6]

2.6 Discussion

We investigate the role of individual skill in a real performance task and the responsiveness of performance in the task to financial incentives. The task is complex, insofar as there is no known algorithm that produces optimal solutions efficiently. Previous literature suggests that performance on complex tasks is not very responsive to incentives. We confirm this in our data: the central tendency and variability of performance is comparable with and without contingent incentives.

Real performance tasks potentially sacrifice some experimental control insofar as individual skill or other characteristics may influence performance on the task in ways the experimenter cannot easily observe. Previous studies on the related Traveling Salesman Problem produced a range of results on the relevance of individual characteristics to performance, from almost no effect to a substantial effect. Our results fall in the middle; we do find that the ranking of a participant's performance on one instance is moderately predictive of the ranking of their performance on another instance.

Combinatorial optimisation problems like the TSP and TDP have some characteristics which are useful for the methodology of experimental economics. Many of these problems are motivated by real-world examples and are easy to explain to participants.[7] They also come with computational complexity results which give a formal characterisation of the difficulty of the problem. Because they are optimisation problems, they are well-defined, with an objective function that can be used to evaluate performance in absolute and/or relative terms, as desired, and therefore can be used to give well-defined incentives. In Chapter One, the TDP was embedded in an experiment which studied the role of leadership; combinatorial optimisation problems can stand in as an experimental task whenever an individual or group is imagined to face a complex decision environment in which the exploration and identification of potentially "good" solutions is important in understanding the decision-making process fully.

[6] In fact, these are significant at much lower levels as well. For example, for the whole sample of 192 participants, significance at $p = .001$ would correspond to a standard deviation of about .090. For a sample of 66 participants, significance at $p = .001$ would correspond to a standard deviation of about .098. In our simulations we never observed a sample in which the simulated standard deviations approached our observed levels.

[7] We presented a version of this work at a conference with participants who do not work in experimental economics. An attendee approached us after our talk to say that our paper was the first time they understood what the experimental task was that participants were asked to do, and why. Likewise, we encountered a participant who had been in one of the session, who remarked the task was unusually "fun" compared to other experiments.

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Appendices

2.A Experimental Instructions

2.A.1 Introduction

Welcome and thank you for taking part in this experiment.

This is an experiment of decision-making. If you follow the instructions and make appropriate decisions, you can earn an appreciable amount of money. You will receive your earnings for today's session in cash before you leave the laboratory.

It is important that you remain silent and do not look at other people's work. If you have any questions, or need any assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, e.t.c., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

Today's session consists of two blocks. Your earnings in each block depend only on the decisions made in that block.

We will now describe the session in more detail. Please follow along with these instructions as they are read aloud.

2.A.2 Block 1

CT

In Block 1, you will be matched randomly and anonymously with one other participant in today's session. You will not know the identity of the participant with whom you are matched, nor will that participant know your identity, either during or after the session.

Your earnings for Block 1 will be determined by your choices and the choices made by the other participant with whom you are matched.

In Block 1, there will be seven (7) decision rounds. In each round you will propose a route which visits checkpoints laid out on a map. Each checkpoint is associated with a letter of the alphabet. We will now show you what your screen will look like during a decision round.

NT

In Block 1, you will be matched randomly and anonymously with one other participant in today's session. You will not know the identity of the participant with whom you are matched, nor will that participant know your identity, either during or after the session.

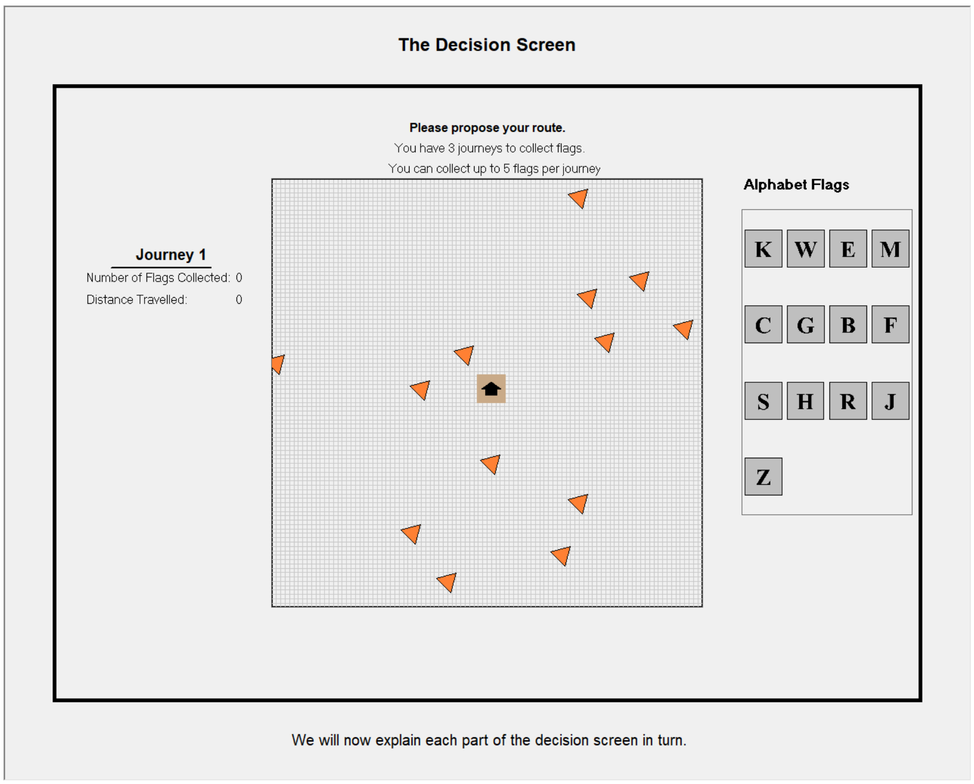
In Block 1, there will be seven (7) decision rounds. In each round you will propose a route which visits checkpoints laid out on a map. Each checkpoint is associated with a letter of the alphabet. We will now show you what your screen will look like during a decision round.

NN

In Block 1, there will be seven (7) decision rounds. In each round you will propose a route which visits checkpoints laid out on a map. Each checkpoint is associated with a letter of the alphabet. We will now show you what your screen will look like during a decision round.

2.A.3 The Decision Screen

Figure 2.10: Example of the Decision Screen

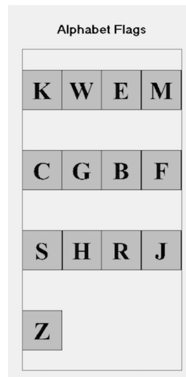


2.A.4 Alphabet Flags

In each round there will be 13 checkpoints for you to visit. When you visit a checkpoint, you will automatically collect a flag with that checkpoint's letter.

The box of 'Alphabet Flags' at the right of the screen keeps track of the lettered flags you have collected so far. When you collect a flag, the corresponding letter box will change from grey to orange.

Figure 2.11: Box of Alphabet Flags

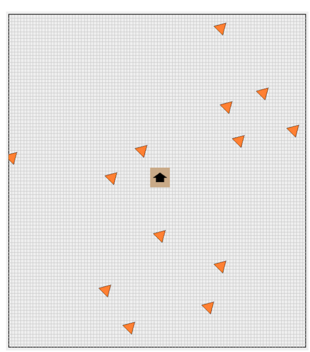


2.A.5 The Map

The checkpoints in each round are laid out on a map like the one below, which will be shown in the middle of your screen. In each round, all participants will see the same map.

The map is 100 units top to bottom and 100 units left to right. In the centre of the map is your home base, indicated by the picture of a house. On the map are the 13 checkpoints, each indicated by a triangle. Each checkpoint has a corresponding alphabet flag.

Figure 2.12: Example of a Map



2.A.6 Choosing Your Route

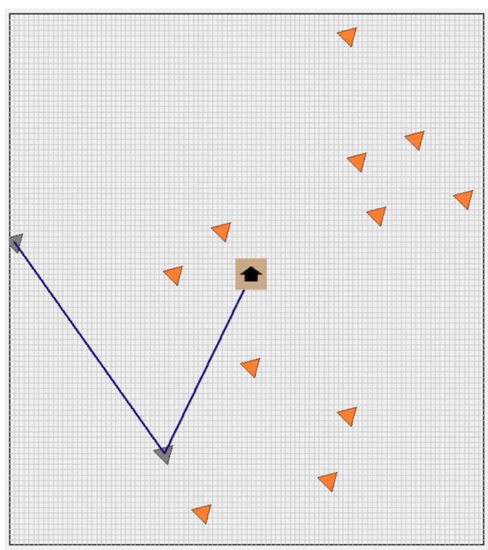
You can make three journeys to collect flags. You begin each journey at your home base. From there, you can visit a checkpoint by clicking on the corresponding triangle. When you visit a checkpoint, you will automatically collect a flag with that checkpoint's letter. That checkpoint's triangle will change colour from orange to grey, and in the Alphabet Flags box the checkpoint's letter will change colour from grey to orange.

You can visit checkpoints in any order while on a journey. However, you can carry no more than five flags at a time. Once you have visited five checkpoints and therefore collected five flags, you must complete the journey by returning to your home base. You may choose to complete a journey at anytime, even if you have not yet collected five flags. But, remember that you have only three journeys in which to visit the 13 checkpoints and collect the corresponding 13 flags.

As you make your journeys, the computer will draw the route you have taken. Your route will be represented by straight lines between checkpoints. Checkpoints which you have already visited will be shown as grey triangles; the checkpoints you have yet to visit will be shown as orange triangles.

Once you collect a flag from a checkpoint you cannot return it. So plan ahead for your journey before setting out.

Figure 2.13: Routes are represented as straight lines between checkpoints



2.A.7 Your Score

Your score for a round is given by the total straight-line distance you travel along the routes you choose for your three journeys. Lower scores are better; therefore in choosing your journeys your aim is to minimise the total distance travelled.

In the event you do not collect all of the flags on your three journeys, an additional penalty distance of 100 will be added to your score for each flag you did not collect. Because the grid is 100 units high and 100 units wide, you can always get a lower score by visiting all checkpoints rather than missing some out.

CT and NT

You will complete seven rounds, with a new map in each round. At the end of each round, you will see a Score Card showing a detailed breakdown of how your score was determined for that round. You will also see a Score Card for the person with whom you are match in Block 1. Their score card will contain question marks, as you will only find out their score for that round at the end of the block. The next screen shows a sample Score Card.

NN

You will complete seven rounds, with a new round in each round. At the end of each round, you will see a score card showing a detailed breakdown of how your score was determined for that round. You will also see a score card for the optimal score of that round. The Optimal Score is the one which has the lowest possible score. The score card will contain question marks, as you will only find out the optimal score for that round at the end of the block. The next screen shows a sample Score Card.

2.A.8 Score Card

Figure 2.14: Example of a Score Card for CT and NT

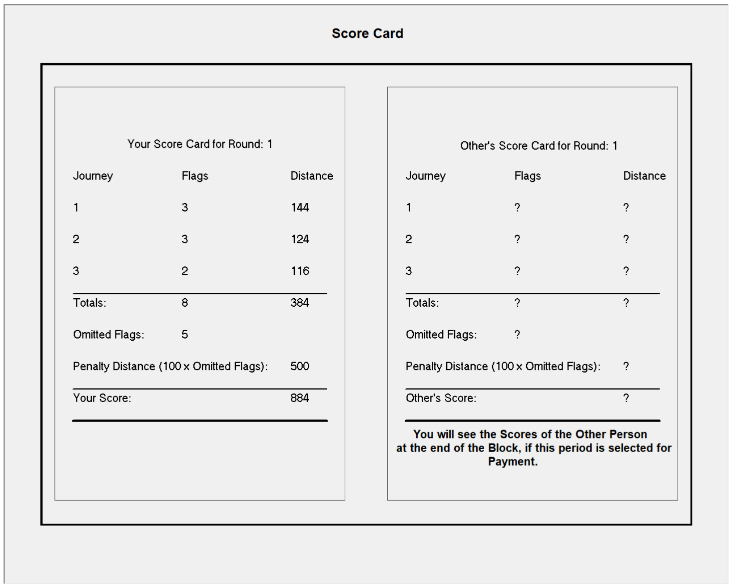
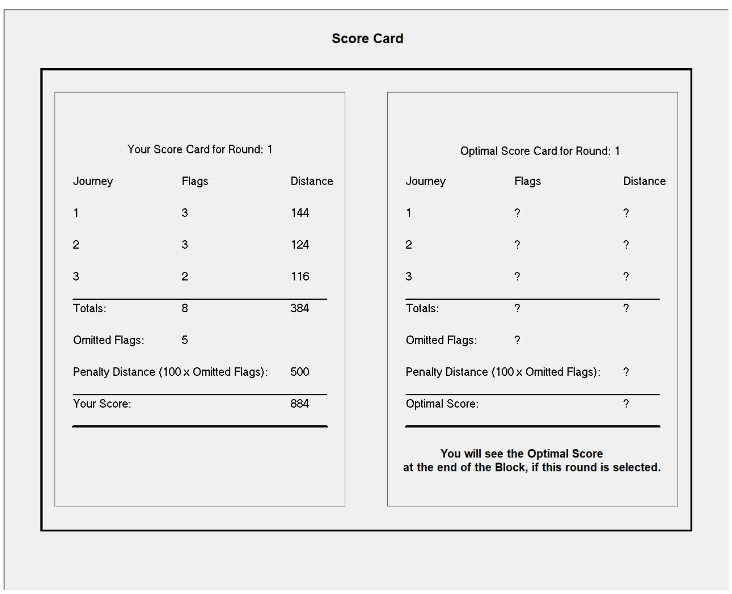


Figure 2.15: Example of a Score Card for NN



2.A.9 Summary Screen

CT

At the end of Block 1, one of the seven rounds in the block will be selected at random. Each round has an equal chance of being select. In each pair the participant who had the lower score in the selected round will earn £10, and the participants who had the higher score in the selected round will earn £5. In the event both participants in a pair have the exact same score (i.e., a tie), both participants will earn £7.50. Because you will not know in advance which round will be selected, you should complete each round as if it will be the one chosen to determine payment for the block.

After the round for payment is determined for Block 1, you will see a summary like the one below. This table will show your score and the score of the other person with whom you are matched for each of the seven rounds. The round which is selected for payment will be highlighted.

NT

At the end of Block 1, one of the seven rounds in the block will be selected at random. The details of this round will be displayed such that you will be shown the breakdown of your own score and the breakdown of the score of the other participant with whom you are matched for Block 1. The participant with the lower score wins the round. In the event that both participants have the exact same score, the round is a tie.

After the round to be displayed in detail is determined for Block 1, you will see a summary like the one below. This table will show your score and the score of the other participant with whom you are match for each of the seven rounds. The round to be displayed in detail will be highlighted.

NN

At the end of Block 1, one of the seven rounds in the block will be selected at random. The details of this round will be displayed such that you will be shown the breakdown of your own score and the breakdown of the Optimal Score for Block 1.

After the round to be displayed in detail is determined for Block 1, you will see a summary like the one below. This table will show your score and the Optimal Score for each of the seven rounds. The round to be displayed in detail will be highlighted. You will earn a fixed amount of £7.50

Figure 2.16: Summary Screen for CT and NT

Round	Your Scores	Other's Scores
1	850	849
2	799	701
3	850	701
4	701	701
5	700	850
6	850	849
7	851	1300

Figure 2.17: Summary Screen for NN

Round	Your Scores	Optimal Scores
1	847	747
2	794	708
3	842	710
4	700	651
5	709	642
6	849	791
7	853	807

2.A.10 Block 2

As you were told earlier, today's session consists of two blocks. Your earnings in each block depend only on the decisions made in that block. You have just completed Block 1. We will now begin Block 2. We will describe the block in more detail. Please follow along with these instructions as they are read aloud.

CT

Block 2 has exactly the same structure as Block 1. You will see a new series of seven maps, 100 units wide by 100 units high, with a home base in the middle and 13 checkpoints. The seven maps you see in Block 2 will be different than those in Block 1. Your objective again is to collect all alphabet flags from the 13 checkpoints. You have three journeys to collect the flags, and on each journey you can collect at most five flags.

The only difference is that in Block 2 you will be matched randomly and anonymously with a different participant, who is not the participant you were matched with in Block 1. You will not know the identity of the participant with whom you are matched, nor will that participant know your identity, either during or after the experiment. Your earnings for this part of the experiment will be determined by your choices and the choices made by the other participant with whom you are matched.

NT

Block 2 has exactly the same structure as Block 1. You will see a new series of seven maps, 100 units wide by 100 units high, with a home base in the middle and 13 checkpoints. The seven maps you see in Block 2 will be different than those in Block 1. Your objective again is to collect all alphabet flags from the 13 checkpoints. You have three journeys to collect the flags, and on each journey you can collect at most five flags.

The only difference is that in Block 2 you will be matched randomly and anonymously with a different participant, who is not the participant you were matched with in Block 1. You will not know the identity of the participant with whom you are matched, nor will that participant know your identity, either during or after the experiment.

NN

Block 2 has exactly the same structure as Block 1. You will see a new series of seven maps, 100 units wide by 100 units high, with a home base in the middle and 13 checkpoints. The seven maps you see in Block 2 will be different than those in Block 1. Your objective again is to collect all alphabet flags from the 13 checkpoints. You have three journeys to collect the flags, and on each journey you can collect at most five flags.

2.A.11 Your Earnings

CT

At the end of the block, one of the seven rounds will be selected at random. Each round has an equal chance of being selected. In each pair, the participant who had the lower score in the selected round will earn £10 and the participant who had the higher score will earn £5. In the event both participants in a pair have the exact same score (i.e., a tie), both participants will earn £7.50. Because you will not know in advance which round will be selected, you should complete each round as if it will be the one chosen to determine payment for the experiment. Your total earnings for the experiment, then, will be your earnings form the randomly-selected round in Block 1 plus your earnings from the randomly selected round in Block 2.

NT

At the end of the block, one of the seven rounds will be selected at random. The details of this round will be displayed such that you will be shown the breakdown of your own score and the breakdown of the score of the other participant with whom you are matched for Block 2. The participant with the lower score wins the round. In the event that both participants have the exact same score, the round is a tie.

Both you and the participant with whom you are matched in Block 2 will earn a fixed amount of £7.50 in Block 2. Your total earnings for the experiment will be your £7.50 earnings from Block 1 plus your £7.50 earnings from Block 2.

NN

At the end of the block, one of the seven rounds will be selected at random. The details of this round will be displayed such that you will be shown the breakdown of your own score and the breakdown of the score of the Optimal Score for Block 2.

You will earn a fixed amount of £7.50 in Block 2. Your total earnings for the experiment will be your £7.50 earnings from Block 1 plus your £7.50 earnings from Block 2.

Chapter 3

Football and Domestic Abuse in England and Wales

In this chapter, we study empirically the effects of domestic and international football tournaments on domestic abuse in England and Wales and how these effects vary with people's expectations of the football match outcomes. Previous studies on domestic abuse and football in England and Wales have focused primarily on international tournaments and have not taken into account the effects of expected match outcomes. This is surprising given the visibility of the English Premier League (EPL). We find in our analysis, that the existence of an EPL fixture is associated with a 1% percent increase in domestic violence while the existence of a FIFA World Cup fixture is associated with a 3% increase in domestic violence in England and Wales. Our results, also suggest that expected match outcomes have strong effects on domestic violence in England and Wales.

3.1 Introduction

The treatment of sports within the field of economics can be split broadly into two broad areas. The first area which is known as Economics *of* sports deals with topics such as competitive balance, labour market regulations and policies (Fort and Quirk, 1995; Kahn, 2000; Szymanski, 2003, 2009). The second area which is known as Economics *through* sports studies the ways in which sports affects activities outside the sports field such as subjective well-being (Kavetsos and Szymanski, 2010; Pawlowski et al., 2014; Dolan et al., 2019), labour market behaviour (Doerrenberg and Siegloch, 2014), general sports participation (Dawson, 2019; Kokolakakis et al., 2019), stock market fluctuations (Edmans et al., 2007), and university enrolment (Weimar and Schauberger, 2018).

For example, Dolan et al. (2019) find that hosting the 2012 Olympics game had a positive effect on the life satisfaction of Londoners particularly around the opening and closing ceremonies. Pawlowski et al. (2014) using panel data from 33 countries over 3 years (2006 -2009) in the International Social Survey Programme (ISSP) find that hosting of sporting events have positive effects on subjective well-being (SWB) of citizens. Doerrenberg and Siegloch (2014) find that international tournaments such as the FIFA World Cup and the UEFA European Cup had a positive effect on the motivation to search for jobs by unemployed citizens in Germany.

Unfortunately, the wider effects of sports can also be negative. Edmans et al. (2007) using a longitudinal panel of 18 countries over 31 years find that negative sports outcome leads to negative fluctuations in stock returns. In North America, Kalist and Lee (2016) find that National Football League (NFL) games days are associated with higher crime rates in host cities. In a similar vein, Williams et al. (2013) find positive associations between game days when traditional rivals (Celtic and Rangers) play one another and domestic abuse rates in Scotland. In this study, we are specifically interested in the links between football tournaments and domestic abuse in England and Wales. At an anecdotical level, whenever there is an upcoming football tournament such as the FIFA World Cup, it is heralded by articles and materials in the general media warning about the links between the sporting event and domestic abuse. There have been studies which have investigated the nature of the relationship between major football tournaments (the FIFA World Cup) and domestic abuse in England (Brimicombe and Cafe, 2012; Kirby et al., 2014; PSCD, 2006; Sivarajasingam et al., 2005).

Drawing on the strand of literature which argues that domestic (club-level) football tournaments affect trends in domestic abuse through loss aversion (Card and Dahl, 2011; Dickson et al., 2016), we aim to study the effects of domestic tournaments such as the English Premier League (EPL) on domestic abuse in England and Wales. In addition we aim to study the combined effects of international tournaments (FIFA World Cup and UEFA European Cup) and domestic (club-level) tournaments (EPL) on domestic abuse in England and Wales. We argue that a combined model, provides a more complete picture of the effects of football on domestic abuse. To the best of our knowledge, ours is the first study to combine international and domestic tournaments in the analysis of the relationship between football and domestic abuse as well as the first study to investigate the effects of club-level (EPL) tournaments (broken by home and away fixtures) on domestic abuse in England and Wales.

In our analysis of the club-level tournaments, we introduce variables which capture pre-game expectations of match outcomes. We find that the EPL is associated with a 1% increase in domestic abuse for parts of England & Wales excluding London, while the FIFA World Cup is associated with about 3% increase in domestic abuse across all regions. We find evidence in support of the hypothesis that match outcome and pre-game match expectations matter for domestic abuse.

As an extension, we investigate the relations between football (domestic and international) tournaments on a different crime measure known as Public Order Offence. In this extension, we draw on literature with finds that college football games (in North America) are associated with higher levels of (other) crimes like assaults, vandalism, arrests for disorderly conduct, and arrests for alcohol-related offences. We find evidence that levels of public order offence are also affected by football tournaments in England and Wales.

3.2 Related Literature

3.2.1 Domestic Tournaments and Domestic Abuse

Two studies which are most related to ours are: Card and Dahl (2011) which study the correlations between daily counts of domestic abuse and matches of the National Football League (NFL) in North America and Dickson et al. (2016) which studies the correlations between domestic abuse in Glasgow and the matches of the Scottish Premier League (SPL).

Card and Dahl (2011) studied the relationship between trends in family violence and games of National Football League(NFL) They hypothesised that the risk of domestic abuse (violence) can be affected by a gain-loss utility around rationally expected match outcomes, such that emotional cues associated with wins and losses by professional football teams could act as visceral factors which affect fluctuations in the rate of reported family violence.[1] They conducted their analysis using police reports on family violence for Sundays during the professional football season obtained from the National Incident-Based Reporting System (NIBRS). Their data spanned the years 1995 to 2006 for over 750 city and county police agencies. They matched their data on family violence with NFL team records for six NFL teams (Carolina Panthers, Detroit Lions, New England Patriots, Denver Broncos, Kansas City Chiefs and Tennessee Titans).[2] Data on expected match outcomes was constructed from the pre-game point spread betting data of the Las Vagas Bookmakers. They defined upset-losses as team losses when teams are ex-

[1]The variable of interest in their study is the rate of Intimate Partner Violence (IPV) committed by men against women. They do however use the term family violence when referring to IPV.

[2]Only the first three teams (Carolina Panthers, Detroit Lions, and New England Patriots) had data for all 12 years, the remaining three teams (Denver Broncos, Kansas City Chiefs and Tennessee Titans) have data in later years.

pected to win and upset-wins as team wins when teams are expected to lose the match. They found that upset-losses led to 10% increase in family violence and upset-wins had no significant effect on levels of reported family violence.[3] In addition, they found that for salient games, the effects of upset-losses were larger than 10%. For example, in games which involved traditional rivals, upset-losses led to 20% increase in family violence. Similarly, they found that when teams were still in play-off contention, upset-losses led to a 13% increase in family violence and they found that, in frustrating games, upset-losses led to a 15% increase in family violence. Comparing the effects of half-time and full-time results, they found evidence which suggests that the gain-loss utility is updated at the end of the match as half-time results had no significant effect on the rates of family violence. They interpreted their results as evidence for loss-aversion, a phenomenon in which agents' sensitivities to losses are much higher than sensitivities to gains of the same magnitude (Kahneman et al., 1991).

Dickson et al. (2016) investigated the relationship between domestic abuse in Glasgow and games of the Scottish Premier League (SPL). Similar to Card and Dahl (2011), they hypothesised that reference-dependent preferences or gain-loss utilities might be relevant in the effects of SPL games on domestic abuse. They conducted their analysis using data on domestic abuse obtained from the Strathclyde Police and historical data on football matches, outcomes and prematch betting odds for games of the SPL. Their data included daily count of reported domestic abuse incidents in and around Glasgow for the period spanning 1st January 2003 to 5th October 2011, disaggregated by each of the 30 Glasgow subdivisions. During the sample period, 18 teams participated in the SPL. The two most dominant teams in the sample period were traditional rivals, Celtics and Rangers.[4] Constructing pre-games expectations from the pre-game betting odds, they found that only matches which involved traditional rivals Celtics and Rangers - commonly referred to as Old Firm matches - led to an increase in domestic abuse regardless of outcome. They remarked that because matches between Celtics and Rangers were expected to be close there was no scope for upset-losses or upset-wins between these two teams. Only in important matches - defined as the last 10 matches of the season (24% of all matches in the sample) or the last 5 matches of the season (8% of all matches in the sample) - did they find evidence for reference-dependence in the relationship between domestic abuse and games of the SPL.

These two studies are situated within a body of literature which argues that the disappointment of sports fans which result from unexpected sports outcomes leads to an increase in recorded violent behaviour. For example, Rees and Schnepel (2009) find that on game days in North American college football, the host community (the home team community) records a sharp increase in assaults, vandalism and arrests for disorderly conduct. They note that the increase in crimes is higher when the home team has suffered an unexpected loss (upset loss). Priks (2010) finds that in Swedish football, fans exhibit higher levels of unruly behaviour i.e.

[3] Interestingly, they also find marginally significant increase in violence following an upset win against a rival.

[4] A point which is buttressed by the fact that either Celtics or Rangers had won the league in all the years in sample as well as in the betting odds.

throwing projectiles into the playing field, when supported teams perform worse relative to fan expectations. Munyo and Rossi (2013) also find that in Uruguay, crimes such as robberies and theft increase after fans experience frustration. They defined frustration as resulting from disappointing sports outcome relative to fans' expectations. These studies argue that in relation to the outcome of sports competition, observed patterns in reported or recorded violent behaviour exhibits what is known to psychologists as Disappointment Aversion (Gul et al., 1991) and to economists as Loss Aversion (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991).

Loss aversion was first proposed in Kahneman and Tversky's Prospect theory of decisions under risky choice (Kahneman and Tversky, 1979) and risk-less choice (Tversky and Kahneman, 1991). Prospect theory was proposed as a better model for explaining individual choice relative to Expected Utility theory.

Expected Utility theory holds that all choices or prospects are evaluated on the final state of their outcomes such that a certain choice should be made or accepted if the added utility of making the choice exceeded the utility from not making the choice. Expected Utility theory also assumes that the utility of wealth has an (everywhere) concave function. Using empirical evidence, Kahneman and Tversky (1979) demonstrated that observed behaviour on risky choices violate the predictions of Expected Utility in systematic ways such as the certainty effect which violates the axiom of substitution, the reflection effect and the isolation effect. Certainty effect refers to the idea that certain outcome given more weight relative to probable outcomes. Reflection effect refers to the idea that under risky choice, risk aversion in the positive domain is associated with risk seeking in the negative domain. This effect violates the assumption that the utility of wealth is everywhere concave because it implies that the utility function is concave in the position domain but convex in the negative domain. The isolation effect refers to the idea that shared features between choices are disregarded so that choices are only considered on their distinguishing features.

Kahneman and Tversky (1979) argued that the real carriers of value are not the final states of wealth but the changes in wealth relative to a neutral reference point such that choices or prospects are evaluated as gains and losses from a given reference point like the current state of wealth. They argued that because the value -utility- function is concave in the positive domain (above the reference point) and convex in the negative domain (below the reference point), losses loom larger than gains. This implies that agents are more sensitive to losses than gains of the same magnitude hence, agents are averse to losses. In Tversky and Kahneman (1991), they argue that loss aversion can be used to explain other behaviour such as the endowment effect where the loss of utility associated with giving up a good is greater than the utility gain associated with receiving it (Thaler, 1980; Kahneman et al., 1990, 1991); the status quo bias in which loss aversion induces a bias that favours the retention of the current status (Knetsch and Sinden, 1984; Samuelson and Zeckhauser, 1988; Knetsch et al., 1989) coined by (Samuelson and Zeckhauser, 1988); and descrepancies between the willingness to pay (WTP) and the willingness to accept (WTA) (Cummings, 1986; Heberlein and Bishop, 1986; Loewenstein, 1988;

Kahneman et al., 1990).

The reference point around which agents evaluate gains or losses could be the current state of wealth, a status quo, an endowment or a rational expectation (Kőszegi and Rabin, 2006). There is a body of literature which provides evidence for loss aversion and reference-dependent preferences both in the experimental literature and in the empirical literature. Kőszegi and Rabin (2006) find evidence for reference dependence in the labour supply behaviour of New York cab drivers where drivers based their labour decisions on expectations about their earnings. Genesove and Mayer (2001) found evidence for loss aversion in the real estate market of downtown Boston where condomininum owners set higher asking prices, attain higher selling prices and exhibit lower sale hazard subject to nominal losses. Benartzi and Thaler (1995) explained the equity premium puzzle - the empirical phenomenon where stocks perform better than bonds - using loss aversion. Closely following Card and Dahl (2011) and Dickson et al. (2016), we hypothesize that the relationship between major football tournaments and trends in reported domestic abuse in the United Kingdom exhibits reference dependence such that wins and losses of supported football teams are evaluated based on pre-game (pre-match) expectations.

3.2.2 International Tournaments and Domestic Abuse in England and Wales

There have been previous studies on the links between domestic abuse and football in England and Wales (Brimicombe and Cafe, 2012; Kirby et al., 2014; PSCD, 2006; Sivarajasingam et al., 2005). These studies have, however, only focused on the FIFA World Cup (international tournament) and have used data on domestic abuse which span only the length of a month (June).

Based on a report by Sivarajasingam et al. (2005) which demonstrated the existence of a link between major sporting events and trends in violent crime. The British Home Office conducted an analysis which demonstrated that the 2006 FIFA World Cup was associated with an increase in incidents of reported domestic abuse (PSCD, 2006). Their analysis involved two domestic abuse Enforcement Campaigns (DVEC): the first, which ran from 3rd February to 31st March 2006 had 46 participating Basic Command Units (BCUs) and the second, which ran from 9th June to 9th July 2006 had 52 participating BCUs. The time period for the second DVEC was selected specifically to capture the effects of the 2006 FIFA World Cup on trends in domestic abuse. By comparing the levels of reported domestic abuse incidents on a FIFA World Cup match day when England played[5] and the match day of the FIFA World Cup final to the average of all equivalent weekdays from the first DVEC, they found that England matches of the FIFA World Cup tournament was associated with an increase in the number of domestic abuse incidents (11%).

In response to PSCD (2006), Brimicombe and Cafe (2012) highlighted that the time of the year in which the 2006 FIFA World Cup was held might have contributed to observed increase

[5]There were five England match days in the 2006 FIFA World Cup

in reported domestic abuse. This is because warmer months are associated with higher levels of reported domestic abuse. They also argued that the participating BCUs of the PSCD study consisted mainly of urban regions and thus the findings of the study might be biased towards urban regions. In addition, Brimicombe and Cafe were interested in the ways outcomes of FIFA England matches might affect trends of reported domestic abuse. They hypothesised that an England win would make fans happy and thus might lead to a decrease in domestic abuse levels. Whilst an England loss would make the fans unhappy and thus lead to an increase in the levels of domestic abuse.

Data for their analysis was obtained from Freedom of Information (FoI) requests[6] made by the BBC to each of the 52 police force areas in the United Kingdom (UK). Their data consisted of of daily count of reported domestic violence for the month of June of 2005, 2006, 2009 and 2010.

With this they captured the 2006 and 2010 FIFA World Cup tournaments along with the preceding years of 2005 and 2009 which served as control periods. From comparing FIFA World Cup England match days with equivalent non-match days, they found that England matches which ended in a definite win or lose outcome led to significant increases in the rate of reported domestic abuse. An England win led to a 27.7% increase whilst an England lose led to a 31.5% increase in the rates of reported domestic abuse.

In a similar study, Kirby et al. (2014) investigated the links between the FIFA World Cup and trends of reported domestic abuse in Lancashire. They obtained their data from the Lancashire police force area. Their data consisted of monthly counts of reported domestic abuse for the years 2001, 2002, 2005, 2006, 2009 and 2010[7] as well as daily counts of reported domestic abuse for the period spanning 1st of June to 1st of July for the FIFA World Cup years of 2002, 2006 and 2010. Using Poisson and Negative Binomial regression analyses, they found that the risk of domestic abuse rose by 26% when the English national team won and 38% when the English national team lost.

The Home Office defines domestic abuse as "Any incident of threatening behaviour, violence or abuse (psychological, physical, sexual, financial or emotional) between adults who are or have been intimate partners or family members, regardless of gender or sexuality"(ONS, 2018). According to the ONS (2018), domestic abuse affects approximately one third of the population, with women being more affected than men. One in five women suffer interpersonal violence, compared with one in ten men who suffer domestic abuse. The ONS (2018) estimates that 6.1% of people aged 16 to 59 years had experienced some form of domestic abuse in the last year. Women were two times more likely than men to be victims of domestic abuse (28.9% women and 13.2% men since the age of 16 and 7.9% women versus 4.2% men in the last year). Younger women (20 -24 years old), women who are divorced and women with lower income were more likely to be victims of domestic abuse. Domestic abuse is characterised by repeat

[6] A Freedom of Information request is a request made under the Freedom of Information Act 2000 which provides public access to information held by public authorities (ICO, 2017).

[7] To account for a change in accounting practices, the data from 2001 was removed from their analysis.

victimisation and is largely underreported (HMIC, 2014, 2015), according to the ONS (2018) of those who experienced domestic abuse in the previous year, only 17.3% told the police. Some of the reasons stated for not reporting to the police includes: "it was a private family matter and not the business of the police", "it was too trivial or not worth reporting", or "victims didn't think the police could help".

Domestic abuse imposes a cost to society beyond the physical and mental cost experienced by victims of domestic abuse and their immediate social circles (Walby, 2004; Oliver et al., 2019). Walby (2004) estimated the cost of domestic abuse to society at £23 billion per year and Oliver et al. (2019) estimated the cost of domestic abuse to society at £66 billion per year. These include the cost to the criminal justice system, health care, social services, housing, civil legal services, and loss in economic output as a result of the incident.

Like PSCD (2006) and Dickson et al. (2016), we argue that from a resource perspective, it is important to identify factors which might affect domestic abuse , so that police resources can be allocated efficiently. It is important to note, however, that we are not suggesting that the only engagement with domestic abuse is via sport but we do posit that sport, and football in particular is an important trigger.

3.3 Theoretical Framework

In this section we present a model which describes the effect of the EPL game outcomes of reported domestic abuse. The model presented here closely follows that of Card and Dahl (2011). The major hypothesis is that EPL local-team wins and losses generate emotional cues which reflect gains or losses around a rationally expected reference point. This model treats domestic abuse (violence) as an unintended outcome of interactions in *conflict-prone*[8] relationships which could by family relationships or intimate partner relationships. Following the loss of control model presented in Card and Dahl (2011), we assume that the perpetrator is more likely to lose control after exposure to negative emotional shocks.[9] Consider a household where each period has some positive risk of heated altercations which could escalate to violence $h \geq 0$. We argue that this positive likelihood of violence h is affected by the emotional cues associated with the outcome of a professional football game y and p, where $y = 1$ indicates a local-team win, $y = 0$ indicates a local-team loss. We denote the probability the individual assigns to a local-team victory with $p \in [0, 1]$. From this we obtain:

$$h = h_0 - \mu(y - p) \tag{3.1}$$

[8] We feel it important to highlight that we do not hold the position that the outcome of professional sports will create the risk of violence where it does not already exist.

[9] In their study, Card and Dahl (2011) assume that men are the primary perpetrators. Although our data suggests that women are more affected than men (ONS, 2018), we choose to stay agnostic to the gender of the perpetrators as the abuse could also (less likely) be female (HMIC, 2015).

where μ is the gain-loss utility associated with the game outcome. Like Card and Dahl (2011), we assume that that μ is piecewise linear such that:

$$\mu(y-p) = \alpha(y-p), y-p < 0 \tag{3.2}$$

$$\mu(y-p) = \beta(y-p), y-p > 0 \tag{3.3}$$

Loss aversion implies that the marginal effects of a loss is weighted higher than the marginal effects of a win. Thus for positive constants α and β, $\alpha > \beta$. These assumptions lead to four extremal outcomes, in the case that the outcome of the game is a loss i.e. $y = 0$, we obtain:

$$h^L(p) = h_0 - \alpha(0-1) = h_0 + \alpha \tag{3.4}$$

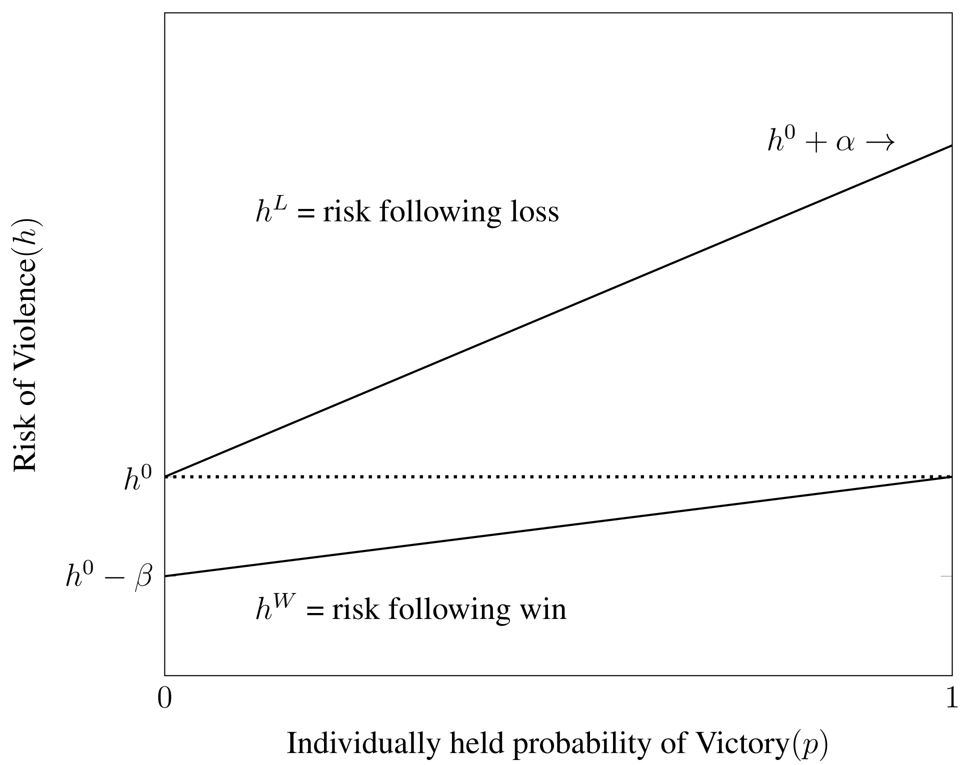
$$h^L(p) = h_0 - \alpha(0-0) = h_0 \tag{3.5}$$

Similarly, in the case that the outcome of the game is a win i.e. $y = 1$, we obtain:

$$h^W(p) = h_0 - \beta(1-1) = h_0 \tag{3.6}$$

$$h^W(p) = h_0 - \beta(1-0) = h_0 - \beta \tag{3.7}$$

Figure 3.1: Risk of Violence Following a Loss or Win (Card and Dahl, 2011)



Given that h is linear in p Figure 3.1 is a plot of the risk of violence following a win or a loss based on the above equations. As we can see Figure 3.1, the risk of violence following a loss out-weighs the risk of violence following a win. In the worst case, the risk of violence following a win is h^0, whilst the risk of violence following a loss is $h^0 + \alpha$.

3.4 Data and Methodology

In this section we present our general econometric model and details on the data used in this study.

3.4.1 Data

Domestic Abuse

We obtained our data on daily count of reported domestic abuse for the period 1st January 2014 to 31st July 2016 from Freedom of Information requests made to police forces in the United Kingdom (UK).

Freedom of Information (FOI) requests are made under the Freedom of Information Act (FOIA) which gives members of the public the right to access recorded information held by public sector organisations (ICO, 2017). We obtained positive responses from 28 police force areas. Data for London is disaggregated by borough so in the empirical analysis we consider these results separately from the other regions of England and Wales. Throughout this chapter, we use *England & Wales* and *County* interchangeably when referring to the Police Force Area which excludes London. We use London or London Boroughs to refer to data obtained for London. In Table 3.1 and Table 3.2, we present the summary statistics of domestic abuse in England & Wales and London Boroughs respectively. From Table 3.1 we can see that Manchester, Thames Valley, West Midlands and West Yorkshire record higher levels of domestic abuse; this might be due to the size of the counties. On the other hand, we can see that Table 3.2 among the London boroughs, Heathrow Airport has the lowest recorded amount of domestic abuse; this is probably because Heathrow Airport is not primarily residential.

In Figure 3.2, we present the plot of the sum of domestic abuse across all the police force areas (or boroughs) in our sample. Figure 3.2 Panel (a) displays incidents of domestic abuse across England and Wales (excluding London) and Panel (b) reports aggregate results for London. We can see that data on daily count of domestic abuse appears to be volatile, with longer spikes around the new year and around the middle of the year (around June). The spikes around the new year are more pronounced for England & Wales than for London. In London the spikes around the new year appear to be only slightly higher than the spikes around June. These and other trends are explored further in the results section.

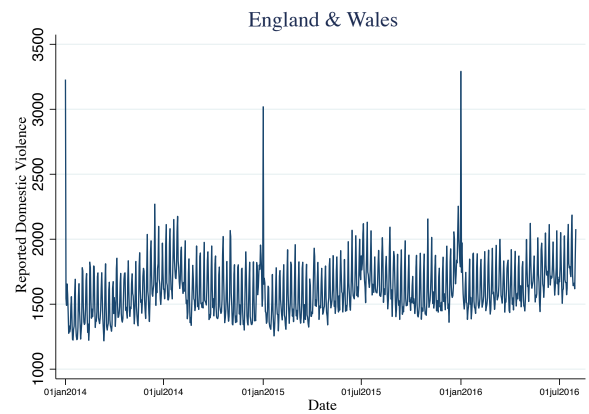
Table 3.1: Summary Statistics of Reported Incidents of Domestic Abuse by Police Force Area for England and Wales

Police Force Area	Mean	Standard Deviation	Minimum	Maximum
Avon and Somerset	63.73	12.88	30	123
Bedfordshire	29.57	8.92	7	81
Cambrigdeshire	13.97	6.70	2	52
Cheshire	15.16	6.45	1	52
Croydon	21.73	5.27	9	41
Cumbria	19.25	5.63	5	55
Derbyshire	49.22	10.19	24	108
Devon and Cornwall	77.32	16.18	30	152
Essex	81.89	14.71	25	146
Gloucestershire	27.71	6.39	10	65
Hertfordshire	25.74	6.29	11	48
Kent	40.82	12.05	15	93
Lancashire	70.85	16.30	33	142
Lincolnshire	26.29	7.13	8	62
Manchester	178.95	31.25	124	417
Norfolk	30.20	16.37	0	98
Northamptonshire	16.38	5.99	1	39
Northumbria	81.79	16.93	41	221
North Wales	28.93	7.98	10	73
North Yorkshire	12.17	4.54	1	32
South Wales	73.39	17.61	22	177
South Yorkshire	67.09	16.50	35	266
Staffordshire	63.04	12.35	29	147
Suffolk	25.40	6.39	9	57
Surrey	18.29	5.46	5	43
Thames Valley	122.66	17.61	76	209
West Mercia	52.45	12.27	25	110
West Midlands	128.33	20.56	80	225
West Yorkshire	122.38	26.53	58	268
Wiltshire	53.07	15.66	19	172

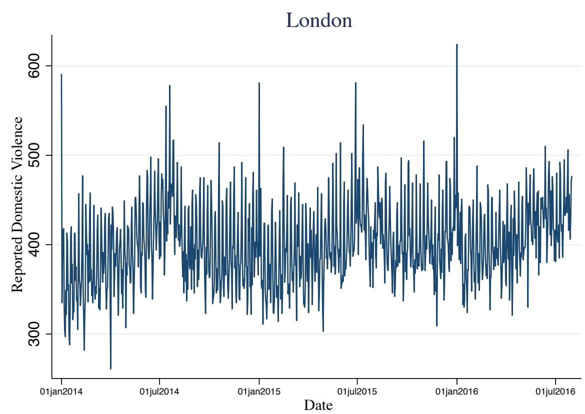
Table 3.2: Summary Statistics of Reported Incidents of Domestic Abuse by Boroughs in London

Police Force Area	Mean	Standard Deviation	Minimum	Maximum
Barking and Dagenham	14.73	4.12	4	29
Barnet	13.21	3.86	3	28
Brent	9.64	3.38	1	24
Bexley	14.51	4.17	3	31
Bromley	12.76	3.88	4	27
Camden	8.76	3.08	1	22
Ealing	15.65	4.50	5	33
Enfield	15.72	4.31	3	34
Greenwich	15.25	4.51	5	33
Hackney	14.80	4.02	5	30
Hammersmith and Fulham	8.69	3.18	0	23
Haringey	15.14	4.07	3	33
Harrow	8.22	2.99	0	20
Havering	11.76	3.73	1	30
Heathrow Airport	.13	.37	0	2
Hillingdon	13.77	4.18	3	29
Hounslow	14.19	4.12	3	30
Islington	11.88	3.71	4	28
Kensington and Chelsea	5.48	2.43	0	14
Kingston upon Thames	5.77	2.56	0	15
Lambeth	16.10	4.34	6	30
Lewisham	16.79	4.54	3	33
Merton	7.32	2.89	1	19
Newham	17.64	4.71	6	34
Redbridge	11.78	3.60	2	27
Richmond Upon Thames	5.18	2.38	0	13
South Wark	16.09	4.30	4	34
Sutton	8.02	3.05	0	23
Tower Hamlets	17.06	4.44	4	37
Waltham Forest	14.12	4.07	4	31
Wandsworth	11.50	3.81	2	24
Westminister	8.21	3.03	1	20

Figure 3.2: Trends in Reported Domestic Abuse from 1st January 2014 - 31st July 2016



(a) England & Wales



(b) London Boroughs

Football

In our sample, we capture three EPL seasons in some part - the second half of the 2013/2014 season, the whole 2014/2015 season and whole 2015/2016 season; the 2014 FIFA World Cup and the 2016 UEFA European Championship.

The EPL is the richest league in the world generating revenue in excess of £5 billion in the 2017/18 season (Deloitte, 2019). According to a report by EY (2019), 43 million people watched the EPL on the TV in the UK and in the 2016 - 2017 season, the EPL achieved a 97% stadium utilisation rate. The EPL currently, and since the late 1990s, has consisted of 20 clubs. Whilst a separate organisation to the Football League, there is promotion to and relegation from the EPL each season with the three highest ranked teams (the third team is determined via a series of play-offs) in the Championship - the tier immediately below the Premier League - replacing the three lowest ranked teams in the EPL (EPL, 2018).

Given the EPL's historical links to football hooliganism (Taylor, 1982; Dunning, 1994; Guilianotti, 1994; Spaaij, 2014), we think it would be appropriate to study the links between the EPL and domestic abuse in England and Wales.

We obtained data on EPL fixtures from *www.football-data.co.uk*. During the period, 26 football teams were active in at least one of the seasons. These include: Arsenal, Aston Villa, Bournemouth, Burnley, Cardiff, Chelsea, Crystal Palace, Everton, Fulham, Hull, Leicester, Liverpool, Manchester City, Manchester United, Newcastle, Norwich, QPR, Southampton, Stoke, Sunderland, Swansea, Tottenham, Watford, West brom, and West Ham. In Table 3.3, we present our pairing of EPL teams and their home counties (or borough) along with whether or not the data is available in our sample.

In addition, we obtained data on the 2014 FIFA World Cup and the 2016 UEFA European Championship. We provide detailed discussions of these in later sections.

Table 3.3: Pairing EPL Teams to Home Counties (or Boroughs)

	EPL Team	Home County	Data in Sample
1	Arsenal	Islington	Yes
2	Aston Villa	West Midlands	Yes
3	Bournemouth	Dorset	No
4	Burnley	Lancashire	Yes
5	Cardiff	South Wales	Yes
6	Chelsea	Kensington and Chelsea	Yes
7	Crystal Palace	Croydon	Yes
8	Everton	Merseyside	No
9	Fulham	Hammersmith and Fulham	Yes
10	Hull	East Yorkshire	No
11	Leicester	Leicester	No
12	Liverpool	Merseyside	No
13	Manchester City	Manchester	Yes
14	Manchester United	Manchester	Yes
15	Newcastle	Northumbria	Yes
16	Norwich	Norfolk	Yes
17	QPR	Hammersmith and Fulham	Yes
18	Southampton	Hampshire	No
19	Stoke	Staffordshire	Yes
20	Sunderland	Northumbria	Yes
21	Swansea	South Wales	Yes
22	Tottenham	Haringey	Yes
23	Watford	Hertfordshire	Yes
24	West Brom	West Midlands	Yes
25	West Ham	Newham	Yes

3.4.2 Econometric Model

As noted above, our dataset is a panel comprising the number of incidents of domestic abuse recorded each day for 28 Police Forces in England and Wales. In the case of London, this information is further disaggregated by borough.

The daily count of reported domestic abuse (DA) is the dependent variable on which we conduct our analyses. This data is classed as count data because it has positive discrete values. This violates the normal distribution assumptions of Ordinary Least Squares (OLS) estimation methods, thus we use an estimation method more suited to count data analysis, Poisson Regression Method (Cameron and Trivedi, 2013).

In equation 3.8 we present our general model specification. This specification closely follows that of Card and Dahl (2011).

$$log(\Gamma_{jt}) = \phi_j + X_t\omega + f(p_{jt}, y_{jt}, \sigma) + \xi_{jt} \tag{3.8}$$

where Γ is the expected number of domestic abuse incidents recorded by police force area j on day t, ϕ_j represents a fixed effect estimator which captures unobserved heterogeneity for the police force area such as size and characteristic of the local population. X_{jt} represents time related variables such as day of the week, holidays, month of the year, and year. $f(p_{jt}, y_{jt}, \sigma)$ is a function of the pregame predicted probability of a home win p_{jt}, the actual outcome of the game y_{jt} and the parameter estimates σ. Each of these factors are discussed in more detail below.

3.4.3 Test for Over-dispersion

Prior to reporting our results, we conducted a test for over-dispersion to determine the appropriateness of the Poisson regression method for our analysis. A simple test of for over-dispersion is to compare the mean of the distribution with the variance of the distribution. If the mean is the mean is greater than the variance, then the distribution is said to under-dispersed. If the mean is less than the variance then the distribution is said to be over-dispersed. Table 3.4, presents a summary statistics of daily counts of domestic abuse for London and for England & Wales.

Table 3.4: Mean and Variance of Domestic Abuse by Region

Region	Mean	Variance
England and Wales	55.73	1832.66
London	12.17	34.20

We see from Table 3.4 that the variance of domestic abuse is much larger than the mean for both regions. This suggest that our sample is over-dispersed. As a more formal test, we conduct a post-estimation test on the poisson estimation of Model 1 (Cameron and Trivedi, 1986). We compare the hypotheses:

$$H_0 : V[\gamma_{jt}|x_{jt}] = E[\gamma_{jt}|x_{jt}] \tag{3.9}$$

$$H_1 : V[\gamma_{jt}|x_{jt}] = E[\gamma_{jt}|x_{jt}] + \alpha(E[\gamma_{jt}|x_{jt}])^2 \tag{3.10}$$

This hypothesis can be reduced to $H_0 : \alpha = 0$ against $H_0 : \alpha > 0$. We implement the following auxiliary regression:

$$((\gamma_{jt} - \hat{\xi}_{jt})^2 - \gamma_{jt})/\hat{\xi}_{jt} = \alpha\hat{\xi}_{jt} + error \tag{3.11}$$

and text the hypothesis of $\hat{\xi}_{jt}$ is zero.

Table 3.5: Test of Over-dispersion

	(1) England & Wales	(2) London
$\hat{\xi}_{jt}$	267469.3***	13906.1***
	(98815.7)	(655.8)
Observations	27231	30987

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

From Table 3.5, we fail to accept the null hypothesis and find that there is over-dispersion in our data. Thus Negative Binomial methods will be better suited to our study. The analysis in the rest of this chapter will be conducted using Negative Binomial methods with bootstrap standard errors.

3.5 Results

3.5.1 Domestic Tournament: English Premier League

Model 1. *Time Effects Only.*

$$log(\Gamma_{jt}) = \phi_j + \omega_1 DOW_t + \omega_2 MOY_t + \omega_3 Holiday_t + \omega_4 Year_t + \xi_{jt} \tag{3.12}$$

In Equation 3.12, we expand only the time components of Equation 3.8. We expand $X_t\omega$ into day of the week, month of the year, holiday and year fixed effects. The variable DOW groups the data by the day of the week. The first day in our sample is Sunday, thus Sunday serves as the base day in our regression analysis. The variable MOY groups the data by the month of the year, starting with January. The variable Holiday is binary variable defined as:

$$Holiday = \begin{cases} 1 & \text{if the day is an official bank holiday,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.13}$$

In England and Wales, there are typically eight bank holidays in a year - New Year's day, Good Friday, Easter Monday, Early May Bank Holiday, Spring Bank Holiday, Summer Bank Holiday, Christmas Day and Boxing Day. Details of which specific dates are associated with the holidays for each year are presented in Appendix 3.A.1 Table 3.41. The variable Year groups the observation based on what year it occurred: 2014, 2015 or 2016.

Table 3.6: Trend in Reported Incidents of Domestic Abuse by Day of Week

	Day of Week	Mean	SD	Max
England and Wales	Sunday	65.44	50.27	280
	Monday	55.64	41.54	244
	Tuesday	51.86	38.64	212
	Wednesday	51.91	39.11	417
	Thursday	51.00	38.35	377
	Friday	53.27	40.55	415
	Saturday	60.92	47.52	269
London	Sunday	13.97	6.43	41
	Monday	12.04	5.73	36
	Tuesday	11.49	5.56	34
	Wednesday	11.34	5.56	39
	Thursday	11.47	5.53	38
	Friday	11.67	5.49	35
	Saturday	13.22	6.03	37

Table 3.6 and Table 3.7 display descriptive statistics of domestic abuse for London and for England & Wales by day of the week and month of the year respectively. From Table 3.6, we see that the general trend for both regional groupings is that mean levels of domestic abuse are lowest around the middle of the week on Tuesdays, Wednesdays and Thursdays. Levels of domestic abuse appear to start rising on Fridays through to Saturdays and start to decline on Mondays. Similarly from Table 3.7, the pattern appears to be that levels of domestic abuse start to rise around May and peaks by June before subsequently starting to decline in August. In addition, another spike in the levels of domestic abuse appears around December. This spike in December, however, appears to be muted in the case of London. The higher levels of domestic abuse around July might be due to the higher temperatures associated with that time of the year (Anderson, 2001).

Our regression results for Model 1 are presented in Table 3.8 for England & Wales and London Boroughs. For both regions, we see that all days of the week are associated with lower levels of domestic abuse relative to Sundays, the base day of our model. Tuesdays, Wednesdays, Thursdays and Fridays are associated with lower levels of domestic abuse compared to the days

Table 3.7: Trend in Reported Incidents of Domestic Abuse by Month of Year

	Month of Year	Mean	S.D.	Max
England and Wales	January	53.32	42.96	417
	February	53.45	40.91	255
	March	53.12	41.19	228
	April	54.31	41.31	249
	May	56.29	43.29	267
	June	58.86	44.86	280
	July	60.85	45.52	271
	August	57.40	43.14	231
	September	55.02	41.84	238
	October	53.71	41.07	242
	November	54.78	42.19	267
	December	57.21	43.64	269
London	January	11.58	5.77	39
	February	11.64	5.52	35
	March	11.72	5.55	37
	April	11.77	5.76	41
	May	12.44	5.96	39
	June	12.78	6.00	33
	July	13.22	6.22	40
	August	12.51	6.01	36
	September	12.02	5.65	33
	October	11.99	5.81	34
	November	12.09	5.72	33
	December	12.25	5.86	38

Saturday and Monday. The loweest level of domestic abuse occurs on a Thursday for England & Wales and occurs on a Wednesday for London Boroughs. In England & Wales, Thursdays are associated with a reduction of 23% in domestic abuse with $p < 0.01$ compared to Sundays. In London, Wednesdays are associated with a reduction of 20% in domestic abuse with $p < 0.01$ compared to Sundays. This result appears to be robust across the other specifications in Table 3.8.

Similarly for both regions, England & Wales and London, we see that the base month, January, is associated with the lowest levels of domestic abuse. In both regions, levels of domestic abuse appear to rise around the months of May and June, peaks in July and begin to decline again around August with an additional spike around December.

Regarding year effects, we find that compared to 2014 (the base year), 2015 and 2016 are associated with higher levels of domestic abuse for both regions. For England & Wales, 2015 is associated with a 4% increase in domestic abuse and 2016 is associated with a 9% increase in domestic abuse relative to levels of domestic abuse in 2014. For London, 2015 is associated with a 1% increase in domestic abuse and 2016 is associated with a 4% increase in domestic abuse relative to levels in 2014. These results are robust across the specifications in Table 3.8. Whilst the result might suggest that levels of domestic abuse have increased over the period in our sample, the rise may be due to the fact that there is an increase in the rates of reporting domestic abuse as opposed to a rise in the occurrence of the incidents (HMIC, 2014, 2015) as well as a changes to the definition of domestic abuse to include coercive and controlling behaviour in 2015 (HO, 2015).

As presented in columns 1b and 2b of Table 3.8, the variable Holiday is associated with a 22% increase in domestic abuse for England & Wales and a 12% increase in domestic abuse for London with $p < 0.01$. In Columns 1c and 1b, we split Holiday into Bh-Oth and Bh-Chris. Bh-Oth accounts for Non-Christmas and New Year bank holidays i.e. all bank holidays except Christmas day and New Year day. Bh-Chris accounts for only Christmas and New Year bank holidays. We find that for both regions, the holiday effect is driven primarily by the Christmas and New Year bank holidays (Bh-Chris). In England & Wales Bh-Oth is associated with a 10% increase in levels of domestic abuse whilst Bh-Chris is associated with a 45% increase in levels of domestic abuse. In London a similar pattern holds. Bh-Oth is associated with a 2% increase in domestic abuse whilst Bh-Chris is associated with a 27% increase in domestic abuse.[10]

[10]Table of results for the sample as a whole is included in Table 3.45 Appendix 3.A.2.

Table 3.8: Regression Showing Time variables for England & Wales and London

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
dv						
Monday	-0.152***	-0.174***	-0.165***	-0.148***	-0.159***	-0.153***
	(0.0321)	(0.0346)	(0.0324)	(0.00684)	(0.00793)	(0.00926)
Tuesday	-0.222***	-0.222***	-0.222***	-0.195***	-0.195***	-0.195***
	(0.0312)	(0.0303)	(0.0295)	(0.00700)	(0.00804)	(0.00931)
Wednesday	-0.222***	-0.223***	-0.224***	-0.208***	-0.209***	-0.210***
	(0.0294)	(0.0286)	(0.0279)	(0.00632)	(0.00862)	(0.00874)
Thursday	-0.239***	-0.242***	-0.246***	-0.197***	-0.198***	-0.201***
	(0.0268)	(0.0248)	(0.0241)	(0.00727)	(0.00933)	(0.00933)
Friday	-0.199***	-0.209***	-0.213***	-0.179***	-0.184***	-0.186***
	(0.0260)	(0.0279)	(0.0260)	(0.00735)	(0.00809)	(0.00895)
Saturday	-0.0735***	-0.0734***	-0.0734***	-0.0539***	-0.0539***	-0.0538***
	(0.00795)	(0.00754)	(0.00930)	(0.00503)	(0.00599)	(0.00654)
February	0.0129*	0.0169**	0.0232***	0.00560	0.00925	0.0146
	(0.00754)	(0.00851)	(0.00878)	(0.0103)	(0.00916)	(0.0113)
March	0.00114	-0.000394	0.00917	0.0118	0.0128**	0.0202***
	(0.00702)	(0.00949)	(0.00819)	(0.00951)	(0.00628)	(0.00772)
April	0.0307***	0.0240***	0.0366***	0.0180*	0.0164**	0.0259***
	(0.00980)	(0.00891)	(0.0103)	(0.0101)	(0.00829)	(0.00894)
May	0.0571***	0.0451***	0.0609***	0.0689***	0.0648***	0.0762***
	(0.0121)	(0.0118)	(0.0129)	(0.00822)	(0.00756)	(0.00759)
June	0.108***	0.112***	0.118***	0.100***	0.104***	0.109***
	(0.0130)	(0.0123)	(0.0136)	(0.00739)	(0.00741)	(0.00780)
July	0.146***	0.150***	0.156***	0.135***	0.138***	0.144***
	(0.0123)	(0.0124)	(0.0146)	(0.00850)	(0.00891)	(0.00766)
August	0.103***	0.0982***	0.109***	0.0839***	0.0837***	0.0920***
	(0.0110)	(0.0107)	(0.0129)	(0.00889)	(0.0104)	(0.00856)
September	0.0678***	0.0717***	0.0779***	0.0546***	0.0582***	0.0636***
	(0.0146)	(0.0136)	(0.0163)	(0.0124)	(0.0114)	(0.0108)
October	0.0453***	0.0489***	0.0555***	0.0512***	0.0548***	0.0604***
	(0.0146)	(0.0122)	(0.0135)	(0.0114)	(0.0114)	(0.0117)
November	0.0552***	0.0589***	0.0650***	0.0511***	0.0546***	0.0600***
	(0.0148)	(0.0138)	(0.0147)	(0.0119)	(0.0112)	(0.0140)
December	0.111***	0.0996***	0.0848***	0.0752***	0.0711***	0.0647***
	(0.0161)	(0.0129)	(0.0152)	(0.00940)	(0.00784)	(0.0107)
2015	0.0433**	0.0427**	0.0421**	0.0154*	0.0153**	0.0153*
	(0.0192)	(0.0183)	(0.0183)	(0.00791)	(0.00783)	(0.00824)
2016	0.0938***	0.0931***	0.0924***	0.0465***	0.0465***	0.0464***
	(0.0361)	(0.0310)	(0.0349)	(0.0107)	(0.0116)	(0.0103)
holiday		0.222***			0.115***	
		(0.0251)			(0.0106)	
Bh-Oth			0.101***			0.0271*
			(0.0282)			(0.0140)
Bh-Chris			0.451***			0.272***
			(0.0329)			(0.0195)
Constant	3.669***	3.725***	3.758***	5.278***	5.341***	5.410***
	(0.276)	(0.327)	(0.310)	(0.137)	(0.138)	(0.144)
Observations	27347	27347	27347	31119	31119	31119

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

Model 2. *Time Effects and Match Day Variables.*

$$log(\Gamma_{jt}) = \phi_j + X_t\omega + \sigma_1 MatchDay_{jt} + \xi_{jt} \tag{3.14}$$

In Model 2, we begin unpacking the football related function $f(p_{jt}, y_{jt}, \sigma)$ by adding a new variable Matchday to Model 1. Matchday is defined as:

$$Matchday = \begin{cases} 1 & \text{if EPL match takes place on that day,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.15}$$

In Table 3.42 of Appendix 3.A.1 we present a full list of all EPL match-days. In this model, we test the hypothesis presented in PSCD (2006), that the mere existence of an EPL match or fixture has an effect on the number of incidents of domestic abuse.

Our results are presented in Table 3.10.[11] From Column 1a, we can see that Matchday is associated with a 0.9% increase in domestic abuse for England & Wales with $p < 0.01$. From Column 2a, we see that Matchday is associated with a 0.3% decrease in levels of domestic abuse for London. The decrease associated with Matchday in London is not statistically significant.

It is possible that levels of domestic abuse in a given county or borough is only affected by whether or not a local team from the county/borough is involved in a match. To test for this possibility, we introduce a new variable Matchpa, which stands for Match by police authority. Matchpa is a binary variable which is defined as:

$$Matchpa = \begin{cases} 1 & \text{if EPL match involves a team from a relevant county/borough,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.16}$$

From Column 1b and 2b of Table 3.10, we see that for England & Wales, Matchpa is associated with a 1% increase in domestic abuse. This result is not statistically significant. In London, Matchpa is associated with 2% decrease in domestic abuse. Like Matchday in Column 2a, the sign associated with this variable is negative, where we expect a positive sign, and is not statistically significant. These results suggest that EPL matches have no effect on levels of domestic violence in London even when the match involves a local team.

Before we settle on this conclusion, we break Matchpa into another variable named Matchcount. Since some counties/boroughs may have more than one local team involved in an EPL fixture on a given match day, Matchcount accounts for the number of relevant games associated

[11]The complete table of full results can be found in Table 3.46 Appendix 3.A.2

with a given county/borough on a match day. Matchcount is defined as:

$$Matchcount = \begin{cases} 2 & \text{if there are up to two relevant EPL fixtures for a county/borough,} \\ 1 & \text{if there is one EPL fixture associated with a county/borough,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.17}$$

In our sample, the maximum number of EPL fixtures associated with a given county/borough is two. From Column 1c, we see that for England & Wales, having up to two relevant matches on a given day is associated with a 7% increase in levels of domestic abuse with $p < 0.05$ and having only one relevant match is associated with a 0.5% decrease in levels of domestic abuse but this is not statistically significant. From Column 2c, we see that for London, the number of relevant matches has no statistically significant effect on level of domestic abuse.

As a further step, we break Matchcount into whether or not the EPL fixtures are home fixtures or away fixtures. We replace Matchcount with two new variables named Hometeam and Awayteam. These variables are binary variables defined as:

$$Hometeam = \begin{cases} 1 & \text{if the EPL fixture associated with a county/borough is a home fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.18}$$

$$Awayteam = \begin{cases} 1 & \text{if the EPL fixture associated with a county/borough is an away fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.19}$$

From Column 1d, we see that in England & Wales Hometeam is associated with about 2% increase in domestic abuse and Awayteam is associated with about 3% increase in domestic abuse. These results are, however, not statistically significant. From Column 2d, we see that in London Hometeam is associated with a 2% decrease in domestic abuse and Awayteam is associated with about 2% decrease in domestic abuse. These variables are not statistically significant. Based on the results in Table 3.10, we find that in England & Wales the existence of an EPL fixture is associated with an upward trend in domestic abuse. In London, we find that trends in domestic abuse are unaffected by the existence of an EPL match. Our results for England and Wales are consistent with the hypothesis of PSCD (2006), that the existence of an (EPL) fixture appears to affect the levels of reported domestic abuse. Table 3.9 displays a summary statistic of the time and match day variables by region.

Table 3.9: Summary Statistics of Time and Match Day Variables

Region	Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales						
	holiday	27,347	.0223	.1476	0	1
	Bh-Oth	27,347	.0148	.1209	0	1
	Bh-Chris	27,347	.0074	.0858	0	1
	2014	27,347	.3871	.4871	0	1
	2015	27,347	.3871	.4871	0	1
	2016	27,347	.2259	.4182	0	1
	matchday	27,347	.2587	.4379	0	1
	matchpa	27,347	.0270	.1621	0	1
	matchcount	27,347	.0333	.2119	0	2
	hometeam	27,347	.0167	.1281	0	1
	awayteam	27,347	.0177	.1318	0	1
London						
	holiday	31,119	.0223	.1476	0	1
	Bh-Oth	31,119	.0148	.1209	0	1
	Bh-Chris	31,119	.0074	.0858	0	1
	2014	31,119	.3871	.4871	0	1
	2015	31,119	.3871	.4871	0	1
	2016	31,119	.2259	.4182	0	1
	matchday	31,119	.2587	.4379543	0	1
	matchpa	31,119	.0171	.12963	0	1
	matchcount	31,119	.0171	.12963	0	1
	hometeam	31,119	.0085	.09206	0	1
	awayteam	31,119	.0085	.09206	0	1

Table 3.10: Regression with Match Day Variables for Both Regions

	England & Wales				London Boroughs			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Domestic Abuse								
Bh-Oth	0.0996***	0.101***	0.101***	0.101***	0.0274**	0.0272**	0.0272**	0.0272**
	(0.0241)	(0.0263)	(0.0271)	(0.0262)	(0.0135)	(0.0124)	(0.0128)	(0.0115)
Bh-Chris	0.448***	0.449***	0.447***	0.447***	0.274***	0.275***	0.275***	0.275***
	(0.0393)	(0.0340)	(0.0347)	(0.0422)	(0.0192)	(0.0203)	(0.0194)	(0.0194)
matchday	0.00931***				-0.00309			
	(0.00357)				(0.00363)			
matchpa		0.0141				-0.0209		
		(0.0319)				(0.0240)		
matchcount=1			-0.00507				-0.0209	
			(0.0375)				(0.0294)	
matchcount=2			0.0712**					
			(0.0306)					
hometeam				0.0161				-0.0221
				(0.0522)				(0.0180)
awayteam				0.0255				-0.0197
				(0.0340)				(0.0282)
Constant	3.753***	3.758***	3.759***	3.758***	5.412***	5.411***	5.411***	5.411***
	(0.347)	(0.405)	(0.316)	(0.434)	(0.146)	(0.142)	(0.124)	(0.118)
Day of the Week Effects	✓	✓	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	27347	31119	31119	31119	31119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Model 3. *Time Effects, Match Day and Match Result Variables.*

$$log(\Gamma_{jt}) = \phi_j + X_t\omega + \sigma_1 MatchOutcome_{jt} + \xi_{jt} \tag{3.20}$$

In Model 3, we introduce variables which capture the full time match outcome of each match for EPL teams and their relevant county/borough. The football outcome variables are defined separately for when the local team plays a home fixture and when the local teams plays an away fixture. When the local team plays a home fixture, the football outcome variables are defined as follows:

$$HW = \begin{cases} 1 & \text{if the local team wins the home fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.21}$$

$$HD = \begin{cases} 1 & \text{if the local team draws in the fixture home fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.22}$$

$$HL = \begin{cases} 1 & \text{if the local team loses the home fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.23}$$

When the local team plays an away fixture the football outcome variables are defined as follows:

$$AW = \begin{cases} 1 & \text{if the local team wins the away fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.24}$$

$$AD = \begin{cases} 1 & \text{if the local team draws the fixture away fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.25}$$

$$AL = \begin{cases} 1 & \text{if the local team loses the away fixture,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.26}$$

With this model, we test the hypothesis put forward by Brimicombe and Cafe (2012) that a local team win will result in a reduction in levels of domestic abuse, while a local team lose will result in an increase in levels of domestic abuse. From Column 1a of Table 3.12 we see that for England and Wales, match outcomes are not associated with statistically significant changes in domestic abuse, except when the local team wins an away fixture (AW). A win in an away fixture (AW) is associated with a 4% increase in domestic abuse with $p < 0.05$. From Column 2a we see that match outcomes are not associated with changes in trends of domestic abuse in London.[12] These results stand in contrast to the hypothesis presented in Brimicombe and Cafe (2012). We find that the outcome of an EPL match has no effect on domestic abuse in the best case and that, in the worst case, a win is associated with an increase and not a decrease in domestic abuse.

Table 3.11 displays a summary statistic of the match outcome variables by region.[13]

Table 3.11: Summary Statistics of Match Outcome Variables

Region	Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales						
	HW	27,347	.0066	.0811	0	1
	HD	27,347	.0041	.0636	0	1
	HL	27,347	.0055	.0743	0	1
	AW	27,347	.0040	.0633	0	1
	AD	27,347	.0039	.0630	0	1
	AL	27,347	.0082	.0903	0	1
London						
	HW	31,119	.0043	.0652	0	1
	HD	31,119	.0019	.0445	0	1
	HL	31,119	.0023	.0477	0	1
	AW	31,119	.0032	.0565	0	1
	AD	31,119	.0022	.0470	0	1
	AL	31,119	.0031	.0557	0	1

[12]The complete table of full results can be found in Table 3.47 Appendix 3.A.2

[13]Table of results for the sample as a whole is included in Table 3.49 Appendix 3.A.2.

Table 3.12: Regression with Match Outcome and Reference Dependent Variables for Both Regions

	England & Wales			London Boroughs		
	(1a)	(1b) 70%	(1c) 50%	(2a)	(2b) 70%	(2c) 50%
Domestic abuse						
Bh-Oth	0.101***	0.101***	0.101***	0.0271*	0.0272**	0.0272***
	(0.0250)	(0.0269)	(0.0290)	(0.0138)	(0.0128)	(0.0104)
Bh-Chris	0.447***	0.447***	0.447***	0.275***	0.274***	0.275***
	(0.0352)	(0.0315)	(0.0319)	(0.0209)	(0.0201)	(0.0205)
HW	0.0231			-0.0210		
	(0.0178)			(0.0285)		
HD	0.0252			-0.0229		
	(0.0222)			(0.0358)		
HL	0.00788			-0.0234		
	(0.0183)			(0.0295)		
AW	0.0432**			-0.00810		
	(0.0188)			(0.0283)		
AD	0.0233			0.00817		
	(0.0203)			(0.0269)		
AL	0.0155			-0.0534		
	(0.0229)			(0.0520)		
H-Expected		0.0266**	0.0197		-0.0211	-0.0180
		(0.0135)	(0.0162)		(0.0138)	(0.0201)
H- UW		0.00133	0.00474		-0.0206	-0.0367
		(0.0131)	(0.0187)		(0.0330)	(0.0514)
H-UL		0.0418*	0.0639***		-0.122	-0.0191
		(0.0252)	(0.0195)		(0.127)	(0.0581)
A-Expected		0.0184	0.0207*		-0.0256	-0.0248
		(0.0201)	(0.0125)		(0.0414)	(0.0309)
A-UW		0.0429***	0.0356**		-0.00920	0.00803
		(0.0151)	(0.0176)		(0.0230)	(0.0359)
A-UL			0.0754***			-0.270***
			(0.0179)			(0.0631)
Constant	3.758***	3.758***	3.758***	5.412***	5.412***	5.413***
	(0.311)	(0.348)	(0.306)	(0.154)	(0.166)	(0.146)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

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

Model 4. *EPL Related Trends in Domestic Abuse: Reference Dependent Match Outcome (RDMO).*

$$log(\Gamma_{jt}) = \phi_j + X_t\omega + \sigma_1 RDMO_{jt} + \xi_{jt} \tag{3.27}$$

In this model, we introduce reference-dependent match outcome variables. The reference dependent variables are defined separately for home fixtures and away fixtures. When the local team plays a home fixture, the reference dependent variables are defined as:

$$H - Expected = \begin{cases} 1 & \text{if the local team's outcome is as expected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.28}$$

$$H - UW = \begin{cases} 1 & \text{if the local team's win is unexpected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.29}$$

$$H - UL = \begin{cases} 1 & \text{if the local team's lose is unexpected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.30}$$

When the local team plays an away fixture, the reference dependent variables are defined as:

$$A - Expected = \begin{cases} 1 & \text{if the local team's outcome is as expected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.31}$$

$$A - UW = \begin{cases} 1 & \text{if the local team's win is unexpected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.32}$$

$$A - UL = \begin{cases} 1 & \text{if the local team's lose is unexpected,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.33}$$

The reference dependent variables were constructed by comparing the pre-game expected match outcome with the actual match outcome of the EPL fixture.

We constructed the pre-game expected match outcomes by using betting odds obtained from a football bookmaker. We chose the Ladbrokes bookmaker prices for our study. Pre-games betting odds are known to be efficient predictors of match outcomes ((Angelini and De Angelis, 2019; Elaad et al., 2019)). Data on betting odds were obtained from *www.football-data.co.uk*. From the betting odds, we constructed the probability of match outcomes and corrected for the *overround* by normalising the outcome probabilities i.e. we divided the each outcome probability by the sum of the all outcome probabilities.

Following Dickson et al. (2016), in the first instance, we define expectedness of a match outcome by a 70% threshold. However, as shown in Table 3.13, a 70% threshold is quite high for our sample. In addition, from the sample of probabilities in the blog posts at http://blogs.reading.ac.uk/econscorecast/ constructed by Reade et al. (2019) a 70% threshold is also considered to be high.

Table 3.13: Summary statistics of Probability of Home Wins and Away Wins across all five EPL seasons

Variables	Mean	Standard Dev.	Min	Max
P(Home Win)	0.45	0.18	0.08	0.87
P(Away Win)	0.30	0.16	0.03	0.77

Thus, along with the 70% threshold, we also present results obtained from a 50% threshold of expectedness. Table 3.14 presents an illustration of how pre-game expectations are mapped unto actual performance and Table 3.16 presents an example of how variables are coded based on EPL fixtures of 8$^{\text{th}}$ August 2015 and 15$^{\text{th}}$ May 2016.

Table 3.14: Mapping of Home-team pregame expected performance on Actual performance

	Home Team Full Time Result		
Expected Probabilty of Winning	Loss	Draw	Win
$\geq x$	Unexpected	Unexpected	Expected
$< x$	Expected	Expected	Unexpected

Where x is the threshold of unexpectedness.

Columns 1b and 2b of Table 3.12 display the results the reference dependence variables using the 70% threshold of expectedness whilst Columns 1c and 2c present the results using the 50% threshold of expectedness.[14]

For England and Wales, we see that for home fixtures at the 70% threshold of expectedness (Col. 1b), H-Expected is associated with a 3% increase in domestic abuse and H-UL is associated with a 4% increase in domestic abuse. These results suggest that the reference dependence of football match outcomes affects trends in domestic abuse such that compared to an expected home outcome (H-Expected) and unexpected home lose (H-UL) leads to almost two times higher increase in domestic abuse.[15] This effect is stronger when we use the 50% threshold in Column 1c. When we use the 50% threshold of expectedness, H-expected loses it's statistical significance and H-UL becomes associated with a 6% increase in domestic abuse with $p < 0.01$. For away fixtures, we see in Col. 1b that an unexpected away win (A-UW) is associated with a 4% increase in domestic abuse at the 70% threshold of expectedness. However at the 50% threshold of expectedness (Col. 1c), we see that overall away fixtures are associated with an increase in domestic abuse but an unexpected away lose (A-UL) is associated with a

[14] In addition to the 70% and 50% threshold, we present results based on a 60% threshold of expectedness. These results can be found in Table 3.48 Appendix 3.A.2

[15] These result are further confirmed by our analysis using a 60% threshold of expectedness. The effects sizes from the 60% threshold are much larger than even those obtained from the 50% threshold of expectedness. These results can be found in Table 3.48 Appendix 3.A.2

much larger increase in domestic abuse. A-Expected is a associated with a 2% increase domestic abuse with $p < 0.1$, A-UW is associated with a 3% increase in domestic abuse with $p < 0.05$ and A-UL is associated with a 7% increase in domestic abuse with $p < 0.01$.

For London, on the other hand, we see that trends in domestic abuse are not affected by the reference dependence of football outcome. All the reference dependence variables are not statistically significant expect A-UL in Col. 2c which is negatively signed. This suggests that in London an unexpected loss in an away fixture is associated with a 27% decrease in domestic abuse. Table 3.15 displays a summary statistic of the reference dependent match outcome variables by region.

Table 3.15: Summary Statistics of Reference Dependence Match Outcome Variables

Region	Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales						
70 Threshold						
	H-Expected	27,347	.0107	.1030	0	1
	H-UW	27,347	.0054	.0731	0	1
	H-UL	27,347	.000146	.0121	0	1
	A-Expected	27,347	.0122	.1098	0	1
	A-UW	27,347	.00402	.0633	0	1
50 Threshold						
	H-Expected	27,347	.0117	.1075	0	1
	H-UW	27,347	.003803	.0615	0	1
	H-UL	27,347	.000731	.02703	0	1
	A-Expected	27,347	.0128	.1125	0	1
	A-UW	27,347	.003108	.0556	0	1
	A-UL	27,347	.0002925	.0171	0	1
London						
70 Threshold						
	H-Expected	31,119	.00530	.0726	0	1
	H-UW	31,119	.00308	.0554	0	1
	H-UL	31,119	.000161	.01267	0	1
	A-Expected	31,119	.00537	.0730	0	1
	A-UW	31,119	.003187	.0563	0	1
50 Threshold						
	H-Expected	31,119	.00643	.0799115	0	1
	H-UW	31,119	.00164	.0404504	0	1
	H-UL	31,119	.000482	.02195	0	1
	A-Expected	31,119	.00627	.0789126	0	1
	A-UW	31,119	.00206	.0453	0	1
	A-UL	31,119	.000225	.0150	0	1

Table 3.16: Construction of the Reference Dependence Variable

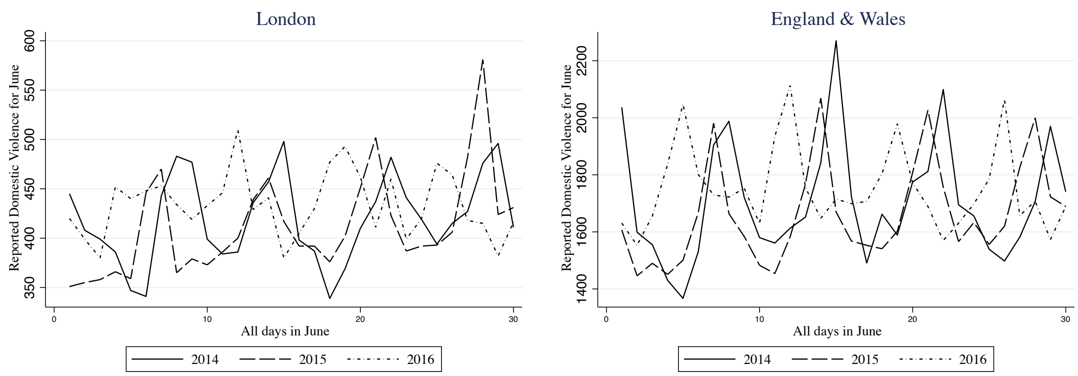
				Labroke Bookmarker Points			Probabilities			
Date	Hometeam	Awayteam	Full Time Result	Home	Draw	Away	Home	Draw	Away	Expectation
08/08/2015	Bournemouth	Aston Villa	A	2.05	3.30	4.00	0.47	0.29	0.24	Expected
08/08/2015	Chelsea	Swansea	D	1.40	4.50	10.00	0.69	0.21	0.10	Expected[a]
08/08/2015	Everton	Watford	D	1.75	3.80	5.00	0.55	0.25	0.19	Expected
08/08/2015	Leicester	Sunderland	H	2.00	3.40	4.20	0.48	0.28	0.23	Unexpected Win
08/08/2015	Man United	Tottenham	H	1.67	4.00	5.50	0.58	0.24	0.18	Unexpected Win
08/08/2015	Norwich	Crystal Palace	A	2.62	3.20	2.90	0.37	0.30	0.33	Expected
15/05/2016	Arsenal	Aston Villa	H	1.15	9.00	19.00	0.84	0.11	0.05	Expected
15/05/2016	Chelsea	Leicester	D	2.30	3.75	3.00	0.42	0.26	0.32	Expected
15/05/2016	Everton	Norwich	H	1.80	4.20	4.20	0.54	0.23	0.23	Unexpected Win
15/05/2016	Newcastle	Tottenham	H	4.33	4.00	1.80	0.22	0.24	0.54	Unexpected Win
15/05/2016	Southampton	Crystal Palace	H	1.33	5.50	9.50	0.72	0.18	0.10	Expected
15/05/2016	Stoke	West Ham	H	3.40	3.75	2.10	0.28	0.26	0.46	Unexpected Win
15/05/2016	Swansea	Man City	D	6.50	4.33	1.53	0.15	0.22	0.63	Expected
15/05/2016	Watford	Sunderland	D	2.05	3.75	3.60	0.47	0.26	0.27	Expected
15/05/2016	West Brom	Liverpool	D	2.40	3.60	2.90	0.40	0.27	0.33	Expected

[a] Using the home-team winning probability threshold of 60% presented in in Table 3.48 of Appendix 3.A.2, this would be classed as an unexpected outcome.

3.5.2 International Tournaments

In this section, we investigate the effects of two international tournaments: the FIFA World Cup and the UEFA European Championship on domestic abuse in England and Wales.

Figure 3.3: Count of Reported Domestic Abuse Incidents for the month of June (2014 - 2016)



(a) London (b) England & Wales

FIFA World Cup

Here, we investigate the effects of the 2014 FIFA World Cup on domestic abuse in England and Wales. We obtained match data for the 2014 FIFA World Cup which took place in Brazil between 12$^{\text{th}}$ June 2014 - 13$^{\text{th}}$ July 2014. We introduce FIFA related variables defined as:

$$FIFA - matchday = \begin{cases} 1 & \text{if there is any FIFA fixture on a given day,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.34}$$

$$FIFA - England = \begin{cases} 1 & \text{if there is any FIFA fixture which involves England,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.35}$$

$$EnglandDraw = \begin{cases} 1 & \text{if the England FIFA fixture ends in a draw,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.36}$$

$$EnglandLose = \begin{cases} 1 & \text{if the England FIFA fixture ends in a lose for England,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.37}$$

We obtained our data from *www.fifa.com*, Table 3.17 presents details about the FIFA 2014 fixture which involved England and the respective match outcomes.

Table 3.17: 2014 FIFA World Cup: England Fixtures

Match Day	Saturday, 14th June	Thursday, 19th June	Tuesday, 24th June
Fixture	England vs Italy	Uruguay vs England	Costa Rica vs England
Result	Lose (1-2)	Lose (2-1)	Draw (0-0)

From Table 3.19, we see that for England & Wales, the existence of a FIFA fixture is associated with a 3% increase in domestic abuse with $p < 0.01$. However when we run the regression for only FIFA matches which involve England (FIFA-England), we find, in Column 1b, that the associated increase in domestic abuse is higher at 4% with $p < 0.05$ than FIFA-matchday. When we take account of the FIFA match outcome of England games in Column 1c, we find that games where England draws are associated with 6% increase in domestic abuse with $p < 0.01$. We also find that FIFA games where England loses have no statistically significant effect on domestic abuse in England & Wales.

In the case of London (Col. 2a - 2c), we find that domestic abuse is only affected by whether or not there is a FIFA fixture (FIFA-matchday). Whether or not the fixture involves England (FIFA-England) and the outcome of the England FIFA match (England draw or lose) has no statistically significant effect in domestic abuse in London. These results support the hypothesis put forward in PSCD (2006) that the existence of a FIFA fixture affects domestic abuse. The hypothesis put forward by Brimicombe and Cafe (2012) and Kirby et al. (2014) that FIFA World Cup match outcomes matter for domestic abuse is not supported in our analysis.[16]

One methodological difference between our study and the other studies (Brimicombe and Cafe, 2012; Kirby et al., 2014) is that whilst we used data over the course of a full calendar year, they used data for only a month around the World Cup. As an extension, we restricted our sample to a small window around the FIFA World Cup 1st June - 31st of July. We find from Table 3.20 that FIFA match days become associated with a decrease in domestic abuse. This decrease in domestic abuse is statistically significant for counties of England & Wales but not statistically significant for London boroughs. Table 3.18 displays a summary statistic of the FIFA World Cup variables by region.[17]

[16] The complete table of results can be found in Table 3.51 Appendix 3.B
[17] The results for all regions combined can be found in Table 3.52 Appendix 3.B

Table 3.18: Summary Statistics of FIFA World Cup Match Variables

Region	Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales						
	FIFA Matchday	27,347	.0329	.1783	0	1
	FIFA England	27,347	.00318	.0563	0	1
	England Draw	27,347	.00106	.0325	0	1
	England Lose	27,347	.00212	.0460	0	1
London						
	FIFA Matchday	31,119	.0329	.1783	0	1
	FIFA England	31,119	.0031	.0563	0	1
	England Draw	31,119	.0011	.0325	0	1
	England Lose	31,119	.0021	.0460	0	1

Table 3.19: Regressions result with FIFA 2014 variables for both regions

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Bh-Oth	0.101***	0.100***	0.100***	0.0270**	0.0271**	0.0271**
	(0.0212)	(0.0311)	(0.0277)	(0.0116)	(0.0136)	(0.0129)
Bh-Chris	0.451***	0.451***	0.451***	0.272***	0.272***	0.272***
	(0.0322)	(0.0368)	(0.0342)	(0.0179)	(0.0186)	(0.0189)
fifa-matchday	0.0292***			0.0304**		
	(0.0108)			(0.0123)		
fifa-england		0.0428**			0.0111	
		(0.0201)			(0.0270)	
England Draw			0.0591***			0.0679
			(0.0224)			(0.0482)
England Lose			0.0351			-0.0163
			(0.0296)			(0.0392)
Constant	3.757***	3.758***	3.758***	5.411***	5.410***	5.411***
	(0.330)	(0.390)	(0.316)	(0.148)	(0.146)	(0.136)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.20: Regression Result with FIFA 2014 variables for both regions restricted to June and July

	England & Wales			London		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Abuse						
Monday	-0.167***	-0.166***	-0.166***	-0.147***	-0.147***	-0.147***
	(0.0273)	(0.0363)	(0.0322)	(0.0167)	(0.0142)	(0.0115)
Tuesday	-0.222***	-0.222***	-0.222***	-0.174***	-0.173***	-0.174***
	(0.0235)	(0.0328)	(0.0316)	(0.0129)	(0.0160)	(0.0154)
Wednesday	-0.235***	-0.234***	-0.234***	-0.183***	-0.183***	-0.183***
	(0.0219)	(0.0351)	(0.0303)	(0.0182)	(0.0181)	(0.0152)
Thursday	-0.248***	-0.248***	-0.248***	-0.201***	-0.200***	-0.199***
	(0.0196)	(0.0296)	(0.0269)	(0.0150)	(0.0174)	(0.0162)
Friday	-0.216***	-0.216***	-0.216***	-0.186***	-0.186***	-0.186***
	(0.0257)	(0.0302)	(0.0296)	(0.0150)	(0.0122)	(0.0138)
Saturday	-0.104***	-0.105***	-0.105***	-0.0702***	-0.0698***	-0.0691***
	(0.0124)	(0.0142)	(0.0130)	(0.0133)	(0.0124)	(0.0138)
July	0.0377***	0.0393***	0.0393***	0.0344***	0.0346***	0.0346***
	(0.00575)	(0.00705)	(0.00572)	(0.00788)	(0.00969)	(0.00819)
2015	0.000515	0.0104	0.0104	-0.0370***	-0.0316***	-0.0316***
	(0.0219)	(0.0232)	(0.0315)	(0.0122)	(0.0117)	(0.0112)
2016	0.0234	0.0333	0.0333	-0.00344	0.00194	0.00190
	(0.0302)	(0.0352)	(0.0426)	(0.0140)	(0.0129)	(0.0104)
fifa-matchday	-0.0179*			-0.0121		
	(0.00978)			(0.0132)		
fifa-england		0.0161			-0.0165	
		(0.0186)			(0.0349)	
England Draw			0.0204			0.0205
			(0.0270)			(0.0531)
England Lose			0.0141			-0.0347
			(0.0236)			(0.0389)
Constant	3.954***	3.943***	3.943***	5.459***	5.449***	5.452***
	(0.282)	(0.382)	(0.329)	(0.243)	(0.287)	(0.406)
Observations	5307	5307	5307	6039	6039	6039

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

UEFA European Championship

We investigate the effects of the 2016 UEFA European Championship on domestic abuse in England and Wales. We obtained data for the 2016 UEFA European Championship which took place in France from 10$^{\text{th}}$ June to 10$^{\text{th}}$ July 2016. We introduce UEFA European Championship related variables defined as:

$$EURO - matchday = \begin{cases} 1 & \text{if there is any UEFA fixture on a given day,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.38}$$

$$EURO - England = \begin{cases} 1 & \text{if there is any UEFA fixture which involves England,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.39}$$

$$EnglandWin = \begin{cases} 1 & \text{if the England UEFA fixture ends in a win for England,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.40}$$

$$EnglandDraw = \begin{cases} 1 & \text{if the England UEFA fixture ends in a draw,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.41}$$

$$EnglandLose = \begin{cases} 1 & \text{if the England UEFA fixture ends in a lose for England,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.42}$$

Data on the 2016 UEFA European Championship was obtained from *www.uefa.com*, Table 3.21 displays details of the 2016 UEFA fixtures and outcomes for England.

Table 3.21: 2016 UEFA European Championship: England Fixtures

Match Day	Saturday 11th June	Thursday 16th June	Monday 20th June	Monday 27th June
Fixture	England vs Russia	England vs Wales	Slovakia vs England	England vs Iceland
Result	Draw (1-1)	Win (2-1)	Draw (0-0)	Lose (1-2)

From the various specifications in Table 3.24, we find that the mere existence of a UEFA European Championship fixture (EURO-matchday) is associated with a statistically significant decrease of 4% in levels of domestic abuse for England & Wales (Col. 1a) and has no effect on domestic abuse in London (Col. 2a).

UEFA European Championship fixtures which involve England (EURO-England) have no statistically significant effect in both regions as can be seen in Col. 1b and Col. 2b.

UEFA match outcomes for England matches are largely not statistically significant. The only statistically significant UEFA outcome variable is England Lose which is associated with a 0.6% decrease in domestic abuse for England & Wales.[18]

As we did in the previous section with the FIFA World Cup, we restricted the sample to a smaller window around the UEFA tournament (1st June - 31st July). We find from estimations in Table 3.25 that the UEFA European Championship has no effect on domestic abuse in the counties of England & Wales as well as the boroughs of London. With the exception of an England win in Col. 1c which is associated with a 7% increase in domestic abuse for England % Wales.[19]

Table 3.22: 2016 UEFA European Championship: Wales Fixtures

Match Day	Saturday 11th June	Thursday 16th June	Monday 20th June	Monday 25th June	Friday 1st July	Wednesday 6th July
Fixture	Wales vs Slovakia	England vs Wales	Russia vs Wales	Wales vs Northern Ireland	Wales vs Belgium	Portugal vs Wales
Result	Win (2-1)	Lose (2-1)	Win (0-3)	Win (1-0)	Win (3-1)	Lose (2-0)

In the 2016 UEFA European Championship, Wales also qualified and had a much more successful tournament compared to England. To exploit this, in Table 3.22 we provide details regarding the UEFA fixtures involving Wales. In Table 3.26, we restrict our regressions to North and South Wales police force areas.[20] We find from Col. 1a that a UEFA European Championship fixture is associated with a 5% decrease in domestic abuse in Wales. However, when restricted to matches involving Wales (Col. 1b), we find that the variables EURO-Wales is associated with a 5% increase in domestic abuse. From Col. 1c, we find that a lose for Wales (Wales Lose) is associated with about 2% increase in domestic abuse while, on the other hand, a win for Wales (Wales Win) is associated with a 0.9% increase in domestic abuse. When restricted to the months of June and July, we find that a lose for Wales is associated with a 20% increase in domestic abuse with $p < 0.1$. Overall, the 2016 UEFA fixtures involving Wales and the outcome of such fixtures have a strong effect on domestic abuse in North and South Wales. Table 3.23 displays a summary statistic of the UEFA European Championship match variables by region.

[18] The complete table of results can be found in Table 3.53 Appendix 3.B

[19] In Appendix 3.B Table 3.54, we present a table of results for all counties combined.

[20] The complete table of results can be found in Table 3.26 Appendix 3.B

Table 3.23: Summary Statistics of UEFA European Championship Match Variables

Region	Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales						
	Euro Matchday	27,347	.0244	.1543	0	1
	Euro England	27,347	.00424	.0649	0	1
	England Lose	27,347	.00106	.0325	0	1
	England Draw	27,347	.00212	.0460	0	1
London						
	Euro Matchday	31,119	.02439	.1542	0	1
	Euro England	31,119	.00424	.0649	0	1
	England Lose	31,119	.00106	.0325	0	1
	England Draw	31,119	.00212	.0460	0	1
Wales						
	Euro Matchday	1,886	.0243	.1542	0	1
	Euro Wales	1,886	.0042	.0650	0	1
	Wales Lose	1,886	.00106	.0325	0	1
	Wales Win	1,886	.00318	.0563	0	1

Table 3.24: Regression Result with UEFA variables for both regions

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Bh-Oth	0.101***	0.101***	0.100***	0.0272**	0.0271**	0.0270**
	(0.0251)	(0.0274)	(0.0209)	(0.0137)	(0.0125)	(0.0137)
Bh-Chris	0.451***	0.451***	0.451***	0.272***	0.272***	0.272***
	(0.0352)	(0.0393)	(0.0336)	(0.0204)	(0.0202)	(0.0215)
euro-matchday	-0.0450***			-0.0153		
	(0.0119)			(0.0136)		
euro-england		-0.00701			-0.00172	
		(0.0213)			(0.0212)	
England Lose			-0.0636**			-0.0229
			(0.0300)			(0.0434)
England Draw			-0.00642			0.00961
			(0.0215)			(0.0277)
England Win			0.0509			-0.00496
			(0.0361)			(0.0397)
Constant	3.758***	3.758***	3.758***	5.410***	5.410***	5.410***
	(0.308)	(0.356)	(0.312)	(0.152)	(0.163)	(0.153)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.25: Regression Results with UEFA variables for both regions restricted to June and July

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Monday	-0.167***	-0.168***	-0.166***	-0.146***	-0.148***	-0.148***
	(0.0344)	(0.0305)	(0.0266)	(0.0141)	(0.0135)	(0.0112)
Tuesday	-0.222***	-0.221***	-0.221***	-0.173***	-0.174***	-0.174***
	(0.0336)	(0.0291)	(0.0250)	(0.0136)	(0.0138)	(0.0132)
Wednesday	-0.235***	-0.234***	-0.234***	-0.182***	-0.183***	-0.183***
	(0.0330)	(0.0270)	(0.0243)	(0.0186)	(0.0139)	(0.0174)
Thursday	-0.248***	-0.248***	-0.250***	-0.200***	-0.201***	-0.201***
	(0.0279)	(0.0229)	(0.0217)	(0.0156)	(0.0140)	(0.0174)
Friday	-0.217***	-0.216***	-0.216***	-0.186***	-0.186***	-0.186***
	(0.0269)	(0.0261)	(0.0253)	(0.0139)	(0.0122)	(0.0130)
Saturday	-0.105***	-0.106***	-0.106***	-0.0702***	-0.0713***	-0.0720***
	(0.0115)	(0.0109)	(0.0124)	(0.0124)	(0.0121)	(0.0121)
July	0.0377***	0.0400***	0.0400***	0.0362***	0.0361***	0.0362***
	(0.00667)	(0.00522)	(0.00542)	(0.00866)	(0.00933)	(0.00961)
2015	0.00963	0.00962	0.00959	-0.0308***	-0.0308***	-0.0308***
	(0.0267)	(0.0237)	(0.0247)	(0.0113)	(0.0115)	(0.0113)
2016	0.0357	0.0307	0.0307	-0.000264	0.00131	0.00133
	(0.0447)	(0.0305)	(0.0369)	(0.0164)	(0.0141)	(0.0136)
euro-matchday	-0.00839			0.00785		
	(0.0101)			(0.0176)		
euro-england		0.0279			0.0216	
		(0.0221)			(0.0206)	
England Lose			-0.0379			-0.00710
			(0.0332)			(0.0494)
England Draw			0.0354			0.0374
			(0.0234)			(0.0320)
England Win			0.0782**			0.0161
			(0.0335)			(0.0437)
Constant	3.945***	3.944***	3.946***	5.448***	5.450***	5.451***
	(0.355)	(0.327)	(0.287)	(0.252)	(0.247)	(0.265)
Observations	5307	5307	5307	6039	6039	6039

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.26: Regression result with UEFA variables for Wales

				Restricted to June and July		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Bh-Oth	0.198***	0.198***	0.198***	0	0	0
	(0.0458)	(0.0491)	(0.0402)	(.)	(.)	(.)
Bh-Chris	0.547***	0.547***	0.547***	0	0	0
	(0.0354)	(0.0384)	(0.0311)	(.)	(.)	(.)
euro-matchday	-0.0505*			-0.0268		
	(0.0291)			(0.0331)		
euro-wales		0.0508***			0.0953	
		(0.0117)			(0.0622)	
Wales Lose			0.190***			0.205*
			(0.0564)			(0.118)
Wales Win			0.00909*			0.0601
			(0.00494)			(0.0714)
Constant	3.966***	3.966***	3.968***	4.623***	4.632***	4.643***
	(0.327)	(0.299)	(0.275)	(0.191)	(0.193)	(0.194)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119
Observations	1886	1886	1886	366	366	366

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

3.5.3 Combined Effects of Domestic and International Tournaments

In this section, we estimate a combined specification which contains variables of the domestic tournament (English Premier League) and the international tournaments (FIFA World Cup and UEFA European Championship). To the best of our knowledge no study on domestic abuse in England and Wales has presented a combined estimation of domestic tournament (English Premier League) and international tournaments (FIFA World Cup and UEFA European Championship). We argue that a combined estimation provides a more complete view of the correlations between major football tournaments and domestic abuse.

In Table 3.27, we present regressions which include Match day and Match outcome variables for EPL, FIFA and UEFA European Championship.[21] From Col. 1a, we see that compared to an EPL match day and a UEFA match day, a FIFA match day is associated with a higher effect on domestic abuse in England & Wales at a 2% increase with $p < 0.10$. Similarly for London, compared to an EPL match day and a UEFA match day, a FIFA match day is a associated with a higher and statistically significant effect on domestic abuse at a 3% increase with $p < 0.01$.

When restricted to only England matches for the international tournaments and relevant counties for the EPL matches, we find that a FIFA match involving England is associated with a 4% increase on domestic abuse in England & Wales with $p < 0.10$. The other variables in Col. 1b and Col. 2b are not statistically significant.

When we consider the match outcome variables for FIFA, UEFA European Championship and for EPL fixtures, we find that for England & Wales (Col. 1c) most outcome variables are not statistically significant except England Draw (FIFA) and England Lose (EURO). An England draw in a FIFA fixture is associated with about 6% increase in domestic abuse with $p < 0.1$ and an England lose in a UEFA European Championship is associated with a 6% decrease in domestic abuse with $p < 0.05$. For London (Col. 2c), none of the match outcome variables have statistical effects on the levels of domestic abuse.

These results conform to those obtained in PSCD (2006). Similar to PSCD (2006) we find that the mere existence of a fixture has an effect on domestic abuse.[22]

[21] The complete table of results can be found in Table 3.55 Appendix 3.B

[22] In Appendix 3.B Table 3.56, we present a table of results for all counties combined.

Table 3.27: Regression results with domestic and international tournaments for both regions

	England & Wales			London		
	1a	1b	1c	2a	2b	2c
Domestic abuse						
Bh-Oth	0.0998***	0.101***	0.100***	0.0274**	0.0272**	0.0270**
	(0.0278)	(0.0216)	(0.0278)	(0.0137)	(0.0118)	(0.0125)
Bh-Chris	0.448***	0.447***	0.447***	0.274***	0.275***	0.275***
	(0.0406)	(0.0261)	(0.0377)	(0.0171)	(0.0190)	(0.0193)
fifa-matchday	0.0238*			0.0289***		
	(0.0123)			(0.0108)		
euro-matchday	-0.0404***			-0.0104		
	(0.0124)			(0.0162)		
matchday	0.00892***			-0.00307		
	(0.00338)			(0.00391)		
fifa-england		0.0432*			0.0108	
		(0.0229)			(0.0280)	
euro-england		-0.00550			-0.00144	
		(0.0180)			(0.0248)	
hometeam		0.0161			-0.0221	
		(0.0331)			(0.0211)	
awayteam		0.0255			-0.0197	
		(0.0244)			(0.0388)	
England Draw FIFA			0.0584*			0.0680
			(0.0309)			(0.0530)
England Lose FIFA			0.0363			-0.0169
			(0.0347)			(0.0339)
England Lose EURO			-0.0631**			-0.0223
			(0.0322)			(0.0488)
England Draw EURO			-0.00399			0.00944
			(0.0204)			(0.0277)
England Win EURO			0.0513			-0.00434
			(0.0334)			(0.0386)
HW			0.0232			-0.0210
			(0.0292)			(0.0274)
HD			0.0252			-0.0230
			(0.0227)			(0.0472)
HL			0.00791			-0.0234
			(0.0332)			(0.0292)
AW			0.0432			-0.00814
			(0.0298)			(0.0256)
AD			0.0234			0.00812
			(0.0349)			(0.0551)
AL			0.0155			-0.0534
			(0.0433)			(0.0489)
Constant	3.752***	3.758***	3.759***	5.414***	5.412***	5.414***
	(0.357)	(0.379)	(0.386)	(0.149)	(0.148)	(0.119)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

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

3.5.4 Extension and Robustness Analysis

In this section, we present some extensions and robustness analysis. Following Card and Dahl (2011) and Dickson et al. (2016), we introduce some concepts of salience. We consider three concepts. First, we consider when a local-team plays against a traditional rival. Then we consider matches towards the end of the season and finally we consider matches which are expected to be close. Although our construction of the second is fairly crude (see Equation 3.44 for details), it allows us capture the potential impact of matches that might be important for determining the overall winner of the title, qualification for European club competitions and matches which matter with regards to relegation from the EPL.

Traditional Rivals

Table 3.28: Football Teams and Traditional Rivals

Manchester United	Manchester City
Manchester United	Liverpool
Newcastle	Sunderland
Aston Villa	West Brom
Any London Derby	

We pair teams with their traditional local rivals as in Table 3.28 and define a new variable, called Derby, as:

$$Derby = \begin{cases} 1 & \text{if rival teams play one another,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.43}$$

From Columns 1b and 2b of Table 3.29, we see that matches between rival teams have no statistically significant effect of levels of domestic abuse in both regions.[23] In Table 3.30, we present the results of regressions in which we restrict the sample to the relevant county of the respective rivalries. For example, we restricted the Manchester rivalry (Manchester United versus Manchester City) to Greater Manchester. We see from the regression results that only the Northumbria rivalry affects domestic abuse in Northumbria. The Northumbria rivalry (Newcastle versus Sunderland) in Col. 2b is associated with a 17% increase in domestic abuse with $p < 0.01$ whereas a match day where a Northumbria team plays any team is associated with a 2% increase in domestic abuse with $p < 0.1$. *We would like to add the caveat that since our study focuses on traditional rivalries when they occur in the EPL and not other divisions, our analysis might be underestimating the effects of derbies on domestic abuse.*

[23]The complete table of results can be found in Table 3.60 Appendix 3.D

Table 3.29: Regression results with traditional rivals for both regions

	England & Wales (1a)	(1b)	London (2a)	(2b)
Domestic abuse				
Monday	-0.164***	-0.165***	-0.153***	-0.154***
	(0.0326)	(0.0330)	(0.00827)	(0.00766)
Tuesday	-0.221***	-0.222***	-0.196***	-0.196***
	(0.0288)	(0.0285)	(0.00687)	(0.00779)
Wednesday	-0.224***	-0.224***	-0.211***	-0.211***
	(0.0275)	(0.0282)	(0.00827)	(0.00821)
Thursday	-0.246***	-0.246***	-0.201***	-0.202***
	(0.0250)	(0.0240)	(0.00837)	(0.00991)
Friday	-0.212***	-0.212***	-0.187***	-0.187***
	(0.0264)	(0.0263)	(0.00895)	(0.00959)
Saturday	-0.0745***	-0.0732***	-0.0531***	-0.0533***
	(0.00940)	(0.0101)	(0.00655)	(0.00640)
February	0.0230***	0.0233***	0.0147	0.0145
	(0.00863)	(0.00834)	(0.0100)	(0.0101)
March	0.00911	0.00907	0.0202**	0.0204**
	(0.00902)	(0.00689)	(0.00833)	(0.00871)
April	0.0364***	0.0367***	0.0261***	0.0260***
	(0.0101)	(0.00790)	(0.00942)	(0.00855)
May	0.0609***	0.0610***	0.0761***	0.0759***
	(0.0109)	(0.00966)	(0.00800)	(0.00892)
June	0.119***	0.119***	0.109***	0.109***
	(0.0112)	(0.0106)	(0.00835)	(0.00720)
July	0.157***	0.157***	0.143***	0.143***
	(0.0112)	(0.0118)	(0.00764)	(0.00717)
August	0.109***	0.109***	0.0920***	0.0921***
	(0.0104)	(0.0120)	(0.00917)	(0.00901)
September	0.0779***	0.0780***	0.0635***	0.0633***
	(0.0115)	(0.0142)	(0.0101)	(0.0114)
October	0.0554***	0.0554***	0.0604***	0.0602***
	(0.0117)	(0.0123)	(0.0101)	(0.0118)
November	0.0650***	0.0651***	0.0600***	0.0598***
	(0.0128)	(0.0131)	(0.0109)	(0.0115)
December	0.0846***	0.0848***	0.0649***	0.0644***
	(0.0119)	(0.0129)	(0.00818)	(0.00894)
2015	0.0420**	0.0420**	0.0153**	0.0153**
	(0.0192)	(0.0171)	(0.00648)	(0.00772)
2016	0.0924***	0.0924***	0.0463***	0.0463***
	(0.0292)	(0.0318)	(0.00912)	(0.0111)
Bh-oth	0.101***	0.101***	0.0272**	0.0275**
	(0.0258)	(0.0214)	(0.0131)	(0.0124)
Bh-Chris	0.449***	0.451***	0.275***	0.275***
	(0.0273)	(0.0356)	(0.0173)	(0.0155)
Matchpa	0.0141		-0.0209	
	(0.0697)		(0.0275)	
Derby		0.0733		-0.00645
		(0.0633)		(0.00674)
Constant	3.758***	3.758***	5.411***	5.412***
	(0.325)	(0.349)	(0.128)	(0.145)
Observations	27347	27347	31119	31119

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

Table 3.30: Regression results with traditional rivals restricted to relevant counties/boroughs

	Manchester		Northumbria		West-Midlands		Liverpool - Manchester	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Domestics abuse								
Bh-Oth	0.138***	0.139***	0.219***	0.217***	0.0534**	0.0538***	0.138***	0.139***
	(0.0274)	(0.0320)	(0.0333)	(0.0394)	(0.0240)	(0.0203)	(0.0331)	(0.0272)
Bh-Chris	0.654***	0.658***	0.654***	0.669***	0.429***	0.423***	0.654***	0.658***
	(0.153)	(0.134)	(0.169)	(0.154)	(0.106)	(0.0999)	(0.148)	(0.123)
matchpa	0.00700		0.0278*		-0.00844		0.00700	
	(0.0117)		(0.0157)		(0.0127)		(0.0120)	
Manchester Derby		-0.000735						
		(0.0530)						
Northumbria Derby				0.174***				
				(0.0637)				
West Midlands Derby						-0.0638		
						(0.0649)		
Liverpool- Manchester Derby								0.0297
								(0.0199)
Constant	5.342***	5.345***	4.524***	4.525***	5.001***	5.001***	5.342***	5.344***
	(0.0153)	(0.0136)	(0.0197)	(0.0190)	(0.0149)	(0.0146)	(0.0173)	(0.0147)
/								
lnalpha	-5.598***	-5.597***	-5.197***	-5.217***	-5.607***	-5.610***	-5.598***	-5.598***
	(0.202)	(0.213)	(0.246)	(0.299)	(0.168)	(0.164)	(0.197)	(0.212)
Day of the Week Effects	✓	✓	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	943	943	943	943	943	943	943	943

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

Matches Towards the End of the Season

For the second concept of salience, following Dickson et al. (2016), we included a binary variable, Title, which is defined as follows:

$$Title = \begin{cases} 1 & \text{for the last 5 matches of any team in the EPL season,} \\ 0 & \text{Otherwise} \end{cases} \tag{3.44}$$

From Table 3.31, we see that the variable Title is associated with a decrease in domestic abuse in both regions across various specifications.[24] In England & Wales, the last five matches of the season (Title) are associated with a decrease of about 4% in domestic abuse with $p < 0.01$. In London, we find that the last five matches of the season (Title) are associated with about 6% decrease in domestic abuse with $p < 0.01$, This result goes against our expectations as we anticipated that the last five matches of the season would be associated with an increase in domestic abuse.

[24]The complete table of results can be found in Table 3.61 Appendix 3.B

Table 3.31: Regression results with the last five matches of the season for both regions

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Title	-0.0368*	-0.0376***	-0.0353***	-0.0623***	-0.0610**	-0.0598***
	(0.0200)	(0.0144)	(0.0125)	(0.0237)	(0.0244)	(0.0217)
hometeam	0.0203			-0.0147		
	(0.0222)			(0.0236)		
awayteam	0.0296**			-0.0106		
	(0.0141)			(0.0362)		
HW		0.0283			-0.0130	
		(0.0264)			(0.0257)	
HD		0.0293			-0.0156	
		(0.0237)			(0.0452)	
HL		0.0115			-0.0172	
		(0.0255)			(0.0316)	
AW		0.0478**			-0.000445	
		(0.0229)			(0.0326)	
AD		0.0273			0.0171	
		(0.0272)			(0.0605)	
AL		0.0197			-0.0432	
		(0.0305)			(0.0545)	
H-expected			0.0237			-0.0107
			(0.0179)			(0.0273)
H-UW			0.00970			-0.0310
			(0.0280)			(0.0366)
H-UL			0.0658***			-0.00827
			(0.0205)			(0.0500)
A-expected			0.0248			-0.0155
			(0.0185)			(0.0471)
A-UW			0.0398*			0.0149
			(0.0205)			(0.0299)
A-UL			0.0739***			-0.255***
			(0.0204)			(0.0704)
Constant	3.758***	3.758***	3.759***	5.413***	5.413***	5.414***
	(0.303)	(0.370)	(0.350)	(0.167)	(0.154)	(0.136)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Holiday Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

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

Close Matches

In this section, we introduce another measure of salience. We define a new variable Close, which is defined as the absolute difference between the probability of home wins and away wins.

$$Close = |p(homewin) - p(awaywin)| \tag{3.45}$$

We anticipate that for the variable Close matches with lower values will be associated with higher levels of domestic abuse than matches with higher values. As such we expect the variable to be negatively signed.

From Table 3.33, we see that the variable Close is associated with a decrease in domestic abuse for both regions.[25] For England & Wales the variable Close is only statistically significant when we use reference dependent variables and is associated with a 5% decrease in domestic abuse. For London, the variable Close is associated with about a 10% statistically significant decrease in domestic abuse. Table 3.32 displays a summary statistic of salience variables by region.

Table 3.32: Summary Statistics of Salience Variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
England & Wales					
Title	27,347	.00483	.0693	0	1
Close	27,347	.007871	.0575	0	.7817
Derby	27,347	.0006216	.0249	0	1
London					
Title	31,119	.002410	.04903	0	1
Close	31,119	.00546	.0494	0	.7906
Derby	31,119	.0615	.2402	0	1
Others					
Manchester Derby	943	.00530	.0727	0	1
Northumbria Derby	943	.00530	.0727	0	1
West Midlands Derby	943	.00530	.0727	0	1
Liverpool Manchester Derby	943	.00530	.0727	0	1

[25] The complete table of results can be found in Table 3.62 Appendix 3.B

Table 3.33: Regression results with the absolute difference in home win and away win probabilities for both regions

	England & Wales			London		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Close	-0.0427	-0.0463	-0.0569**	-0.106**	-0.0939*	-0.110***
	(0.0523)	(0.0375)	(0.0270)	(0.0459)	(0.0516)	(0.0421)
hometeam	0.0239			0.0109		
	(0.0202)			(0.0235)		
awayteam	0.0342***			0.0105		
	(0.0127)			(0.0316)		
HW		0.0325			0.0129	
		(0.0201)			(0.0366)	
HD		0.0312*			0.000663	
		(0.0186)			(0.0334)	
HL		0.0163			0.00267	
		(0.0208)			(0.0288)	
AW		0.0530**			0.0171	
		(0.0206)			(0.0260)	
AD		0.0325**			0.0281	
		(0.0153)			(0.0243)	
AL		0.0266			-0.0195	
		(0.0269)			(0.0439)	
H-expected			0.0308			0.0193
			(0.0195)			(0.0177)
H-UW			0.0102			-0.0166
			(0.0327)			(0.0396)
H-UL			0.0804***			0.0361
			(0.0282)			(0.0585)
A-expected			0.0337**			0.00904
			(0.0168)			(0.0383)
A-UW			0.0457*			0.0327
			(0.0236)			(0.0282)
A-UL			0.0968***			-0.226***
			(0.0215)			(0.0550)
Constant	3.758***	3.758***	3.759***	5.414***	5.414***	5.416***
	(0.372)	(0.368)	(0.376)	(0.133)	(0.140)	(0.145)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Holiday Effects	✓	✓	✓	✓	✓	✓
Observations	27347	27347	27347	31119	31119	31119

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

Public Order Offence

Following studies which find links between sporting tournaments and other crimes (Rees and Schnepel, 2009), we investigate the link between football tournaments and a different crime measure. For example, Rees and Schnepel (2009) find evidence that host communities register sharp increases in assaults, vandalism, arrests for disorderly conduct and arrests for alcohol-related offences on games days especially when the game ends in an unexpected loss. We chose a variable to capture disorderly conduct known as Public Order Offences.

According to CPS (2019), Public Order Offence as documented in Part 1 of the Public Order Act 1986 includes offences such as riots, violent disorder, affray, threatening behaviour, disorderly behaviour with intent and disorderly behaviour and racially or religiously aggravated threatening behaviour, disorderly behaviour with intent and disorderly behaviour.

We obtained data on Public Order Offence in England from 26 police force areas. This set of 26 police force areas is not the same as the set of police force areas used for our study on domestic abuse. Table 3.34 presents summary statistics of the police force areas used in our analysis. We did not receive data on Public Order Offence for London, so we conducted only one set of analysis in this section. From Figure 3.4, we can see that public order offences have been rising steadily since 2014. According to ONS (2019), a large part of the increase in public order offence is likely due improvements, as incidents would have been recorded as anti-social behaviour are now being recorded as public order offence and also due to genuine increases in public order offences. Using public order offence as our dependent variable, we preform the analysis for domestic tournament (EPL club-level) and international tournaments (FIFA World Cup and UEFA Euro Cup). Table 3.35 presents the pairing of EPL teams with their respective home counties and their availability in our data.

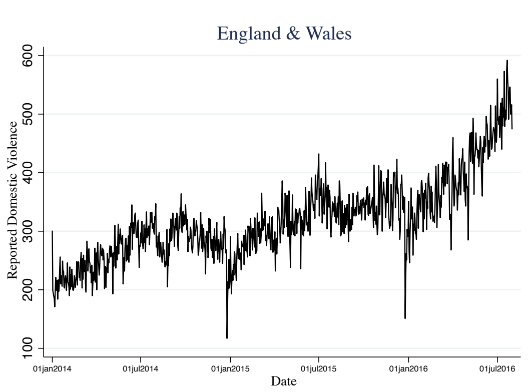


Figure 3.4: Reported Public Order Offence for England & Wales from January 2014 - July 2016

Table 3.34: Summary Statistics of Reported Incidents of Public Order Offence by Police Force Area

County	Mean	Standard Deviation	Min	Max
British Transport Police	18.60	5.61	2	43
Cambridgeshire	5.30	2.82	0	17
Cheshire	10.26	6.42	1	55
Cleveland	4.83	2.49	1	19
Cumbria	4.35	2.36	1	15
Devon	12.49	4.28	2	30
Dorset	3.62	2.16	1	17
Durham	4.39	2.75	1	17
Dyfed	2.83	1.74	1	13
Essex	9.13	5.25	1	36
Humberside	7.09	3.40	1	25
Kent	8.48	3.77	1	28
Lancashire	7.03	3.28	1	23
Leicester	2.42	1.35	1	7
Lincolnshire	3.84	2.29	1	28
Manchester	31.60	11.06	8	71
Metropolitan Police Service	111.38	23.49	42	188
Northamptonshire	3.55	1.91	1	12
Northern Ireland	3.97	2.09	0	13
Northumbria	13.39	9.86	1	53
North Yorkshire	3.59	1.94	1	11
South Yorkshire	8.66	5.18	1	61
Staffordshire	5.68	3.61	1	18
West Midlands	11.18	4.13	1	25
West Yorkshire	23.14	11.91	4	69
Wiltshire	5.76	3.99	1	24
Overall	13.14	22.55	0	188

Table 3.35: Pairing EPL Teams to Home Counties - Public Order Offence

	EPL Team	Home County	Data in Sample
1	Arsenal	Islington	No
2	Aston Villa	West Midlands	Yes
3	Bournemouth	Dorset	Yes
4	Burnley	Lancashire	No
5	Cardiff	South Wales	No
6	Chelsea	Kensington and Chelsea	No
7	Crystal Palace	Croydon	No
8	Everton	Merseyside	No
9	Fulham	Hammersmith and Fulham	No
10	Hull	East Yorkshire	No
11	Leicester	Leicester	Yes
12	Liverpool	Merseyside	No
13	Manchester City	Manchester	Yes
14	Manchester United	Manchester	Yes
15	Newcastle	Northumbria	Yes
16	Norwich	Norfolk	No
17	QPR	Hammersmith and Fulham	No
18	Southampton	Hampshire	No
19	Stoke	Staffordshire	Yes
20	Sunderland	Northumbria	Yes
21	Swansea	South Wales	No
22	Tottenham	Haringey	No
23	Watford	Hertfordshire	No
24	West Brom	West Midlands	Yes
25	West Ham	Newham	No

The model specifications and variables used in this section are the same as defined in Section 3.5.1. Regression results with time variables (day of the week, month of the year, year and holiday) are presented in Table 3.36. Across all three specifications in the table, we can see that the day of the week variables are not statistically significant, except for Tuesday in Col. 1 which has $p < 0.1$. The coefficients of the day of the week variables suggest that Tuesdays maybe associated with the lowest levels of public order offence in a week while Fridays are associated with the highest levels of public order offence.

Similar to the monthly trends in domestic abuse, we find that levels of public order offence tend to rise towards and peak at July, then somewhat decline towards January. July is associated with a 35% increase in public order offence with $p < 0.01$ across all specifications.

Compared to 2014 (the base year), 2015 and 2016 are associated with higher levels of public order offence. 2015 is associated with a statistically significant 1% increase in public order offence while 2016 is associated with a statistically significant 4% increase in public order offence.

In contrast to the results obtained on domestic abuse, we find in Col. 2 that bank holidays are associated with about 2% decrease in levels of public order offence. However, this seems primarily driven by the non-christmas bank holidays (Bh-Oth). From Col. 3 we see that Bh-Oth is associated with about 2% decrease in public order offence with $p < 0.01$ while the Christmas and New year bank holidays (Bh-Chris) has no statistically significant effect on levels of public order offence.

Regression results with EPL variables are presented in Table 3.37.[26] We see from Col. 1 that an EPL match day is associated with about 2% increase in public order offence with $p < 0.01$. When we restrict the analysis to only counties whose local team have a match on a given day (matchpa), the effect is not statistically significant. The same goes for the number of matches associated with local teams of a relevant county (matchcount) and whether the matches are home or away fixtures (hometeam & awayteam).

We find for Col. 5 that the match outcomes do not affect public order offence, except when a local team draws in an away fixture. A local team draw in an away fixture is associated with 9% decrease in levels of public order offence with $p < 0.05$. From Col. 6, we find no evidence for reference dependence in the association between EPL matches and trends in public order offence. The reference dependent variables have no statistically significant effect on public order offence except when a local team's match outcome in an away match is as expected (A-Expected). A-Expected is associated with about 7% decrease in levels of public order offence with $p < 0.05$.

[26]The complete table of results can be found in Table 3.63 Appendix 3.E

Table 3.36: Regression results with time variables

	(1)	(2)	(3)
Public order offence			
Monday	-0.0336	-0.0190	-0.0181
	(0.0218)	(0.0358)	(0.0342)
Tuesday	-0.0347*	-0.0346	-0.0345
	(0.0206)	(0.0305)	(0.0278)
Wednesday	0.00127	0.00206	0.00199
	(0.0222)	(0.0289)	(0.0294)
Thursday	0.00638	0.00853	0.00819
	(0.0219)	(0.0289)	(0.0273)
Friday	0.0143	0.0215	0.0211
	(0.0216)	(0.0290)	(0.0256)
Saturday	0.000137	0.000206	0.000210
	(0.0158)	(0.0171)	(0.0158)
February	0.0812***	0.0767***	0.0775***
	(0.0104)	(0.00938)	(0.00872)
March	0.138***	0.138***	0.139***
	(0.0161)	(0.0154)	(0.0176)
April	0.171***	0.173***	0.174***
	(0.0302)	(0.0265)	(0.0288)
May	0.219***	0.225***	0.227***
	(0.0290)	(0.0307)	(0.0292)
June	0.305***	0.301***	0.302***
	(0.0286)	(0.0262)	(0.0272)
July	0.355***	0.351***	0.352***
	(0.0284)	(0.0329)	(0.0309)
August	0.236***	0.237***	0.238***
	(0.0340)	(0.0342)	(0.0321)
September	0.302***	0.298***	0.299***
	(0.0310)	(0.0398)	(0.0333)
October	0.284***	0.280***	0.281***
	(0.0330)	(0.0470)	(0.0398)
November	0.289***	0.285***	0.286***
	(0.0363)	(0.0533)	(0.0411)
December	0.225***	0.232***	0.230***
	(0.0380)	(0.0545)	(0.0390)
2015	0.139**	0.139*	0.139***
	(0.0585)	(0.0722)	(0.0527)
2016	0.439***	0.440***	0.440***
	(0.0821)	(0.117)	(0.0891)
holiday		-0.165***	
		(0.0610)	
Bh-Oth			-0.181***
			(0.0432)
Bh-Chris			-0.130
			(0.0916)
Constant	2.252***	2.265***	2.264***
	(0.207)	(0.326)	(0.281)
Observations	22935	22935	22935

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

Table 3.37: Regression results with EPL variables

	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
matchday	0.0199***					
	(0.00511)					
matchpa		-0.0495				
		(0.155)				
matchcount=1			-0.0303			
			(0.0367)			
matchcount=2			-0.0815			
			(0.0504)			
hometeam				-0.0130		
				(0.0552)		
awayteam				-0.0621		
				(0.110)		
HW					-0.0101	
					(0.0656)	
HD					-0.0325	
					(0.0617)	
HL					-0.00629	
					(0.0692)	
AW					-0.0507	
					(0.0687)	
AD					-0.0932**	
					(0.0408)	
AL					-0.0481	
					(0.0538)	
H-expected						-0.0227
						(0.0445)
H-UW						0.0211
						(0.0529)
H-UL						-0.0120
						(0.308)
A-Expected						-0.0661**
						(0.0330)
A-UW						-0.0736
						(0.0472)
A-UL						0.0475
						(0.0915)
Constant	2.253***	2.265***	2.267***	2.268***	2.268***	2.268***
	(0.291)	(0.284)	(0.314)	(0.331)	(0.300)	(0.375)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Holiday Effects	✓	✓	✓	✓	✓	✓
Observations	22935	22935	22935	22935	22935	22935

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

Regression results with variables of international tournaments (FIFA and UEFA European Championship) are presented in Table 3.39.[27] We find from Columns 1 - 3 that the FIFA world cup has no statistically significant effect on levels of public order offence. Neither the FIFA match day with any fixture, with fixtures involving England nor the outcome the England FIFA matches have statistically significant effect on public order offence. From Column 4 - 6, we find that only UEFA fixtures where England loses is associated with a statistically significant effect on levels of public order offence. UEFA European Championship matches in which England loses is associated with a 12% increase in the levels of public order offence with $p < 0.05$.

In Table 3.40 we present regression results in with variables of both domestic (EPL) and international tournaments.[28] We find in Col. 1 that only the EPL match day is associated with a 2% increase in levels of public order offence with $p < 0.01$. From Col. 2 we find that only EPL away fixtures are associated with a statistically significant 6% decrease in levels of public order offence with $p < 0.1$ From Col. 3 we find that of all the match outcome variables, only England loses in the UEFA European Championship associated with a statistically significant about 13% increase in public order offence with $p < 0.05$.

Our result on trends in public order offence suggests that the existence of a domestic (club level) fixture matters more compared to international tournaments while the outcome of international tournaments matter more compared to the outcome of domestic tournaments.

A step for future research could be to study the associations between major sporting events in England & Wales and other types of crime. Table 3.38 displays a summary statistic of variables used in the analysis of this section.

[27] The complete table of results can be found in Table 3.64 Appendix 3.E

[28] The complete table of results can be found in Table 3.65 Appendix 3.E

Table 3.38: Summary Statistics of Public Order Offence variables

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Public order offence	22,935	13.1367	22.5517	0	188
matchpa	24,518	.0116	.1072	0	1
matchcount	24,518	.0294	.2040	0	2
hometeam	24,518	.01476	.1206	0	1
awayteam	24,518	.01464	.1201	0	1
HW	24,518	.00619	.0785	0	1
HD	24,518	.00347	.0588	0	1
HL	24,518	.00509	.0712	0	1
AW	24,518	.00387	.0621	0	1
AD	24,518	.00379	.0615	0	1
AL	24,518	.00697	.0832	0	1
50% Threshold					
H-Expected	24,518	.0106	.1024	0	1
H-UW	24,518	.00343	.0584	0	1
H-UL	24,518	.000734	.0271	0	1
A-Expected	24,518	.01073	.1030	0	1
A-UW	24,518	.00310	.0556	0	1
A-UL	24,518	.000816	.0285	0	1
FIFA matchday	24,518	.0329	.1783	0	1
FIFA England	24,518	.00318	.0563	0	1
England Draw	24,518	.00106	.0325	0	1
England Lose	24,518	.00212	.0460	0	1
EURO Matchday	24,518	.0244	.1543	0	1
EURO England	24,518	.00424	.0650	0	1
England Lose	24,518	.00106	.0325	0	1
England Draw	24,518	.00212	.0460	0	1
England Win	24,518	.00106	.0325	0	1

Table 3.39: Regression results with variables International Tournaments

	FIFA			UEFA European Championship		
	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
fifa-matchday	-0.00140					
	(0.0188)					
fifa-england		0.0406				
		(0.0312)				
England Draw (fifa)			0.0722			
			(0.0956)			
England Lose (fifa)			0.0250			
			(0.0360)			
euro-matchday				0.00525		
				(0.0288)		
euro-england					0.0306	
					(0.0379)	
England Lose (uefa)						0.125**
						(0.0577)
England Draw (uefa)						-0.0101
						(0.0509)
England Win (uefa)						0.0165
						(0.0666)
Constant	2.264***	2.264***	2.264***	2.264***	2.265***	2.265***
	(0.319)	(0.313)	(0.254)	(0.273)	(0.278)	(0.309)
Day of the Week Effects	✓	✓	✓	✓	✓	✓
Month of the Year Effects	✓	✓	✓	✓	✓	✓
Year Effects	✓	✓	✓	✓	✓	✓
Holiday Effects	✓	✓	✓	✓	✓	✓
Observations	22935	22935	22935	22935	22935	22935

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.40: Regression results with Domestic (EPL) and international tournaments variables

	(1)	(2)	(3)
Public order offence			
fifa-matchday	-0.0000133		
	(0.0133)		
euro-matchday	0.00665		
	(0.0277)		
matchday	0.0200***		
	(0.00659)		
fifa-england		0.0412	
		(0.0449)	
euro-england		0.0313	
		(0.0389)	
hometeam		-0.0130	
		(0.0317)	
awayteam		-0.0620*	
		(0.0362)	
England Draw (fifa)			0.0741
			(0.0901)
England Lose (fifa)			0.0247
			(0.0365)
England Lose (uefa)			0.126**
			(0.0592)
England Draw (uefa)			-0.0108
			(0.0544)
England Win (uefa)			0.0187
			(0.0553)
HW			-0.0103
			(0.0555)
HD			-0.0326
			(0.148)
HL			-0.00646
			(0.0755)
AW			-0.0508
			(0.139)
AD			-0.0933
			(0.148)
AL			-0.0482
			(0.107)
Constant	2.253***	2.268***	2.268***
	(0.269)	(0.296)	(0.283)
Day of the Week Effects	✓	✓	✓
Month of the Year Effects	✓	✓	✓
Year Effects	✓	✓	✓
Holiday Effects	✓	✓	✓
Observations	22935	22935	22935

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

3.6 Concluding Remarks

This chapter has contributed to the literature which focuses on the relationship between domestic abuse and football. Our empirical evidence shows that for domestic (club-level) analysis game days are associated with a 1% increase in number of domestic abuse incidents in England & Wales but have no effects on levels of domestic abuse in London. When we restrict our analysis to only counties/boroughs with local teams playing EPL fixtures on a given day, we find no effects on domestic abuse in England & Wales or in London.

We find evidence that pre-game expectation affect trends in domestic abuse more than the win or lose outcomes of EPL fixtures. Match outcome only affect domestic abuse when a local team wins in an away fixture in England & Wales. We do not find any statistically significant effects of match outcome on domestic abuse in London. Pre-game expectations have a strong and positive effect on trends of domestic abuse in England & Wales and a strong and negative effect in trends of domestic abuse in London. In England & Wales, a local team's unexpected loss in an away fixture is associated with a 7.5% increase in domestic abuse. A local team's unexpected win in an away fixture is associated with a 3.5 increase in domestic abuse and a local team's expected outcome (win, loss or draw) is associated with a 2% increase in domestic abuse. For home fixtures, only a local team's unexpected loss is statistically significant at a 6% increase in domestic abuse. For London, a local team's lose in an away fixture is associated with a 27% decrease in domestic abuse in London.

For the FIFA World Cup, we find that only the presence of (any) game appears to matter for levels of domestic abuse in London with a magnitude of about 3%. Whilst for England & Wales, FIFA World cup matches involving England and the outcomes of such matches also matter for levels of domestic abuse. The magnitudes associated with match effects for FIFA World Cup fixtures range between 2-6%.

For UEFA European Championship, we find that match effects are negative for levels of domestic abuse England & Wales but not statistically significant for London. For UEFA European Championship involving Wales, we find that the match outcome of such fixture are important, leading to up to 19% increase in domestic abuse when Wales loses.

Overall our results are support by Card and Dahl (2011) who argue that reference dependence play an important role in the trends of domestic abuse as they relate to football games.

One of the limitations of this study is that we restrict attention to one domestic league and major football tournaments. Further work could consider other domestic leagues in England (e.g. Championship) as well as other domestic club competitions (such as the FA and League Cups) and European club competitions (UEFA Champions League and Europa League). Consideration could also be given to other sporting tournaments, especially those that took place in England and Wales during the sample period (such as the Rugby World Cup 2015). Future work could look more closely at whether contests are televised live and what effects this might have on trends in violent behaviour. Overall we believe our investigation opens up a number of avenues for future work in what remains a relatively under-developed area.

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Appendices

3.A Domestic Tournament: EPL

3.A.1 Construction of Variables

Table 3.41: Construction of the Holiday Variable

Holiday	2014 1st Jan - 31st Dec	2015 1st Jan - 31st Dec	2016 1st Jan - 31st Jul
New Year's Day	1st January	1st January	1st January
Good Friday	18th April	3rd April	25th March
Easter Monday	21st April	6th April	28th March
Early May Bank Holiday	5th May	4th May	2nd May
Spring Bank Holiday	26th May	25th May	30th May
Summer Bank Holiday	25th August	31st August	29th August
Christmas Day	25th December	25th December	-
Boxing Day	26th December	28th December	-

Table 3.42: List of all EPL Match Days in Sample Period (Part One)

	Year		
Month	2014	2015	2016
January	01-Jan-14	01-Jan-15	02-Jan-16
	11-Jan-14	10-Jan-15	03-Jan-16
	12-Jan-14	11-Jan-15	12-Jan-16
	13-Jan-14	17-Jan-15	13-Jan-16
	18-Jan-14	18-Jan-15	16-Jan-16
	19-Jan-14	19-Jan-15	17-Jan-16
	20-Jan-14	31-Jan-15	18-Jan-16
	28-Jan-14		23-Jan-16
	29-Jan-14		24-Jan-16
February	01-Feb-14	01-Feb-15	02-Feb-16
	02-Feb-14	07-Feb-15	03-Feb-16
	03-Feb-14	08-Feb-15	06-Feb-16
	08-Feb-14	10-Feb-15	07-Feb-16
	09-Feb-14	11-Feb-15	13-Feb-16
	11-Feb-14	21-Feb-15	14-Feb-16
	12-Feb-14	22-Feb-15	27-Feb-16
	22-Feb-14	28-Feb-15	28-Feb-16
	23-Feb-14		
March	01-Mar-14	01-Mar-15	01-Mar-16
	02-Mar-14	03-Mar-15	02-Mar-16
	08-Mar-14	04-Mar-15	05-Mar-16
	15-Mar-14	07-Mar-15	06-Mar-16
	16-Mar-14	14-Mar-15	12-Mar-16
	22-Mar-14	15-Mar-15	13-Mar-16
	23-Mar-14	16-Mar-15	14-Mar-16
	25-Mar-14	21-Mar-15	19-Mar-16
	26-Mar-14	22-Mar-15	20-Mar-16
	29-Mar-14		
	30-Mar-14		
	31-Mar-14		

Table 3.43: List of all EPL Match Days in Sample Period (Part Two)

	Year		
Month	2014	2015	2016
April	05-Apr-14	04-Apr-15	02-Apr-16
	06-Apr-14	05-Apr-15	03-Apr-16
	07-Apr-14	06-Apr-15	09-Apr-16
	12-Apr-14	07-Apr-15	10-Apr-16
	13-Apr-14	11-Apr-15	13-Apr-16
	15-Apr-14	12-Apr-15	16-Apr-16
	16-Apr-14	13-Apr-15	17-Apr-16
	19-Apr-14	18-Apr-15	18-Apr-16
	20-Apr-14	19-Apr-15	19-Apr-16
	21-Apr-14	25-Apr-15	20-Apr-16
	26-Apr-14	26-Apr-15	21-Apr-16
	27-Apr-14	28-Apr-15	23-Apr-16
	28-Apr-14	29-Apr-15	24-Apr-16
			25-Apr-16
			30-Apr-16
May	03-May-14	02-May-15	01-May-16
	04-May-14	03-May-15	02-May-16
	05-May-14	04-May-15	07-May-16
	06-May-14	09-May-15	08-May-16
	07-May-14	10-May-15	10-May-16
	11-May-14	11-May-15	11-May-16
		16-May-15	15-May-16
		17-May-15	17-May-16
		18-May-15	
		20-May-15	
		24-May-15	
August	16-Aug-14	08-Aug-15	
	17-Aug-14	09-Aug-15	
	18-Aug-14	10-Aug-15	
	23-Aug-14	14-Aug-15	
	24-Aug-14	15-Aug-15	
	25-Aug-14	16-Aug-15	
	30-Aug-14	17-Aug-15	
	31-Aug-14	22-Aug-15	
		23-Aug-15	
		24-Aug-15	
		29-Aug-15	
		30-Aug-15	

Table 3.44: List of all EPL Match Days in Sample Period (Part Three)

	Year		
Month	2014	2015	2016
September	13-Sep-14	12-Sep-15	
	14-Sep-14	13-Sep-15	
	15-Sep-14	14-Sep-15	
	20-Sep-14	19-Sep-15	
	21-Sep-14	20-Sep-15	
	27-Sep-14	26-Sep-15	
	28-Sep-14	27-Sep-15	
	29-Sep-14	28-Sep-15	
October	04-Oct-14	03-Oct-15	
	05-Oct-14	04-Oct-15	
	18-Oct-14	17-Oct-15	
	19-Oct-14	18-Oct-15	
	20-Oct-14	19-Oct-15	
	25-Oct-14	24-Oct-15	
	26-Oct-14	25-Oct-15	
	27-Oct-14	31-Oct-15	
November	01-Nov-14	01-Nov-15	
	02-Nov-14	02-Nov-15	
	03-Nov-14	07-Nov-15	
	08-Nov-14	08-Nov-15	
	09-Nov-14	21-Nov-15	
	22-Nov-14	22-Nov-15	
	23-Nov-14	23-Nov-15	
	24-Nov-14	28-Nov-15	
	29-Nov-14	29-Nov-15	
	30-Nov-14		
December	02-Dec-14	05-Dec-15	
	03-Dec-14	06-Dec-15	
	06-Dec-14	07-Dec-15	
	07-Dec-14	12-Dec-15	
	08-Dec-14	13-Dec-15	
	13-Dec-14	14-Dec-15	
	14-Dec-14	19-Dec-15	
	15-Dec-14	20-Dec-15	
	20-Dec-14	21-Dec-15	
	21-Dec-14	26-Dec-15	
	22-Dec-14	28-Dec-15	
	26-Dec-14	29-Dec-15	
	28-Dec-14	30-Dec-15	
	29-Dec-14		

3.A.2 Regression Results

Table 3.45: Regression for Time and Match Day Variables (All regions combined)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Domestic abuse							
Monday	-0.151***	-0.170***	-0.161***	-0.160***	-0.161***	-0.161***	-0.161***
	(0.0229)	(0.0223)	(0.0276)	(0.0238)	(0.0180)	(0.0248)	(0.0222)
Tuesday	-0.214***	-0.214***	-0.214***	-0.211***	-0.214***	-0.214***	-0.213***
	(0.0226)	(0.0186)	(0.0238)	(0.0221)	(0.0172)	(0.0217)	(0.0207)
Wednesday	-0.218***	-0.219***	-0.220***	-0.218***	-0.220***	-0.220***	-0.220***
	(0.0215)	(0.0182)	(0.0226)	(0.0206)	(0.0166)	(0.0219)	(0.0200)
Thursday	-0.226***	-0.229***	-0.232***	-0.229***	-0.232***	-0.232***	-0.231***
	(0.0195)	(0.0161)	(0.0209)	(0.0193)	(0.0153)	(0.0184)	(0.0183)
Friday	-0.193***	-0.201***	-0.204***	-0.201***	-0.204***	-0.204***	-0.204***
	(0.0191)	(0.0166)	(0.0215)	(0.0202)	(0.0155)	(0.0211)	(0.0185)
Saturday	-0.0668***	-0.0669***	-0.0669***	-0.0668***	-0.0674***	-0.0683***	-0.0685***
	(0.00662)	(0.00661)	(0.00659)	(0.00689)	(0.00640)	(0.00623)	(0.00601)
February	0.0108*	0.0149**	0.0209***	0.0207***	0.0209***	0.0210**	0.0208***
	(0.00619)	(0.00657)	(0.00642)	(0.00702)	(0.00692)	(0.00879)	(0.00669)
March	0.00505	0.00452	0.0133*	0.0130**	0.0133**	0.0132**	0.0133**
	(0.00534)	(0.00641)	(0.00699)	(0.00550)	(0.00677)	(0.00570)	(0.00621)
April	0.0265***	0.0217***	0.0333***	0.0322***	0.0332***	0.0333***	0.0331***
	(0.00742)	(0.00730)	(0.00773)	(0.00641)	(0.00797)	(0.00703)	(0.00673)
May	0.0611***	0.0520***	0.0662***	0.0662***	0.0663***	0.0660***	0.0663***
	(0.00806)	(0.00827)	(0.00841)	(0.00664)	(0.00884)	(0.00812)	(0.00818)
June	0.106***	0.110***	0.116***	0.117***	0.116***	0.116***	0.117***
	(0.00790)	(0.00810)	(0.00767)	(0.00785)	(0.00944)	(0.00895)	(0.00910)
July	0.142***	0.146***	0.153***	0.154***	0.153***	0.153***	0.153***
	(0.00795)	(0.00844)	(0.00864)	(0.00826)	(0.00826)	(0.00889)	(0.00979)
August	0.0960***	0.0934***	0.104***	0.103***	0.103***	0.104***	0.104***
	(0.00704)	(0.00884)	(0.00838)	(0.00875)	(0.00791)	(0.00870)	(0.00888)
September	0.0638***	0.0678***	0.0738***	0.0737***	0.0738***	0.0738***	0.0739***
	(0.0102)	(0.0108)	(0.00951)	(0.00963)	(0.0115)	(0.0112)	(0.00883)
October	0.0471***	0.0509***	0.0571***	0.0571***	0.0571***	0.0572***	0.0572***
	(0.00960)	(0.00936)	(0.00988)	(0.00873)	(0.00934)	(0.0102)	(0.00974)

Regression for Time and Match Day Variables (All regions combined) - Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Domestic Abuse							
November	0.0537***	0.0576***	0.0635***	0.0632***	0.0635***	0.0635***	0.0635***
	(0.0101)	(0.00964)	(0.0109)	(0.00894)	(0.0105)	(0.0108)	(0.0110)
December	0.0990***	0.0904***	0.0786***	0.0778***	0.0785***	0.0784***	0.0784***
	(0.0106)	(0.00963)	(0.0109)	(0.0101)	(0.0116)	(0.00989)	(0.0119)
year=2015	0.0331***	0.0328***	0.0325**	0.0324**	0.0325**	0.0325**	0.0325*
	(0.0123)	(0.0121)	(0.0134)	(0.0129)	(0.0160)	(0.0128)	(0.0171)
year=2016	0.0773***	0.0770***	0.0767***	0.0767***	0.0767***	0.0767***	0.0767***
	(0.0214)	(0.0214)	(0.0235)	(0.0207)	(0.0280)	(0.0210)	(0.0286)
holiday		0.188***					
		(0.0201)					
Bh-Oth			0.0774***	0.0768***	0.0774***	0.0775***	0.0775***
			(0.0220)	(0.0201)	(0.0171)	(0.0165)	(0.0169)
Bh-Chris			0.397***	0.395***	0.396***	0.394***	0.394***
			(0.0309)	(0.0312)	(0.0233)	(0.0296)	(0.0300)
matchday				0.00529*			
				(0.00275)			
matchpa					0.00799		
					(0.0227)		
matchcount=1						-0.00818	
						(0.0151)	
matchcount=2						0.0714**	
						(0.0336)	
hometeam							0.0124
							(0.0210)
awayteam							0.0203
							(0.0187)
Constant	3.843***	3.892***	3.924***	3.921***	3.924***	3.926***	3.924***
	(0.289)	(0.293)	(0.321)	(0.342)	(0.232)	(0.307)	(0.316)
Observations	58466	58466	58466	58466	58466	58466	58466

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

Table 3.46: Regression with Match Day Variables for Both Regions

	England & Wales				London Boroughs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Domestic Abuse								
Monday	-0.162***	-0.164***	-0.164***	-0.164***	-0.154***	-0.153***	-0.153***	-0.153***
	(0.0352)	(0.0380)	(0.0342)	(0.0408)	(0.00746)	(0.00907)	(0.00803)	(0.00826)
Tuesday	-0.218***	-0.221***	-0.222***	-0.221***	-0.197***	-0.196***	-0.196***	-0.196***
	(0.0327)	(0.0339)	(0.0309)	(0.0362)	(0.00708)	(0.00828)	(0.00840)	(0.00895)
Wednesday	-0.220***	-0.224***	-0.224***	-0.223***	-0.212***	-0.211***	-0.211***	-0.211***
	(0.0320)	(0.0323)	(0.0296)	(0.0358)	(0.00876)	(0.00998)	(0.00949)	(0.00953)
Thursday	-0.241***	-0.246***	-0.246***	-0.245***	-0.203***	-0.201***	-0.201***	-0.201***
	(0.0276)	(0.0279)	(0.0262)	(0.0296)	(0.00886)	(0.0104)	(0.00928)	(0.00837)
Friday	-0.207***	-0.212***	-0.212***	-0.211***	-0.188***	-0.187***	-0.187***	-0.187***
	(0.0274)	(0.0319)	(0.0283)	(0.0327)	(0.00773)	(0.0103)	(0.00874)	(0.00895)
Saturday	-0.0733***	-0.0745***	-0.0756***	-0.0760***	-0.0539***	-0.0531***	-0.0531***	-0.0531***
	(0.00846)	(0.00731)	(0.00963)	(0.00907)	(0.00515)	(0.00752)	(0.00581)	(0.00626)
February	0.0228***	0.0230***	0.0232**	0.0229**	0.0147	0.0147*	0.0147	0.0147
	(0.00842)	(0.00879)	(0.00951)	(0.00892)	(0.00999)	(0.00889)	(0.0116)	(0.00919)
March	0.00865	0.00911	0.00902	0.00905	0.0203**	0.0202**	0.0202**	0.0202***
	(0.00891)	(0.00735)	(0.00709)	(0.00751)	(0.00795)	(0.00818)	(0.00788)	(0.00618)
April	0.0347***	0.0364***	0.0365***	0.0362***	0.0266***	0.0261***	0.0261***	0.0261***
	(0.00881)	(0.00961)	(0.00878)	(0.0103)	(0.00902)	(0.00923)	(0.00792)	(0.00888)
May	0.0609***	0.0609***	0.0607***	0.0610***	0.0762***	0.0761***	0.0761***	0.0761***
	(0.0117)	(0.0116)	(0.0106)	(0.0128)	(0.0101)	(0.00872)	(0.00777)	(0.00830)
June	0.121***	0.119***	0.119***	0.120***	0.108***	0.109***	0.109***	0.109***
	(0.0118)	(0.0131)	(0.0111)	(0.0130)	(0.00923)	(0.00643)	(0.00735)	(0.00733)
July	0.159***	0.157***	0.157***	0.158***	0.143***	0.143***	0.143***	0.143***
	(0.0108)	(0.0120)	(0.0121)	(0.0120)	(0.00830)	(0.00784)	(0.00807)	(0.00643)
August	0.109***	0.109***	0.110***	0.109***	0.0922***	0.0920***	0.0920***	0.0920***
	(0.00998)	(0.0117)	(0.0122)	(0.0117)	(0.00896)	(0.00997)	(0.00925)	(0.00978)
September	0.0778***	0.0779***	0.0780***	0.0780***	0.0636***	0.0635***	0.0635***	0.0635***
	(0.0137)	(0.0153)	(0.0139)	(0.0126)	(0.0107)	(0.0122)	(0.00844)	(0.0110)
October	0.0553***	0.0554***	0.0555***	0.0555***	0.0604***	0.0604***	0.0604***	0.0604***
	(0.0112)	(0.0137)	(0.0113)	(0.0121)	(0.0108)	(0.0112)	(0.0103)	(0.0125)

Regression with Match Day Variables for Both Regions (continued)

	England & Wales				London Boroughs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
November	0.0646***	0.0650***	0.0651***	0.0650***	0.0601***	0.0600***	0.0600***	0.0600***
	(0.0132)	(0.0153)	(0.0110)	(0.0132)	(0.0106)	(0.0119)	(0.0115)	(0.0104)
December	0.0833***	0.0846***	0.0845***	0.0845***	0.0652***	0.0649***	0.0649***	0.0649***
	(0.0147)	(0.0147)	(0.0128)	(0.0145)	(0.00812)	(0.00967)	(0.00909)	(0.00987)
2015	0.0420*	0.0420**	0.0421**	0.0421**	0.0153*	0.0153*	0.0153**	0.0153**
	(0.0240)	(0.0210)	(0.0186)	(0.0212)	(0.00821)	(0.00804)	(0.00686)	(0.00676)
2016	0.0925**	0.0924***	0.0925***	0.0925**	0.0464***	0.0463***	0.0463***	0.0463***
	(0.0388)	(0.0340)	(0.0304)	(0.0376)	(0.0115)	(0.0112)	(0.00800)	(0.0109)
Bh-Oth	0.0996***	0.101***	0.101***	0.101***	0.0274**	0.0272**	0.0272**	0.0272**
	(0.0241)	(0.0263)	(0.0271)	(0.0262)	(0.0135)	(0.0124)	(0.0128)	(0.0115)
Bh-Chris	0.448***	0.449***	0.447***	0.447***	0.274***	0.275***	0.275***	0.275***
	(0.0393)	(0.0340)	(0.0347)	(0.0422)	(0.0192)	(0.0203)	(0.0194)	(0.0194)
matchday	0.00931***				-0.00309			
	(0.00357)				(0.00363)			
matchpa		0.0141				-0.0209		
		(0.0319)				(0.0240)		
matchcount=1			-0.00507				-0.0209	
			(0.0375)				(0.0294)	
match_count=2			0.0712**					
			(0.0306)					
hometeam				0.0161				-0.0221
				(0.0522)				(0.0180)
awayteam				0.0255				-0.0197
				(0.0340)				(0.0282)
Constant	3.753***	3.758***	3.759***	3.758***	5.412***	5.411***	5.411***	5.411***
	(0.347)	(0.405)	(0.316)	(0.434)	(0.146)	(0.142)	(0.124)	(0.118)
Observations	27347	27347	27347	27347	31119	31119	31119	31119

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

Table 3.47: Regression with Match Outcome and Reference Dependent Variables for Both Regions

	England & Wales				London Boroughs			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Domestic Abuse								
Monday	-0.164***	-0.164***	-0.164***	-0.164***	-0.153***	-0.153***	-0.153***	-0.153***
	(0.0341)	(0.0342)	(0.0304)	(0.0370)	(0.00723)	(0.00733)	(0.00782)	(0.00774)
Tuesday	-0.221***	-0.221***	-0.221***	-0.221***	-0.196***	-0.196***	-0.196***	-0.196***
	(0.0313)	(0.0325)	(0.0293)	(0.0325)	(0.00725)	(0.00844)	(0.00775)	(0.00840)
Wednesday	-0.223***	-0.223***	-0.223***	-0.223***	-0.211***	-0.211***	-0.211***	-0.211***
	(0.0296)	(0.0307)	(0.0275)	(0.0318)	(0.00855)	(0.00756)	(0.00768)	(0.00882)
Thursday	-0.245***	-0.245***	-0.245***	-0.245***	-0.201***	-0.201***	-0.201***	-0.201***
	(0.0274)	(0.0265)	(0.0240)	(0.0281)	(0.00921)	(0.0100)	(0.00847)	(0.00974)
Friday	-0.211***	-0.211***	-0.211***	-0.212***	-0.187***	-0.187***	-0.187***	-0.187***
	(0.0272)	(0.0264)	(0.0252)	(0.0307)	(0.00763)	(0.00948)	(0.00823)	(0.00996)
Saturday	-0.0758***	-0.0759***	-0.0760***	-0.0755***	-0.0530***	-0.0531***	-0.0530***	-0.0527***
	(0.00827)	(0.00780)	(0.00865)	(0.00756)	(0.00551)	(0.00599)	(0.00641)	(0.00655)
Bh-Oth	0.101***	0.101***	0.101***	0.100***	0.0271*	0.0272**	0.0272***	0.0270**
	(0.0250)	(0.0269)	(0.0290)	(0.0259)	(0.0138)	(0.0128)	(0.0104)	(0.0113)
Bh-Chris	0.447***	0.447***	0.447***	0.450***	0.275***	0.274***	0.275***	0.274***
	(0.0352)	(0.0315)	(0.0319)	(0.0388)	(0.0209)	(0.0201)	(0.0205)	(0.0207)
February	0.0230***	0.0230***	0.0229***	0.0229***	0.0147	0.0147	0.0147*	0.0147
	(0.00797)	(0.00869)	(0.00868)	(0.00753)	(0.00927)	(0.0112)	(0.00791)	(0.0101)
March	0.00906	0.00904	0.00906	0.00816	0.0203***	0.0202**	0.0204***	0.0206**
	(0.00693)	(0.00915)	(0.00862)	(0.00714)	(0.00737)	(0.00796)	(0.00659)	(0.00814)
April	0.0363***	0.0362***	0.0363***	0.0358***	0.0260***	0.0261***	0.0261***	0.0264***
	(0.00939)	(0.00886)	(0.0112)	(0.00949)	(0.00850)	(0.00911)	(0.00845)	(0.00822)
May	0.0608***	0.0610***	0.0611***	0.0607***	0.0763***	0.0762***	0.0763***	0.0763***
	(0.0116)	(0.0127)	(0.0134)	(0.0106)	(0.00953)	(0.00953)	(0.00825)	(0.00852)
June	0.120***	0.120***	0.120***	0.119***	0.109***	0.109***	0.109***	0.109***
	(0.0135)	(0.0133)	(0.0138)	(0.0121)	(0.00652)	(0.00774)	(0.00766)	(0.00691)
July	0.158***	0.158***	0.158***	0.157***	0.143***	0.144***	0.144***	0.144***
	(0.0124)	(0.0133)	(0.0153)	(0.0120)	(0.00787)	(0.00866)	(0.00751)	(0.00792)
August	0.109***	0.109***	0.109***	0.110***	0.0919***	0.0920***	0.0919***	0.0919***
	(0.0108)	(0.0114)	(0.0135)	(0.00997)	(0.00842)	(0.00930)	(0.00982)	(0.00908)
September	0.0780***	0.0780***	0.0780***	0.0781***	0.0635***	0.0635***	0.0635***	0.0634***
	(0.0147)	(0.0144)	(0.0164)	(0.0134)	(0.0120)	(0.00935)	(0.0105)	(0.0101)
October	0.0555***	0.0555***	0.0555***	0.0546***	0.0604***	0.0604***	0.0604***	0.0604***
	(0.0148)	(0.0122)	(0.0141)	(0.0114)	(0.0116)	(0.0116)	(0.00987)	(0.0105)
November	0.0649***	0.0650***	0.0650***	0.0650***	0.0600***	0.0600***	0.0601***	0.0599***
	(0.0151)	(0.0151)	(0.0146)	(0.0119)	(0.0108)	(0.0115)	(0.0102)	(0.0120)
December	0.0845***	0.0845***	0.0845***	0.0847***	0.0647***	0.0649***	0.0649***	0.0647***
	(0.0155)	(0.0142)	(0.0154)	(0.0124)	(0.00931)	(0.0102)	(0.00764)	(0.00984)

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

Regression with Match Outcome and Reference Dependent Variables for Both Regions (Continued)

	England & Wales				London Boroughs			
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
Domestic Abuse								
2015	0.0421**	0.0420**	0.0420**	0.0426**	0.0152**	0.0153**	0.0152**	0.0151**
	(0.0190)	(0.0179)	(0.0190)	(0.0196)	(0.00645)	(0.00653)	(0.00709)	(0.00617)
2016	0.0925***	0.0925***	0.0925**	0.0933***	0.0462***	0.0463***	0.0463***	0.0461***
	(0.0358)	(0.0348)	(0.0369)	(0.0310)	(0.00980)	(0.0103)	(0.0115)	(0.00860)
HW	0.0231				-0.0210			
	(0.0178)				(0.0285)			
HD	0.0252				-0.0229			
	(0.0222)				(0.0358)			
HL	0.00788				-0.0234			
	(0.0183)				(0.0295)			
AW	0.0432**				-0.00810			
	(0.0188)				(0.0283)			
AD	0.0233				0.00817			
	(0.0203)				(0.0269)			
AL	0.0155				-0.0534			
	(0.0229)				(0.0520)			
H-Expected		0.0266**	0.0197			-0.0211	-0.0180	
		(0.0135)	(0.0162)			(0.0138)	(0.0201)	
H-UW		0.00133	0.00474			-0.0206	-0.0367	
		(0.0131)	(0.0187)			(0.0330)	(0.0514)	
H-UL		0.0418*	0.0639***			-0.122	-0.0191	
		(0.0252)	(0.0195)			(0.127)	(0.0581)	
A-Expected		0.0184	0.0207*			-0.0256	-0.0248	
		(0.0201)	(0.0125)			(0.0414)	(0.0309)	
A-UW		0.0429***	0.0356**			-0.00920	0.00803	
		(0.0151)	(0.0176)			(0.0230)	(0.0359)	
A-UL			0.0754***				-0.270***	
			(0.0179)				(0.0631)	
H-DUL				0.0158				-0.0327
				(0.0618)				(0.0429)
H-DUW				0.0323				-0.0375
				(0.0627)				(0.0577)
A-DUL				0.0279				-0.0918
				(0.0894)				(0.0944)
A-DUW				0.0464				-0.0141
				(0.0378)				(0.0472)
Constant	3.758***	3.758***	3.758***	3.751***	5.412***	5.412***	5.413***	5.414***
	(0.311)	(0.348)	(0.306)	(0.383)	(0.154)	(0.166)	(0.146)	(0.144)
Observations	27347	27347	27347	27245	31119	31119	31119	31104

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

Table 3.48: Regression with Match Outcome and 60% Reference Dependent Variables for both Regions

	(England & Wales)		(London)	
	1a	1b	2a	2b
Domestic abuse				
Monday	-0.164***	-0.164***	-0.153***	-0.153***
	(0.0312)	(0.0333)	(0.00720)	(0.00842)
Tuesday	-0.221***	-0.221***	-0.196***	-0.196***
	(0.0287)	(0.0285)	(0.00841)	(0.00808)
Wednesday	-0.223***	-0.223***	-0.211***	-0.211***
	(0.0273)	(0.0286)	(0.00949)	(0.00876)
Thursday	-0.245***	-0.245***	-0.201***	-0.201***
	(0.0243)	(0.0243)	(0.00995)	(0.00838)
Friday	-0.211***	-0.211***	-0.187***	-0.187***
	(0.0260)	(0.0272)	(0.00975)	(0.00804)
Saturday	-0.0758***	-0.0761***	-0.0530***	-0.0529***
	(0.00834)	(0.00809)	(0.00593)	(0.00611)
Bh-Oth	0.101***	0.101***	0.0271**	0.0273*
	(0.0222)	(0.0201)	(0.0118)	(0.0142)
Bh-Chris	0.447***	0.447***	0.275***	0.274***
	(0.0308)	(0.0355)	(0.0208)	(0.0230)
February	0.0230***	0.0230***	0.0147	0.0147*
	(0.00722)	(0.00663)	(0.0102)	(0.00890)
March	0.00906	0.00903	0.0203**	0.0203**
	(0.00682)	(0.00648)	(0.00834)	(0.00792)
April	0.0363***	0.0362***	0.0260**	0.0261***
	(0.00923)	(0.00787)	(0.0105)	(0.00850)
May	0.0608***	0.0610***	0.0763***	0.0761***
	(0.0121)	(0.00895)	(0.00865)	(0.00877)
June	0.120***	0.120***	0.109***	0.109***
	(0.0138)	(0.00945)	(0.00781)	(0.00835)
July	0.158***	0.158***	0.143***	0.144***
	(0.0142)	(0.0103)	(0.00843)	(0.00619)
August	0.109***	0.109***	0.0919***	0.0919***
	(0.0134)	(0.00861)	(0.0100)	(0.00808)
September	0.0780***	0.0780***	0.0635***	0.0635***
	(0.0156)	(0.0128)	(0.00960)	(0.0109)

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

Regression with Match Outcome and 60% Reference Dependent Variables for both Regions(Continued)

	(England & Wales)		(London)	
	1a	1b	2a	2b
Domestic abuse				
October	0.0555***	0.0554***	0.0604***	0.0604***
	(0.0129)	(0.0106)	(0.0114)	(0.0117)
November	0.0649***	0.0650***	0.0600***	0.0601***
	(0.0142)	(0.0117)	(0.00947)	(0.0101)
December	0.0845***	0.0846***	0.0647***	0.0649***
	(0.0150)	(0.0128)	(0.00856)	(0.00748)
2015	0.0421**	0.0420**	0.0152**	0.0152*
	(0.0184)	(0.0172)	(0.00665)	(0.00794)
2016	0.0925***	0.0926***	0.0462***	0.0463***
	(0.0332)	(0.0327)	(0.0104)	(0.0112)
HL	0.00788		-0.0234	
	(0.0393)		(0.0320)	
HD	0.0252		-0.0229	
	(0.0279)		(0.0358)	
HW	0.0231		-0.0210	
	(0.0363)		(0.0276)	
AW	0.0432		-0.00810	
	(0.0274)		(0.0286)	
AD	0.0233		0.00817	
	(0.0355)		(0.0262)	
AL	0.0155		-0.0534	
	(0.0446)		(0.0552)	
H-Expected		0.0270*		-0.0211
		(0.0161)		(0.0163)
H-UW		-0.00323		-0.0308
		(0.0218)		(0.0348)
H-UL		0.0626***		0.0308
		(0.0209)		(0.0869)
A-Expected		0.0187		-0.0227
		(0.0197)		(0.0386)
A-UW		0.0401**		-0.00629
		(0.0198)		(0.0343)
A-UL		0.129***		-0.407***
		(0.0256)		(0.0312)
Constant	3.758***	3.758***	5.412***	5.413***
	(0.352)	(0.365)	(0.128)	(0.155)
Observations	27347	27347	31119	31119

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

Table 3.49: Regression with Match Outcome and Reference Dependent Variables for all regions combined

	(1)	(2)	(3)	(4)	(5)
Domestic abuse					
Monday	-0.161***	-0.161***	-0.161***	-0.161***	-0.161***
	(0.0212)	(0.0275)	(0.0244)	(0.0241)	(0.0170)
Tuesday	-0.213***	-0.213***	-0.213***	-0.213***	-0.213***
	(0.0196)	(0.0248)	(0.0228)	(0.0227)	(0.0161)
Wednesday	-0.220***	-0.220***	-0.220***	-0.220***	-0.220***
	(0.0185)	(0.0239)	(0.0216)	(0.0217)	(0.0153)
Thursday	-0.231***	-0.231***	-0.231***	-0.231***	-0.231***
	(0.0174)	(0.0217)	(0.0195)	(0.0197)	(0.0141)
Friday	-0.203***	-0.204***	-0.204***	-0.204***	-0.204***
	(0.0176)	(0.0238)	(0.0199)	(0.0208)	(0.0148)
Saturday	-0.0684***	-0.0684***	-0.0685***	-0.0684***	-0.0680***
	(0.00759)	(0.00725)	(0.00642)	(0.00705)	(0.00568)
Bh-Oth	0.0775***	0.0775***	0.0775***	0.0774***	0.0767***
	(0.0195)	(0.0201)	(0.0200)	(0.0199)	(0.0159)
Bh-Chris	0.394***	0.394***	0.394***	0.394***	0.395***
	(0.0263)	(0.0259)	(0.0329)	(0.0283)	(0.0239)
February	0.0208***	0.0208***	0.0208***	0.0208***	0.0207***
	(0.00805)	(0.00662)	(0.00667)	(0.00626)	(0.00636)
March	0.0133**	0.0133**	0.0133**	0.0133**	0.0128**
	(0.00615)	(0.00543)	(0.00640)	(0.00520)	(0.00621)
April	0.0331***	0.0330***	0.0331***	0.0331***	0.0329***
	(0.00731)	(0.00705)	(0.00699)	(0.00611)	(0.00747)
May	0.0662***	0.0663***	0.0663***	0.0663***	0.0662***
	(0.00857)	(0.00856)	(0.00814)	(0.00817)	(0.00865)
June	0.117***	0.117***	0.117***	0.117***	0.116***
	(0.00924)	(0.00951)	(0.00840)	(0.00984)	(0.00837)
July	0.153***	0.153***	0.153***	0.153***	0.153***
	(0.00849)	(0.00971)	(0.00838)	(0.00941)	(0.00840)
August	0.103***	0.103***	0.103***	0.104***	0.104***
	(0.00761)	(0.00789)	(0.00910)	(0.00842)	(0.00785)
September	0.0739***	0.0738***	0.0738***	0.0739***	0.0739***
	(0.00834)	(0.0106)	(0.00903)	(0.0114)	(0.00917)
October	0.0572***	0.0571***	0.0572***	0.0572***	0.0566***
	(0.00895)	(0.00931)	(0.00903)	(0.00945)	(0.00849)

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

Table 3.50: Regression with Match Outcome and Reference Dependent Variables for all regions combined (Combined)

	(1)	(2)	(3)	(4)	(5)
Domestic abuse					
November	0.0634***	0.0635***	0.0634***	0.0634***	0.0635***
	(0.00896)	(0.0106)	(0.00991)	(0.0102)	(0.00874)
December	0.0784***	0.0784***	0.0784***	0.0784***	0.0785***
	(0.0106)	(0.00994)	(0.0102)	(0.0111)	(0.00886)
2015	0.0325**	0.0324***	0.0324***	0.0324**	0.0327***
	(0.0136)	(0.0124)	(0.0118)	(0.0140)	(0.0124)
2016	0.0767***	0.0767***	0.0767***	0.0767***	0.0771***
	(0.0238)	(0.0212)	(0.0228)	(0.0249)	(0.0190)
HL	0.00669				
	(0.0273)				
HD	0.0193				
	(0.0234)				
HW	0.0175				
	(0.0255)				
AW	0.0329**				
	(0.0166)				
AD	0.0232				
	(0.0205)				
AL	0.00957				
	(0.0357)				
H-Expected		0.0219	0.0214	0.0159	
		(0.0238)	(0.0247)	(0.0150)	
H-UW		-0.0000137	-0.00519	0.000750	
		(0.0172)	(0.0261)	(0.0199)	
H-UL		0.00789	0.0507	0.0507	
		(0.0859)	(0.0632)	(0.0350)	
A-Expected		0.0145	0.0155	0.0164	
		(0.0286)	(0.0266)	(0.0200)	
A-UW		0.0323**	0.0308*	0.0305*	
		(0.0152)	(0.0182)	(0.0184)	
A-UL			0.0403	0.0323	
			(0.226)	(0.147)	
H-DUL					0.0131
					(0.0412)
H-DUW					0.0261
					(0.0523)
A-DUL					0.0160
					(0.0603)
A-DUW					0.0363
					(0.0265)
Constant	3.924***	3.925***	3.925***	3.924***	3.919***
	(0.290)	(0.376)	(0.263)	(0.264)	(0.245)
Observations	58466	58466	58466	58466	58349

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

3.B International Tournaments

Table 3.51: Regressions result with FIFA 2014 variables for both regions

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Monday	-0.165***	-0.165***	-0.165***	-0.152***	-0.153***	-0.153***
	(0.0292)	(0.0377)	(0.0363)	(0.00835)	(0.00589)	(0.00676)
Tuesday	-0.222***	-0.222***	-0.222***	-0.195***	-0.195***	-0.196***
	(0.0251)	(0.0343)	(0.0341)	(0.00855)	(0.00690)	(0.00823)
Wednesday	-0.224***	-0.224***	-0.224***	-0.210***	-0.210***	-0.210***
	(0.0247)	(0.0323)	(0.0321)	(0.00918)	(0.00779)	(0.00721)
Thursday	-0.246***	-0.247***	-0.247***	-0.200***	-0.201***	-0.201***
	(0.0212)	(0.0288)	(0.0282)	(0.00852)	(0.00740)	(0.00704)
Friday	-0.213***	-0.213***	-0.213***	-0.186***	-0.186***	-0.186***
	(0.0236)	(0.0310)	(0.0301)	(0.00869)	(0.00732)	(0.00865)
Saturday	-0.0735***	-0.0737***	-0.0737***	-0.0539***	-0.0539***	-0.0537***
	(0.00871)	(0.0112)	(0.00920)	(0.00675)	(0.00623)	(0.00754)
February	0.0232***	0.0232***	0.0232***	0.0146	0.0146	0.0146
	(0.00766)	(0.00756)	(0.00787)	(0.0107)	(0.0111)	(0.0100)
March	0.00917	0.00917	0.00917	0.0202***	0.0202**	0.0202***
	(0.00861)	(0.00735)	(0.00868)	(0.00781)	(0.00836)	(0.00760)
April	0.0366***	0.0366***	0.0366***	0.0259***	0.0259**	0.0259***
	(0.00801)	(0.00813)	(0.0109)	(0.00759)	(0.0103)	(0.00849)
May	0.0609***	0.0609***	0.0609***	0.0762***	0.0762***	0.0762***
	(0.00884)	(0.00998)	(0.0125)	(0.00850)	(0.00883)	(0.0104)
June	0.113***	0.117***	0.117***	0.103***	0.109***	0.109***
	(0.00975)	(0.0102)	(0.0136)	(0.00861)	(0.00884)	(0.00908)
July	0.153***	0.156***	0.156***	0.140***	0.144***	0.144***
	(0.0118)	(0.0103)	(0.0129)	(0.00904)	(0.00824)	(0.00712)
August	0.110***	0.109***	0.109***	0.0929***	0.0921***	0.0921***
	(0.0114)	(0.00995)	(0.0124)	(0.00860)	(0.00865)	(0.00832)
September	0.0787***	0.0780***	0.0780***	0.0644***	0.0636***	0.0636***
	(0.0118)	(0.0129)	(0.0157)	(0.00951)	(0.0113)	(0.0113)
October	0.0562***	0.0556***	0.0556***	0.0612***	0.0604***	0.0604***
	(0.0117)	(0.0118)	(0.0156)	(0.0100)	(0.0123)	(0.0126)
November	0.0658***	0.0651***	0.0651***	0.0608***	0.0600***	0.0600***
	(0.0130)	(0.0132)	(0.0172)	(0.00980)	(0.0116)	(0.0107)

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

Regressions result with FIFA 2014 variables for both regions (Continued)

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
December	0.0856***	0.0850***	0.0850***	0.0655***	0.0648***	0.0648***
	(0.0134)	(0.0134)	(0.0165)	(0.00933)	(0.00828)	(0.00918)
2015	0.0447**	0.0424**	0.0424**	0.0181***	0.0154**	0.0154***
	(0.0198)	(0.0186)	(0.0206)	(0.00602)	(0.00683)	(0.00530)
2016	0.0961***	0.0929***	0.0929***	0.0502***	0.0465***	0.0465***
	(0.0350)	(0.0322)	(0.0337)	(0.00854)	(0.0104)	(0.0110)
Bh-Oth	0.101***	0.100***	0.100***	0.0270**	0.0271**	0.0271**
	(0.0212)	(0.0311)	(0.0277)	(0.0116)	(0.0136)	(0.0129)
Bh-Chris	0.451***	0.451***	0.451***	0.272***	0.272***	0.272***
	(0.0322)	(0.0368)	(0.0342)	(0.0179)	(0.0186)	(0.0189)
fifa-matchday	0.0292***			0.0304**		
	(0.0108)			(0.0123)		
fifa-england		0.0428**			0.0111	
		(0.0201)			(0.0270)	
England Draw			0.0591***			0.0679
			(0.0224)			(0.0482)
England Lose			0.0351			-0.0163
			(0.0296)			(0.0392)
Constant	3.757***	3.758***	3.758***	5.411***	5.410***	5.411***
	(0.330)	(0.390)	(0.316)	(0.148)	(0.146)	(0.136)
Observations	27347	27347	27347	31119	31119	31119

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

Table 3.52: Regression results with FIFA 2014 variables for all regions combined

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Monday	-0.161***	-0.161***	-0.161***	-0.161***	-0.160***	-0.160***
	(0.0178)	(0.0227)	(0.0222)	(0.0173)	(0.0216)	(0.0246)
Tuesday	-0.214***	-0.214***	-0.214***	-0.207***	-0.207***	-0.207***
	(0.0158)	(0.0200)	(0.0199)	(0.0153)	(0.0208)	(0.0236)
Wednesday	-0.220***	-0.220***	-0.220***	-0.219***	-0.218***	-0.218***
	(0.0146)	(0.0195)	(0.0194)	(0.0170)	(0.0214)	(0.0224)
Thursday	-0.232***	-0.232***	-0.232***	-0.234***	-0.233***	-0.233***
	(0.0146)	(0.0170)	(0.0178)	(0.0161)	(0.0176)	(0.0206)
Friday	-0.204***	-0.204***	-0.204***	-0.207***	-0.207***	-0.207***
	(0.0149)	(0.0192)	(0.0189)	(0.0137)	(0.0182)	(0.0220)
Saturday	-0.0670***	-0.0672***	-0.0670***	-0.0931***	-0.0937***	-0.0934***
	(0.00643)	(0.00696)	(0.00733)	(0.0104)	(0.0102)	(0.00872)
February	0.0209***	0.0209***	0.0209***			
	(0.00592)	(0.00671)	(0.00699)			
March	0.0133**	0.0133**	0.0133**			
	(0.00530)	(0.00555)	(0.00674)			
April	0.0333***	0.0333***	0.0333***			
	(0.00622)	(0.00724)	(0.00678)			
May	0.0662***	0.0662***	0.0662***			
	(0.00732)	(0.00931)	(0.00783)			
June	0.110***	0.115***	0.115***			
	(0.00813)	(0.00963)	(0.00875)			
July	0.149***	0.153***	0.153***	0.0365***	0.0375***	0.0375***
	(0.00962)	(0.0107)	(0.00873)	(0.00436)	(0.00440)	(0.00488)
August	0.104***	0.104***	0.104***			
	(0.00786)	(0.00960)	(0.00790)			
September	0.0746***	0.0739***	0.0739***			
	(0.00905)	(0.0115)	(0.00964)			
October	0.0579***	0.0572***	0.0572***			
	(0.00966)	(0.0113)	(0.00935)			

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

Regression results with FIFA 2014 variables for all regions combined (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
November	0.0643***	0.0636***	0.0636***			
	(0.00890)	(0.0121)	(0.0107)			
December	0.0794***	0.0787***	0.0787***			
	(0.0103)	(0.0118)	(0.0121)			
2015	0.0352**	0.0327**	0.0327**	-0.0123	-0.00411	-0.00411
	(0.0140)	(0.0152)	(0.0153)	(0.0169)	(0.0160)	(0.0173)
2016	0.0804***	0.0771***	0.0770***	0.0142	0.0224	0.0224
	(0.0231)	(0.0223)	(0.0268)	(0.0227)	(0.0257)	(0.0264)
Bh-Oth	0.0773***	0.0772***	0.0772***	0	0	0
	(0.0159)	(0.0187)	(0.0208)	(0)	(0)	(0)
Bh-Chris	0.397***	0.397***	0.397***	0	0	0
	(0.0239)	(0.0243)	(0.0268)	(0)	(0)	(0)
fifa-matchday	0.0298***			-0.0156***		
	(0.00970)			(0.00531)		
fifa-england		0.0318*			0.00506	
		(0.0168)			(0.0150)	
England Draw			0.0612**			0.0198
			(0.0270)			(0.0257)
England Lose			0.0180			-0.00202
			(0.0211)			(0.0196)
Constant	3.923***	3.924***	3.924***	4.108***	4.099***	4.099***
	(0.268)	(0.278)	(0.268)	(0.231)	(0.295)	(0.289)
Observations	58466	58466	58466	11346	11346	11346

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

Table 3.53: Regression Results with UEFA variables for both regions

	(England & Wales)			(London)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Monday	-0.166***	-0.165***	-0.164***	-0.153***	-0.153***	-0.153***
	(0.0331)	(0.0420)	(0.0279)	(0.00857)	(0.00796)	(0.00688)
Tuesday	-0.223***	-0.222***	-0.222***	-0.196***	-0.195***	-0.195***
	(0.0311)	(0.0366)	(0.0255)	(0.00757)	(0.00889)	(0.00857)
Wednesday	-0.225***	-0.224***	-0.224***	-0.210***	-0.210***	-0.210***
	(0.0293)	(0.0354)	(0.0245)	(0.00995)	(0.0103)	(0.00901)
Thursday	-0.247***	-0.246***	-0.247***	-0.201***	-0.201***	-0.201***
	(0.0257)	(0.0313)	(0.0216)	(0.00954)	(0.0105)	(0.00796)
Friday	-0.214***	-0.213***	-0.213***	-0.187***	-0.186***	-0.186***
	(0.0276)	(0.0347)	(0.0225)	(0.0103)	(0.0103)	(0.00838)
Saturday	-0.0737***	-0.0733***	-0.0733***	-0.0539***	-0.0538***	-0.0539***
	(0.00961)	(0.00757)	(0.00673)	(0.00630)	(0.00717)	(0.00707)
February	0.0232***	0.0232***	0.0232***	0.0146	0.0146	0.0146*
	(0.00696)	(0.00854)	(0.00699)	(0.0105)	(0.00982)	(0.00851)
March	0.00920	0.00917	0.00916	0.0202**	0.0202**	0.0202***
	(0.00811)	(0.00728)	(0.00814)	(0.00813)	(0.00870)	(0.00675)
April	0.0366***	0.0366***	0.0366***	0.0259***	0.0259***	0.0259***
	(0.00748)	(0.0104)	(0.00747)	(0.00883)	(0.00914)	(0.00834)
May	0.0609***	0.0609***	0.0609***	0.0762***	0.0762***	0.0762***
	(0.00992)	(0.0131)	(0.00920)	(0.00794)	(0.00807)	(0.00794)
June	0.127***	0.119***	0.119***	0.112***	0.109***	0.109***
	(0.0112)	(0.0131)	(0.0102)	(0.00853)	(0.00705)	(0.00857)
July	0.160***	0.156***	0.156***	0.145***	0.144***	0.144***
	(0.0110)	(0.0121)	(0.0113)	(0.00803)	(0.00839)	(0.00780)
August	0.111***	0.109***	0.109***	0.0926***	0.0921***	0.0921***
	(0.0106)	(0.0112)	(0.0103)	(0.00921)	(0.0102)	(0.00894)
September	0.0798***	0.0780***	0.0780***	0.0642***	0.0636***	0.0636***
	(0.0134)	(0.0142)	(0.0119)	(0.0104)	(0.0107)	(0.0108)

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

Regression Results with UEFA variables for both regions(Continued)

	(England & Wales)			(London)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
October	0.0573***	0.0555***	0.0555***	0.0610***	0.0604***	0.0604***
	(0.0112)	(0.0124)	(0.0109)	(0.0102)	(0.0110)	(0.00854)
November	0.0668***	0.0650***	0.0650***	0.0606***	0.0600***	0.0600***
	(0.0143)	(0.0146)	(0.0125)	(0.0121)	(0.0117)	(0.0105)
December	0.0867***	0.0849***	0.0849***	0.0654***	0.0648***	0.0647***
	(0.0147)	(0.0142)	(0.0142)	(0.0107)	(0.00856)	(0.00919)
2015	0.0420**	0.0420**	0.0420**	0.0153**	0.0153**	0.0153**
	(0.0194)	(0.0182)	(0.0195)	(0.00709)	(0.00734)	(0.00677)
2016	0.0977***	0.0926***	0.0926***	0.0482***	0.0464***	0.0464***
	(0.0324)	(0.0349)	(0.0354)	(0.0104)	(0.0107)	(0.0112)
Bh-Oth	0.101***	0.101***	0.100***	0.0272**	0.0271**	0.0270**
	(0.0251)	(0.0274)	(0.0209)	(0.0137)	(0.0125)	(0.0137)
Bh-Chris	0.451***	0.451***	0.451***	0.272***	0.272***	0.272***
	(0.0352)	(0.0393)	(0.0336)	(0.0204)	(0.0202)	(0.0215)
euro-matchday	-0.0450***			-0.0153		
	(0.0119)			(0.0136)		
euro-england		-0.00701			-0.00172	
		(0.0213)			(0.0212)	
England Lose			-0.0636**			-0.0229
			(0.0300)			(0.0434)
England Draw			-0.00642			0.00961
			(0.0215)			(0.0277)
England Win			0.0509			-0.00496
			(0.0361)			(0.0397)
Constant	3.758***	3.758***	3.758***	5.410***	5.410***	5.410***
	(0.308)	(0.356)	(0.312)	(0.152)	(0.163)	(0.153)
Observations	27347	27347	27347	31119	31119	31119

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

Table 3.54: Regression results with UEFA variables for all regions combined

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Monday	-0.162***	-0.161***	-0.161***	-0.161***	-0.162***	-0.161***
	(0.0207)	(0.0231)	(0.0203)	(0.0195)	(0.0266)	(0.0203)
Tuesday	-0.215***	-0.214***	-0.214***	-0.207***	-0.207***	-0.207***
	(0.0189)	(0.0216)	(0.0176)	(0.0203)	(0.0260)	(0.0209)
Wednesday	-0.221***	-0.220***	-0.220***	-0.219***	-0.218***	-0.218***
	(0.0177)	(0.0199)	(0.0169)	(0.0197)	(0.0275)	(0.0206)
Thursday	-0.233***	-0.232***	-0.232***	-0.233***	-0.234***	-0.235***
	(0.0158)	(0.0187)	(0.0156)	(0.0163)	(0.0231)	(0.0179)
Friday	-0.205***	-0.204***	-0.204***	-0.207***	-0.207***	-0.207***
	(0.0175)	(0.0179)	(0.0164)	(0.0172)	(0.0242)	(0.0183)
Saturday	-0.0672***	-0.0669***	-0.0669***	-0.0936***	-0.0945***	-0.0950***
	(0.00775)	(0.00558)	(0.00552)	(0.00805)	(0.00832)	(0.00831)
February	0.0209***	0.0209***	0.0209***			
	(0.00729)	(0.00610)	(0.00713)			
March	0.0134**	0.0133***	0.0133**			
	(0.00585)	(0.00502)	(0.00580)			
April	0.0333***	0.0333***	0.0334***			
	(0.00620)	(0.00697)	(0.00643)			
May	0.0662***	0.0662***	0.0662***			
	(0.00590)	(0.00699)	(0.00773)			
June	0.123***	0.116***	0.116***			
	(0.00704)	(0.00779)	(0.00822)			
July	0.155***	0.153***	0.153***	0.0369***	0.0385***	0.0385***
	(0.00769)	(0.00818)	(0.00832)	(0.00423)	(0.00526)	(0.00460)
August	0.105***	0.104***	0.104***			
	(0.00717)	(0.00740)	(0.00894)			
September	0.0753***	0.0738***	0.0738***			
	(0.00904)	(0.00987)	(0.00958)			
October	0.0586***	0.0572***	0.0572***			
	(0.00800)	(0.00832)	(0.00917)			

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

Regression results with UEFA variables for all regions combined (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
November	0.0649***	0.0635***	0.0635***			
	(0.00982)	(0.00955)	(0.00879)			
December	0.0801***	0.0787***	0.0786***			
	(0.00927)	(0.0104)	(0.0105)			
2015	0.0324**	0.0325*	0.0325**	-0.00434	-0.00435	-0.00436
	(0.0146)	(0.0171)	(0.0142)	(0.0196)	(0.0170)	(0.0145)
2016	0.0808***	0.0768***	0.0768***	0.0234	0.0204	0.0205
	(0.0252)	(0.0272)	(0.0270)	(0.0260)	(0.0222)	(0.0239)
Bh-Oth	0.0775***	0.0773***	0.0770***	0	0	0
	(0.0162)	(0.0196)	(0.0143)	(0)	(0)	(0)
Bh-Chris	0.397***	0.397***	0.397***	0	0	0
	(0.0236)	(0.0320)	(0.0275)	(0)	(0)	(0)
euro-matchday	-0.0354***			-0.00324		
	(0.00712)			(0.00934)		
euro-england		-0.00519			0.0260*	
		(0.0191)			(0.0151)	
England Lose			-0.0512*			-0.0288
			(0.0273)			(0.0285)
England Draw			-0.00118			0.0361**
			(0.0197)			(0.0156)
England Win			0.0337			0.0592**
			(0.0256)			(0.0267)
Constant	3.924***	3.924***	3.924***	4.100***	4.100***	4.101***
	(0.274)	(0.279)	(0.282)	(0.252)	(0.310)	(0.267)
Observations	58466	58466	58466	11346	11346	11346

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

Table 3.55: Regression results with domestic and international tournaments for both regions

	England & Wales			London		
	1a	1b	1c	2a	2b	2c
Domestic abuse						
Monday	-0.163***	-0.164***	-0.163***	-0.153***	-0.153***	-0.153***
	(0.0369)	(0.0317)	(0.0387)	(0.00805)	(0.00663)	(0.00901)
Tuesday	-0.219***	-0.221***	-0.221***	-0.197***	-0.196***	-0.196***
	(0.0338)	(0.0290)	(0.0341)	(0.00842)	(0.00795)	(0.00997)
Wednesday	-0.221***	-0.223***	-0.223***	-0.211***	-0.211***	-0.211***
	(0.0322)	(0.0284)	(0.0328)	(0.00910)	(0.00741)	(0.0103)
Thursday	-0.242***	-0.245***	-0.246***	-0.202***	-0.202***	-0.201***
	(0.0275)	(0.0248)	(0.0276)	(0.00948)	(0.00909)	(0.00992)
Friday	-0.208***	-0.211***	-0.211***	-0.188***	-0.187***	-0.187***
	(0.0286)	(0.0267)	(0.0302)	(0.00948)	(0.00705)	(0.00999)
Saturday	-0.0736***	-0.0763***	-0.0760***	-0.0540***	-0.0532***	-0.0529***
	(0.00691)	(0.00852)	(0.00768)	(0.00644)	(0.00639)	(0.00767)
February	0.0228***	0.0229***	0.0230***	0.0147	0.0147	0.0147
	(0.00811)	(0.00756)	(0.00843)	(0.0108)	(0.0111)	(0.00930)
March	0.00870	0.00905	0.00906	0.0203**	0.0202**	0.0203**
	(0.00823)	(0.00745)	(0.00933)	(0.00793)	(0.00792)	(0.00847)
April	0.0347***	0.0362***	0.0363***	0.0266***	0.0261***	0.0260***
	(0.0103)	(0.00751)	(0.0100)	(0.00981)	(0.00785)	(0.00806)
May	0.0609***	0.0610***	0.0609***	0.0762***	0.0761***	0.0763***
	(0.0116)	(0.00906)	(0.0110)	(0.00924)	(0.00663)	(0.00874)
June	0.124***	0.118***	0.118***	0.105***	0.108***	0.108***
	(0.0126)	(0.00959)	(0.0115)	(0.0108)	(0.00768)	(0.00702)
July	0.159***	0.158***	0.158***	0.140***	0.143***	0.143***
	(0.0117)	(0.0109)	(0.0107)	(0.00887)	(0.00878)	(0.00790)
August	0.111***	0.109***	0.109***	0.0934***	0.0920***	0.0919***
	(0.0125)	(0.0128)	(0.0102)	(0.00896)	(0.00912)	(0.0102)
September	0.0801***	0.0782***	0.0782***	0.0648***	0.0636***	0.0635***
	(0.0138)	(0.0120)	(0.0140)	(0.0101)	(0.00968)	(0.0112)
October	0.0576***	0.0556***	0.0556***	0.0616***	0.0604***	0.0604***
	(0.0127)	(0.0121)	(0.0122)	(0.00869)	(0.00846)	(0.0115)
November	0.0669***	0.0651***	0.0650***	0.0613***	0.0600***	0.0600***
	(0.0142)	(0.0133)	(0.0139)	(0.00918)	(0.0119)	(0.0105)
December	0.0857***	0.0846***	0.0846***	0.0664***	0.0649***	0.0647***
	(0.0152)	(0.0156)	(0.0143)	(0.00878)	(0.00791)	(0.00851)
2015	0.0442***	0.0424*	0.0424**	0.0180***	0.0154**	0.0153**
	(0.0159)	(0.0234)	(0.0184)	(0.00593)	(0.00600)	(0.00679)
2016	0.100***	0.0931**	0.0931***	0.0512***	0.0465***	0.0464***
	(0.0294)	(0.0402)	(0.0341)	(0.00739)	(0.00867)	(0.00983)

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

Regression results with domestic and international tournaments for both regions (Continued)

	England & Wales			London		
	1a	1b	1c	2a	2b	2c
Domestic abuse						
Bh-Oth	0.0998***	0.101***	0.100***	0.0274**	0.0272**	0.0270**
	(0.0278)	(0.0216)	(0.0278)	(0.0137)	(0.0118)	(0.0125)
Bh-Chris	0.448***	0.447***	0.447***	0.274***	0.275***	0.275***
	(0.0406)	(0.0261)	(0.0377)	(0.0171)	(0.0190)	(0.0193)
fifa-matchday	0.0238*			0.0289***		
	(0.0123)			(0.0108)		
euro-matchday	-0.0404***			-0.0104		
	(0.0124)			(0.0162)		
matchday	0.00892***			-0.00307		
	(0.00338)			(0.00391)		
fifa-england		0.0432*			0.0108	
		(0.0229)			(0.0280)	
euro-england		-0.00550			-0.00144	
		(0.0180)			(0.0248)	
hometeam		0.0161			-0.0221	
		(0.0331)			(0.0211)	
awayteam		0.0255			-0.0197	
		(0.0244)			(0.0388)	
England Draw FIFA			0.0584*			0.0680
			(0.0309)			(0.0530)
England Lose FIFA			0.0363			-0.0169
			(0.0347)			(0.0339)
England Lose EURO			-0.0631**			-0.0223
			(0.0322)			(0.0488)
England Draw EURO			-0.00399			0.00944
			(0.0204)			(0.0277)
England Win EURO			0.0513			-0.00434
			(0.0334)			(0.0386)
HW			0.0232			-0.0210
			(0.0292)			(0.0274)
HD			0.0252			-0.0230
			(0.0227)			(0.0472)
HL			0.00791			-0.0234
			(0.0332)			(0.0292)
AW			0.0432			-0.00814
			(0.0298)			(0.0256)
AD			0.0234			0.00812
			(0.0349)			(0.0551)
AL			0.0155			-0.0534
			(0.0433)			(0.0489)
Constant	3.752***	3.758***	3.759***	5.414***	5.412***	5.414***
	(0.357)	(0.379)	(0.386)	(0.149)	(0.148)	(0.119)
Observations	27347	27347	27347	31119	31119	31119

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

Table 3.56: Regression results with domestic and international tournaments for all regions combined

	(Full time period)			(Restricted to June and July)		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Abuse						
Monday	-0.160***	-0.161***	-0.160***	-0.161***	-0.162***	-0.161***
	(0.0261)	(0.0248)	(0.0246)	(0.0206)	(0.0241)	(0.0263)
Tuesday	-0.212***	-0.213***	-0.214***	-0.208***	-0.207***	-0.207***
	(0.0237)	(0.0215)	(0.0228)	(0.0190)	(0.0234)	(0.0244)
Wednesday	-0.218***	-0.220***	-0.220***	-0.219***	-0.218***	-0.218***
	(0.0229)	(0.0207)	(0.0223)	(0.0188)	(0.0253)	(0.0253)
Thursday	-0.230***	-0.232***	-0.232***	-0.234***	-0.234***	-0.235***
	(0.0209)	(0.0187)	(0.0201)	(0.0161)	(0.0213)	(0.0236)
Friday	-0.202***	-0.204***	-0.203***	-0.207***	-0.207***	-0.207***
	(0.0218)	(0.0195)	(0.0186)	(0.0170)	(0.0208)	(0.0214)
Saturday	-0.0671***	-0.0687***	-0.0685***	-0.0933***	-0.0948***	-0.0950***
	(0.00592)	(0.00571)	(0.00614)	(0.00932)	(0.00852)	(0.00948)
February	0.0207***	0.0207***	0.0208***			
	(0.00621)	(0.00659)	(0.00720)			
March	0.0131*	0.0133**	0.0133**			
	(0.00753)	(0.00530)	(0.00666)			
April	0.0323***	0.0331***	0.0332***			
	(0.00743)	(0.00706)	(0.00750)			
May	0.0662***	0.0663***	0.0663***			
	(0.00821)	(0.00849)	(0.00921)			
June	0.118***	0.116***	0.116***			
	(0.00935)	(0.00846)	(0.00936)			
July	0.153***	0.153***	0.153***	0.0360***	0.0387***	0.0388***
	(0.00901)	(0.00934)	(0.00853)	(0.00437)	(0.00500)	(0.00478)
August	0.105***	0.104***	0.104***			
	(0.00856)	(0.00950)	(0.00888)			
September	0.0757***	0.0740***	0.0740***			
	(0.00977)	(0.0119)	(0.0115)			
October	0.0590***	0.0573***	0.0573***			
	(0.00976)	(0.0109)	(0.00763)			

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

Regression results with domestic and international tournaments for all regions combined (Continued)

	(Full time period)			(Restricted to June and July)		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Abuse						
November	0.0652***	0.0636***	0.0635***			
	(0.00893)	(0.0113)	(0.0105)			
December	0.0798***	0.0785***	0.0785***			
	(0.0109)	(0.0107)	(0.0107)			
2015	0.0348***	0.0327***	0.0327**	-0.0123	-0.00408	-0.00406
	(0.0134)	(0.0125)	(0.0136)	(0.0167)	(0.0151)	(0.0181)
2016	0.0835***	0.0772***	0.0772***	0.0155	0.0207	0.0208
	(0.0256)	(0.0224)	(0.0243)	(0.0242)	(0.0231)	(0.0235)
Bh-Oth	0.0769***	0.0773***	0.0770***	0	0	0
	(0.0182)	(0.0192)	(0.0207)	(0)	(0)	(0)
Bh-Chris	0.395***	0.394***	0.394***	0	0	0
	(0.0323)	(0.0292)	(0.0302)	(0)	(0)	(0)
fifa-matchday	0.0257***			-0.0157**		
	(0.00789)			(0.00755)		
euro-matchday	-0.0307***			-0.00372		
	(0.00955)			(0.00736)		
matchday	0.00504			0		
	(0.00325)			(0)		
fifa-england		0.0321			0.00583	
		(0.0206)			(0.0150)	
euro-england		-0.00410			0.0261*	
		(0.0147)			(0.0157)	
hometeam		0.0125			0	
		(0.0252)			(0)	
awayteam		0.0203			0	
		(0.0199)			(0)	
England Draw FIFA			0.0607**			0.0200
			(0.0256)			(0.0249)
England Lose FIFA			0.0187			-0.00000895
			(0.0204)			(0.0234)
England Lose EURO			-0.0507*			-0.0288
			(0.0283)			(0.0318)
England Draw EURO			0.000468			0.0361*
			(0.0227)			(0.0215)
England Win EURO			0.0341			0.0592**
			(0.0268)			(0.0288)
HL			0.00670			
			(0.0306)			
HD			0.0194			
			(0.0292)			
HW			0.0175			
			(0.0278)			
AW			0.0329**			
			(0.0148)			
AD			0.0232			
			(0.0278)			
AL			0.00958			
			(0.0381)			
Constant	3.921***	3.924***	3.925***	4.109***	4.099***	4.101***
	(0.335)	(0.288)	(0.284)	(0.313)	(0.326)	(0.335)
Observations	58466	58466	58466	11346	11346	11346

Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

3.C Merging all international tournaments

Table 3.57: Regression results with both international tournaments combined for both regions

	(England & Wales)			(London)		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Monday	-0.165***	-0.165***	-0.165***	-0.152***	-0.153***	-0.153***
	(0.0324)	(0.0368)	(0.0336)	(0.00765)	(0.00734)	(0.00851)
Tuesday	-0.222***	-0.222***	-0.222***	-0.195***	-0.195***	-0.196***
	(0.0290)	(0.0336)	(0.0310)	(0.00821)	(0.00899)	(0.00903)
Wednesday	-0.224***	-0.224***	-0.224***	-0.210***	-0.210***	-0.210***
	(0.0277)	(0.0321)	(0.0292)	(0.00884)	(0.00925)	(0.00907)
Thursday	-0.246***	-0.246***	-0.246***	-0.200***	-0.201***	-0.201***
	(0.0238)	(0.0291)	(0.0261)	(0.00871)	(0.00971)	(0.0105)
Friday	-0.213***	-0.213***	-0.213***	-0.186***	-0.186***	-0.186***
	(0.0251)	(0.0307)	(0.0287)	(0.00912)	(0.00978)	(0.00888)
Saturday	-0.0734***	-0.0734***	-0.0732***	-0.0538***	-0.0540***	-0.0538***
	(0.00924)	(0.00918)	(0.00845)	(0.00685)	(0.00674)	(0.00728)
February	0.0232***	0.0232***	0.0232***	0.0146	0.0146*	0.0146
	(0.00764)	(0.00835)	(0.00833)	(0.00974)	(0.00878)	(0.0129)
March	0.00917	0.00917	0.00918	0.0201**	0.0202***	0.0202**
	(0.00752)	(0.00843)	(0.00841)	(0.00810)	(0.00751)	(0.00822)
April	0.0366***	0.0366***	0.0366***	0.0259***	0.0259***	0.0260***
	(0.00893)	(0.00950)	(0.0101)	(0.00942)	(0.00975)	(0.00838)
May	0.0609***	0.0609***	0.0609***	0.0762***	0.0762***	0.0762***
	(0.0105)	(0.0111)	(0.0123)	(0.00913)	(0.00882)	(0.00938)
June	0.120***	0.118***	0.119***	0.104***	0.109***	0.109***
	(0.0128)	(0.0120)	(0.0114)	(0.00952)	(0.00834)	(0.00866)
July	0.158***	0.156***	0.156***	0.141***	0.144***	0.144***
	(0.0125)	(0.0129)	(0.0106)	(0.00784)	(0.00687)	(0.00948)
August	0.109***	0.109***	0.109***	0.0919***	0.0920***	0.0921***
	(0.0108)	(0.0120)	(0.0104)	(0.00844)	(0.00915)	(0.00793)
September	0.0780***	0.0779***	0.0781***	0.0634***	0.0635***	0.0636***
	(0.0127)	(0.0139)	(0.0131)	(0.0110)	(0.0112)	(0.0114)
October	0.0555***	0.0555***	0.0556***	0.0602***	0.0604***	0.0604***
	(0.0123)	(0.0130)	(0.0120)	(0.0132)	(0.0101)	(0.0131)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression results with both international tournaments combined for both regions(Continued)

	(England & Wales)				(London)	
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
November	0.0651***	0.0650***	0.0651***	0.0598***	0.0600***	0.0600***
	(0.0142)	(0.0159)	(0.0119)	(0.0124)	(0.0107)	(0.0125)
December	0.0849***	0.0848***	0.0850***	0.0646***	0.0647***	0.0648***
	(0.0147)	(0.0165)	(0.0125)	(0.00920)	(0.0108)	(0.00874)
year=2015	0.0416**	0.0420*	0.0422**	0.0164*	0.0153**	0.0154**
	(0.0196)	(0.0236)	(0.0203)	(0.00838)	(0.00716)	(0.00751)
year=2016	0.0924***	0.0925**	0.0929***	0.0465***	0.0463***	0.0465***
	(0.0343)	(0.0418)	(0.0315)	(0.0125)	(0.0108)	(0.0120)
Bh-Oth	0.101***	0.101***	0.100***	0.0270*	0.0271**	0.0270**
	(0.0255)	(0.0265)	(0.0243)	(0.0141)	(0.0136)	(0.0136)
Bh-Chris	0.451***	0.451***	0.451***	0.272***	0.272***	0.272***
	(0.0343)	(0.0352)	(0.0291)	(0.0220)	(0.0210)	(0.0168)
int-matchday	-0.00504			0.0123		
	(0.00773)			(0.00908)		
int-england		-0.000255			0.00486	
		(0.0163)			(0.0189)	
Eng Lose			-0.000403			-0.0183
			(0.0236)			(0.0327)
Eng Draw			0.0578*			0.0679
			(0.0304)			(0.0663)
Eng Win			-0.0127			0.00670
			(0.0170)			(0.0211)
Constant	3.758***	3.758***	3.758***	5.410***	5.410***	5.411***
	(0.301)	(0.347)	(0.380)	(0.146)	(0.165)	(0.150)
Observations	27347	27347	27347	31119	31119	31119

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.58: Regression results with both international tournaments combined for both regions restricted to June and July

	England & Wales			(London)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Monday	-0.168***	-0.167***	-0.167***	-0.147***	-0.148***	-0.147***
	(0.0313)	(0.0293)	(0.0324)	(0.0133)	(0.0165)	(0.0121)
Tuesday	-0.223***	-0.222***	-0.222***	-0.174***	-0.174***	-0.174***
	(0.0287)	(0.0277)	(0.0297)	(0.0137)	(0.0142)	(0.0131)
Wednesday	-0.236***	-0.234***	-0.234***	-0.183***	-0.183***	-0.183***
	(0.0289)	(0.0265)	(0.0293)	(0.0145)	(0.0159)	(0.0111)
Thursday	-0.249***	-0.248***	-0.248***	-0.201***	-0.201***	-0.201***
	(0.0254)	(0.0245)	(0.0251)	(0.0161)	(0.0174)	(0.0157)
Friday	-0.217***	-0.216***	-0.216***	-0.186***	-0.186***	-0.186***
	(0.0267)	(0.0257)	(0.0259)	(0.0123)	(0.0124)	(0.0107)
Saturday	-0.105***	-0.106***	-0.107***	-0.0705***	-0.0719***	-0.0725***
	(0.0118)	(0.0102)	(0.0108)	(0.0128)	(0.0135)	(0.0111)
July	0.0362***	0.0402***	0.0403***	0.0347***	0.0363***	0.0363***
	(0.00598)	(0.00547)	(0.00461)	(0.00806)	(0.00918)	(0.00975)
2015	0.00265	0.0104	0.00983	-0.0322***	-0.0302**	-0.0312**
	(0.0209)	(0.0229)	(0.0257)	(0.0114)	(0.0123)	(0.0139)
2016	0.0307	0.0319	0.0308	0.00236	0.00231	0.000277
	(0.0393)	(0.0308)	(0.0317)	(0.0115)	(0.0139)	(0.0114)
int-matchday	-0.0137***			-0.00270		
	(0.00490)			(0.00926)		
int-england		0.0168			0.0121	
		(0.0139)			(0.0192)	
Eng Lose			-0.00280			-0.0235
			(0.0218)			(0.0338)
Eng Draw			0.0199			0.0210
			(0.0255)			(0.0519)
Eng Win			0.0305			0.0361**
			(0.0192)			(0.0184)
Constant	3.954***	3.943***	3.944***	5.451***	5.450***	5.454***
	(0.286)	(0.290)	(0.331)	(0.250)	(0.286)	(0.252)
Observations	5307	5307	5307	6039	6039	6039

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.59: Regression results with both international tournaments combined for all regions combined

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Monday	-0.161***	-0.161***	-0.161***	-0.161***	-0.161***	-0.161***
	(0.0229)	(0.0247)	(0.0238)	(0.0191)	(0.0219)	(0.0255)
Tuesday	-0.214***	-0.214***	-0.214***	-0.208***	-0.207***	-0.207***
	(0.0201)	(0.0214)	(0.0226)	(0.0162)	(0.0213)	(0.0236)
Wednesday	-0.220***	-0.220***	-0.220***	-0.219***	-0.218***	-0.218***
	(0.0196)	(0.0208)	(0.0202)	(0.0159)	(0.0224)	(0.0240)
Thursday	-0.232***	-0.232***	-0.232***	-0.234***	-0.234***	-0.234***
	(0.0174)	(0.0194)	(0.0186)	(0.0158)	(0.0191)	(0.0209)
Friday	-0.204***	-0.204***	-0.204***	-0.207***	-0.207***	-0.207***
	(0.0180)	(0.0198)	(0.0198)	(0.0157)	(0.0195)	(0.0218)
Saturday	-0.0669***	-0.0669***	-0.0668***	-0.0936***	-0.0953***	-0.0958***
	(0.00563)	(0.00595)	(0.00715)	(0.00926)	(0.00953)	(0.00913)
February	0.0209***	0.0209***	0.0209***			
	(0.00566)	(0.00628)	(0.00525)			
March	0.0133**	0.0133**	0.0134**			
	(0.00539)	(0.00589)	(0.00569)			
April	0.0333***	0.0333***	0.0334***			
	(0.00737)	(0.00704)	(0.00540)			
May	0.0662***	0.0662***	0.0662***			
	(0.00868)	(0.00812)	(0.00607)			
June	0.116***	0.116***	0.116***			
	(0.00944)	(0.00812)	(0.00641)			
July	0.152***	0.153***	0.153***	0.0355***	0.0387***	0.0388***
	(0.00922)	(0.00824)	(0.00758)	(0.00392)	(0.00513)	(0.00515)
August	0.103***	0.103***	0.104***			
	(0.00705)	(0.00838)	(0.00732)			
September	0.0738***	0.0738***	0.0739***			
	(0.00939)	(0.00964)	(0.00879)			
October	0.0571***	0.0571***	0.0572***			
	(0.0103)	(0.00986)	(0.00843)			

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

Regression results with both international tournaments combined for all regions combined(Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
November	0.0635***	0.0635***	0.0636***			
	(0.00956)	(0.0104)	(0.00912)			
December	0.0786***	0.0786***	0.0787***			
	(0.00903)	(0.0119)	(0.00855)			
2015	0.0325**	0.0325**	0.0326**	-0.00941	-0.00363	-0.00436
	(0.0132)	(0.0154)	(0.0128)	(0.0170)	(0.0150)	(0.0221)
2016	0.0767***	0.0767***	0.0770***	0.0208	0.0216	0.0201
	(0.0219)	(0.0266)	(0.0205)	(0.0281)	(0.0205)	(0.0295)
Bh-Oth	0.0774***	0.0774***	0.0773***	0	0	0
	(0.0192)	(0.0174)	(0.0193)	(0)	(0)	(0)
Bh-Chris	0.397***	0.397***	0.397***	0	0	0
	(0.0277)	(0.0325)	(0.0273)	(0)	(0)	(0)
int-matchday	0.000853			-0.00995*		
	(0.00651)			(0.00590)		
int-england		0.00135			0.0152	
		(0.0121)			(0.0125)	
Eng Lose			-0.00646			-0.00980
			(0.0172)			(0.0188)
Eng Draw			0.0603**			0.0196
			(0.0267)			(0.0241)
Eng Win			-0.00621			0.0325*
			(0.0153)			(0.0175)
Constant	3.924***	3.924***	3.924***	4.107***	4.099***	4.100***
	(0.311)	(0.302)	(0.304)	(0.236)	(0.291)	(0.306)
Observations	58466	58466	58466	11346	11346	11346

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

3.D Salient Matches

Table 3.60: Regression results with traditional rivals restricted to relevant counties/boroughs

	Manchester		Northumbria		West-Midlands		Liverpool - Manchester	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Domestic abuse								
Monday	-0.209***	-0.211***	-0.253***	-0.251***	-0.187***	-0.187***	-0.209***	-0.210***
	(0.0101)	(0.0139)	(0.0166)	(0.0167)	(0.0143)	(0.0140)	(0.0110)	(0.0114)
Tuesday	-0.282***	-0.284***	-0.312***	-0.310***	-0.236***	-0.235***	-0.282***	-0.283***
	(0.00907)	(0.00930)	(0.0152)	(0.0170)	(0.0131)	(0.0111)	(0.0136)	(0.00919)
Wednesday	-0.285***	-0.287***	-0.311***	-0.308***	-0.268***	-0.267***	-0.285***	-0.286***
	(0.0124)	(0.0125)	(0.0179)	(0.0139)	(0.0126)	(0.0145)	(0.0135)	(0.0113)
Thursday	-0.310***	-0.312***	-0.327***	-0.327***	-0.281***	-0.280***	-0.310***	-0.311***
	(0.0114)	(0.0112)	(0.0187)	(0.0152)	(0.0115)	(0.0134)	(0.0123)	(0.0116)
Friday	-0.249***	-0.252***	-0.245***	-0.245***	-0.220***	-0.219***	-0.249***	-0.251***
	(0.0127)	(0.0112)	(0.0175)	(0.0138)	(0.0113)	(0.0110)	(0.0150)	(0.0118)
Saturday	-0.0461***	-0.0452***	-0.0517***	-0.0390**	-0.0390***	-0.0407***	-0.0461***	-0.0445***
	(0.0107)	(0.0117)	(0.0127)	(0.0152)	(0.0143)	(0.0111)	(0.0114)	(0.0108)
February	0.0425**	0.0426***	0.0470**	0.0457**	0.00353	0.00156	0.0425**	0.0430***
	(0.0168)	(0.0157)	(0.0232)	(0.0179)	(0.0174)	(0.0160)	(0.0174)	(0.0136)
March	0.0229	0.0228*	0.0320	0.0308	-0.0228	-0.0236	0.0229	0.0225
	(0.0141)	(0.0136)	(0.0255)	(0.0203)	(0.0141)	(0.0179)	(0.0163)	(0.0144)
April	0.0457***	0.0461***	0.0475*	0.0476**	0.0158	0.0140	0.0457***	0.0465***
	(0.0131)	(0.0133)	(0.0260)	(0.0233)	(0.0161)	(0.0174)	(0.0158)	(0.0153)
May	0.0839***	0.0837***	0.0842***	0.0835***	0.0369**	0.0358**	0.0839***	0.0841***
	(0.0149)	(0.0140)	(0.0229)	(0.0184)	(0.0159)	(0.0167)	(0.0163)	(0.0159)
June	0.127***	0.126***	0.138***	0.134***	0.0914***	0.0913***	0.127***	0.126***
	(0.0154)	(0.0170)	(0.0231)	(0.0198)	(0.0168)	(0.0148)	(0.0160)	(0.0145)
July	0.123***	0.121***	0.177***	0.173***	0.0923***	0.0922***	0.123***	0.122***
	(0.0152)	(0.0166)	(0.0194)	(0.0208)	(0.0181)	(0.0174)	(0.0159)	(0.0142)
August	0.0598***	0.0599***	0.125***	0.125***	0.0691***	0.0676***	0.0598***	0.0603***
	(0.0159)	(0.0154)	(0.0271)	(0.0222)	(0.0185)	(0.0202)	(0.0171)	(0.0155)
September	0.0492***	0.0489***	0.0569**	0.0567***	0.0196	0.0191	0.0492***	0.0487***
	(0.0154)	(0.0156)	(0.0244)	(0.0205)	(0.0152)	(0.0159)	(0.0160)	(0.0161)

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

Regression results with traditional rivals restricted to relevant counties/boroughs (Continued)

	Manchester		Northumbria		West-Midlands		Liverpool - Manchester	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Domestic abuse								
October	0.0249	0.0249	0.0536**	0.0505**	0.0227	0.0214	0.0249	0.0253
	(0.0177)	(0.0160)	(0.0243)	(0.0224)	(0.0198)	(0.0155)	(0.0181)	(0.0160)
November	0.0402**	0.0399**	0.0423	0.0430*	0.0157	0.0138	0.0402**	0.0403**
	(0.0167)	(0.0173)	(0.0267)	(0.0244)	(0.0192)	(0.0188)	(0.0201)	(0.0177)
December	0.0495*	0.0498*	0.0771**	0.0758***	0.0199	0.0195	0.0495*	0.0496**
	(0.0267)	(0.0270)	(0.0348)	(0.0274)	(0.0255)	(0.0191)	(0.0262)	(0.0251)
2015	-0.0481***	-0.0481***	-0.0187*	-0.0187*	-0.000192	-0.000132	-0.0481***	-0.0481***
	(0.00697)	(0.00647)	(0.0102)	(0.0111)	(0.00782)	(0.00840)	(0.00818)	(0.00808)
2016	-0.0621***	-0.0621***	0.0192	0.0191*	-0.0483***	-0.0481***	-0.0621***	-0.0621***
	(0.00894)	(0.00747)	(0.0119)	(0.0116)	(0.00805)	(0.00890)	(0.00938)	(0.00868)
Bh-Oth	0.138***	0.139***	0.219***	0.217***	0.0534**	0.0538***	0.138***	0.139***
	(0.0274)	(0.0320)	(0.0333)	(0.0394)	(0.0240)	(0.0203)	(0.0331)	(0.0272)
Bh-Chris	0.654***	0.658***	0.654***	0.669***	0.429***	0.423***	0.654***	0.658***
	(0.153)	(0.134)	(0.169)	(0.154)	(0.106)	(0.0999)	(0.148)	(0.123)
matchpa	0.00700		0.0278*		-0.00844		0.00700	
	(0.0117)		(0.0157)		(0.0127)		(0.0120)	
man-derby		-0.000735						
		(0.0530)						
nor-derby				0.174***				
				(0.0637)				
wmid-derby						-0.0638		
						(0.0649)		
liv-derby								0.0297
								(0.0199)
Constant	5.342***	5.345***	4.524***	4.525***	5.001***	5.001***	5.342***	5.344***
	(0.0153)	(0.0136)	(0.0197)	(0.0190)	(0.0149)	(0.0146)	(0.0173)	(0.0147)
/ lnalpha	-5.598***	-5.597***	-5.197***	-5.217***	-5.607***	-5.610***	-5.598***	-5.598***
	(0.202)	(0.213)	(0.246)	(0.299)	(0.168)	(0.164)	(0.197)	(0.212)
Observations	943	943	943	943	943	943	943	943

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

Table 3.61: Regression results with the last five matches of the season for both regions

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Domestic abuse						
Monday	-0.164***	-0.164***	-0.164***	-0.153***	-0.153***	-0.153***
	(0.0273)	(0.0366)	(0.0311)	(0.00672)	(0.00712)	(0.00816)
Tuesday	-0.221***	-0.221***	-0.221***	-0.196***	-0.196***	-0.196***
	(0.0241)	(0.0329)	(0.0312)	(0.00738)	(0.00754)	(0.00918)
Wednesday	-0.224***	-0.224***	-0.224***	-0.211***	-0.211***	-0.211***
	(0.0233)	(0.0317)	(0.0288)	(0.00771)	(0.00775)	(0.00899)
Thursday	-0.245***	-0.245***	-0.245***	-0.202***	-0.202***	-0.201***
	(0.0202)	(0.0280)	(0.0269)	(0.00840)	(0.00883)	(0.00998)
Friday	-0.212***	-0.212***	-0.212***	-0.187***	-0.187***	-0.187***
	(0.0221)	(0.0301)	(0.0240)	(0.00927)	(0.00838)	(0.00779)
Saturday	-0.0763***	-0.0760***	-0.0762***	-0.0534***	-0.0533***	-0.0533***
	(0.00669)	(0.00953)	(0.00582)	(0.00565)	(0.00526)	(0.00675)
February	0.0229**	0.0229***	0.0229***	0.0147*	0.0147	0.0147
	(0.0102)	(0.00811)	(0.00753)	(0.00771)	(0.00927)	(0.00991)
March	0.00904	0.00905	0.00905	0.0202***	0.0202**	0.0203***
	(0.00919)	(0.00722)	(0.00955)	(0.00703)	(0.00799)	(0.00696)
April	0.0372***	0.0374***	0.0373***	0.0268**	0.0266***	0.0267***
	(0.0113)	(0.00928)	(0.00897)	(0.0106)	(0.00819)	(0.00795)
May	0.0625***	0.0624***	0.0625***	0.0771***	0.0772***	0.0772***
	(0.0121)	(0.0116)	(0.00842)	(0.00876)	(0.00811)	(0.00777)
June	0.120***	0.120***	0.120***	0.109***	0.109***	0.109***
	(0.0132)	(0.0125)	(0.0101)	(0.00804)	(0.00775)	(0.00630)
July	0.158***	0.158***	0.158***	0.144***	0.144***	0.144***
	(0.0140)	(0.0128)	(0.0115)	(0.00789)	(0.00677)	(0.00772)
August	0.109***	0.109***	0.109***	0.0920***	0.0919***	0.0919***
	(0.0137)	(0.0124)	(0.0110)	(0.00939)	(0.00874)	(0.00883)
September	0.0781***	0.0781***	0.0780***	0.0636***	0.0635***	0.0636***
	(0.0149)	(0.0149)	(0.0141)	(0.0121)	(0.00917)	(0.00871)
October	0.0555***	0.0555***	0.0556***	0.0604***	0.0604***	0.0604***
	(0.0142)	(0.0135)	(0.0148)	(0.0128)	(0.0107)	(0.0102)
November	0.0650***	0.0649***	0.0650***	0.0600***	0.0600***	0.0601***
	(0.0156)	(0.0145)	(0.0158)	(0.0126)	(0.0113)	(0.0116)
December	0.0844***	0.0844***	0.0845***	0.0648***	0.0646***	0.0648***
	(0.0160)	(0.0155)	(0.0149)	(0.0103)	(0.00842)	(0.00946)
2015	0.0420**	0.0420**	0.0420**	0.0153**	0.0152**	0.0152**
	(0.0191)	(0.0198)	(0.0186)	(0.00747)	(0.00685)	(0.00705)
2016	0.0925**	0.0925***	0.0925***	0.0464***	0.0463***	0.0464***
	(0.0363)	(0.0323)	(0.0351)	(0.0123)	(0.0107)	(0.0102)

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

Regression results with the last five matches of the season for both regions (Continued)

	England & Wales			London		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Bh-Oth	0.100***	0.100***	0.100***	0.0272**	0.0271**	0.0272**
	(0.0265)	(0.0230)	(0.0295)	(0.0130)	(0.0123)	(0.0127)
Bh-Chris	0.446***	0.446***	0.447***	0.274***	0.274***	0.274***
	(0.0278)	(0.0326)	(0.0307)	(0.0183)	(0.0191)	(0.0175)
title	-0.0368*	-0.0376***	-0.0353***	-0.0623***	-0.0610**	-0.0598***
	(0.0200)	(0.0144)	(0.0125)	(0.0237)	(0.0244)	(0.0217)
hometeam	0.0203			-0.0147		
	(0.0222)			(0.0236)		
awayteam	0.0296**			-0.0106		
	(0.0141)			(0.0362)		
HW		0.0283			-0.0130	
		(0.0264)			(0.0257)	
HD		0.0293			-0.0156	
		(0.0237)			(0.0452)	
HL		0.0115			-0.0172	
		(0.0255)			(0.0316)	
AW		0.0478**			-0.000445	
		(0.0229)			(0.0326)	
AD		0.0273			0.0171	
		(0.0272)			(0.0605)	
AL		0.0197			-0.0432	
		(0.0305)			(0.0545)	
H-expected			0.0237			-0.0107
			(0.0179)			(0.0273)
H-UW			0.00970			-0.0310
			(0.0280)			(0.0366)
H-UL			0.0658***			-0.00827
			(0.0205)			(0.0500)
A-expected			0.0248			-0.0155
			(0.0185)			(0.0471)
A-UW			0.0398*			0.0149
			(0.0205)			(0.0299)
A-UL			0.0739***			-0.255***
			(0.0204)			(0.0704)
Constant	3.758***	3.758***	3.759***	5.413***	5.413***	5.414***
	(0.303)	(0.370)	(0.350)	(0.167)	(0.154)	(0.136)
Observations	27347	27347	27347	31119	31119	31119

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

Table 3.62: Regression results with the absolute difference in home win and away win probabilities for both regions

	England & Wales			London		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
Monday	-0.164***	-0.164***	-0.164***	-0.153***	-0.153***	-0.153***
	(0.0390)	(0.0328)	(0.0340)	(0.00690)	(0.00841)	(0.00778)
Tuesday	-0.221***	-0.221***	-0.221***	-0.196***	-0.196***	-0.196***
	(0.0365)	(0.0292)	(0.0330)	(0.00798)	(0.00880)	(0.00838)
Wednesday	-0.223***	-0.223***	-0.223***	-0.211***	-0.211***	-0.211***
	(0.0343)	(0.0286)	(0.0301)	(0.00750)	(0.00900)	(0.00941)
Thursday	-0.245***	-0.245***	-0.245***	-0.202***	-0.201***	-0.201***
	(0.0303)	(0.0247)	(0.0274)	(0.00793)	(0.00925)	(0.00988)
Friday	-0.212***	-0.211***	-0.212***	-0.187***	-0.187***	-0.187***
	(0.0321)	(0.0265)	(0.0290)	(0.00837)	(0.00945)	(0.00976)
Saturday	-0.0759***	-0.0757***	-0.0758***	-0.0533***	-0.0532***	-0.0532***
	(0.00891)	(0.00825)	(0.00981)	(0.00460)	(0.00659)	(0.00638)
February	0.0229***	0.0230***	0.0230***	0.0147	0.0147	0.0147
	(0.00773)	(0.00861)	(0.00820)	(0.00957)	(0.00929)	(0.00900)
March	0.00905	0.00903	0.00905	0.0203***	0.0204***	0.0205***
	(0.00819)	(0.00859)	(0.00836)	(0.00746)	(0.00703)	(0.00774)
April	0.0363***	0.0364***	0.0364***	0.0262**	0.0261***	0.0262***
	(0.00832)	(0.00982)	(0.00806)	(0.0109)	(0.00867)	(0.00895)
May	0.0609***	0.0608***	0.0610***	0.0763***	0.0763***	0.0764***
	(0.00883)	(0.00970)	(0.0106)	(0.0100)	(0.00894)	(0.00886)
June	0.119***	0.119***	0.119***	0.109***	0.109***	0.109***
	(0.00925)	(0.0108)	(0.0119)	(0.00768)	(0.00759)	(0.00742)
July	0.158***	0.157***	0.158***	0.144***	0.144***	0.144***
	(0.00914)	(0.0116)	(0.0131)	(0.00881)	(0.00849)	(0.00588)
August	0.109***	0.109***	0.109***	0.0921***	0.0920***	0.0919***
	(0.00833)	(0.00906)	(0.0130)	(0.00874)	(0.00844)	(0.00839)
September	0.0780***	0.0780***	0.0779***	0.0636***	0.0635***	0.0636***
	(0.0105)	(0.0130)	(0.0140)	(0.0113)	(0.00902)	(0.00967)
October	0.0554***	0.0554***	0.0554***	0.0604***	0.0603***	0.0604***
	(0.00880)	(0.0120)	(0.0144)	(0.0111)	(0.0113)	(0.0117)
November	0.0650***	0.0650***	0.0651***	0.0601***	0.0601***	0.0602***
	(0.0107)	(0.0117)	(0.0151)	(0.0116)	(0.0123)	(0.00932)
December	0.0845***	0.0845***	0.0845***	0.0649***	0.0647***	0.0648***
	(0.0121)	(0.0124)	(0.0160)	(0.00668)	(0.00913)	(0.00948)

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

Regression results with the absolute difference in home win and away win probabilities for both regions (Continued)

	England & Wales			London		
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic abuse						
2015	0.0421**	0.0420**	0.0420*	0.0152**	0.0152**	0.0152**
	(0.0176)	(0.0184)	(0.0224)	(0.00741)	(0.00644)	(0.00747)
2016	0.0925***	0.0925***	0.0925***	0.0462***	0.0462***	0.0462***
	(0.0325)	(0.0326)	(0.0345)	(0.00968)	(0.0105)	(0.0113)
Bh-Oth	0.101***	0.101***	0.101***	0.0272**	0.0271**	0.0272**
	(0.0279)	(0.0240)	(0.0270)	(0.0115)	(0.0128)	(0.0130)
Bh-Chris	0.447***	0.447***	0.447***	0.274***	0.275***	0.274***
	(0.0379)	(0.0331)	(0.0274)	(0.0208)	(0.0184)	(0.0164)
Close	-0.0427	-0.0463	-0.0569**	-0.106**	-0.0939*	-0.110***
	(0.0523)	(0.0375)	(0.0270)	(0.0459)	(0.0516)	(0.0421)
hometeam	0.0239			0.0109		
	(0.0202)			(0.0235)		
awayteam	0.0342***			0.0105		
	(0.0127)			(0.0316)		
HW		0.0325			0.0129	
		(0.0201)			(0.0366)	
HD		0.0312*			0.000663	
		(0.0186)			(0.0334)	
HL		0.0163			0.00267	
		(0.0208)			(0.0288)	
AW		0.0530**			0.0171	
		(0.0206)			(0.0260)	
AD		0.0325**			0.0281	
		(0.0153)			(0.0243)	
AL		0.0266			-0.0195	
		(0.0269)			(0.0439)	
H-expected			0.0308			0.0193
			(0.0195)			(0.0177)
H-UW			0.0102			-0.0166
			(0.0327)			(0.0396)
H-UL			0.0804***			0.0361
			(0.0282)			(0.0585)
A-expected			0.0337**			0.00904
			(0.0168)			(0.0383)
A-UW			0.0457*			0.0327
			(0.0236)			(0.0282)
A-UL			0.0968***			-0.226***
			(0.0215)			(0.0550)
Constant	3.758***	3.758***	3.759***	5.414***	5.414***	5.416***
	(0.372)	(0.368)	(0.376)	(0.133)	(0.140)	(0.145)
Observations	27347	27347	27347	31119	31119	31119

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

3.E Public Order Offence

Table 3.63: Regression results with EPL variables

	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
Monday	-0.0125	-0.0187	-0.0197	-0.0197	-0.0197	-0.0196
	(0.0305)	(0.0359)	(0.0263)	(0.0274)	(0.0280)	(0.0311)
Tuesday	-0.0254	-0.0353	-0.0360	-0.0361	-0.0361	-0.0359
	(0.0251)	(0.0314)	(0.0233)	(0.0266)	(0.0266)	(0.0301)
Wednesday	0.0111	0.00140	0.000561	0.000456	0.000396	0.000504
	(0.0232)	(0.0304)	(0.0238)	(0.0262)	(0.0223)	(0.0294)
Thursday	0.0195	0.00735	0.00624	0.00612	0.00611	0.00622
	(0.0250)	(0.0314)	(0.0250)	(0.0291)	(0.0262)	(0.0308)
Friday	0.0326	0.0203	0.0192	0.0190	0.0190	0.0191
	(0.0217)	(0.0242)	(0.0250)	(0.0265)	(0.0237)	(0.0274)
Saturday	0.000542	0.00159	0.00365	0.00361	0.00346	0.00372
	(0.0185)	(0.0144)	(0.0178)	(0.0151)	(0.0179)	(0.0175)
February	0.0769***	0.0777***	0.0778***	0.0778***	0.0777***	0.0777***
	(0.00925)	(0.0107)	(0.00869)	(0.0111)	(0.00865)	(0.00876)
March	0.138***	0.140***	0.139***	0.140***	0.139***	0.140***
	(0.0175)	(0.0153)	(0.0145)	(0.0172)	(0.0170)	(0.0154)
April	0.170***	0.175***	0.175***	0.175***	0.174***	0.175***
	(0.0319)	(0.0317)	(0.0272)	(0.0298)	(0.0282)	(0.0279)
May	0.227***	0.227***	0.227***	0.227***	0.227***	0.227***
	(0.0309)	(0.0333)	(0.0323)	(0.0322)	(0.0266)	(0.0268)
June	0.307***	0.301***	0.300***	0.300***	0.300***	0.300***
	(0.0288)	(0.0294)	(0.0263)	(0.0288)	(0.0238)	(0.0264)
July	0.357***	0.351***	0.350***	0.350***	0.350***	0.350***
	(0.0344)	(0.0333)	(0.0346)	(0.0292)	(0.0276)	(0.0296)
August	0.237***	0.238***	0.238***	0.238***	0.238***	0.238***
	(0.0371)	(0.0336)	(0.0353)	(0.0386)	(0.0318)	(0.0278)
September	0.299***	0.299***	0.299***	0.299***	0.299***	0.299***
	(0.0362)	(0.0370)	(0.0329)	(0.0397)	(0.0301)	(0.0270)
October	0.280***	0.281***	0.280***	0.280***	0.280***	0.280***
	(0.0419)	(0.0432)	(0.0427)	(0.0469)	(0.0313)	(0.0320)
November	0.285***	0.286***	0.286***	0.286***	0.286***	0.286***
	(0.0456)	(0.0477)	(0.0484)	(0.0485)	(0.0390)	(0.0351)
December	0.227***	0.231***	0.231***	0.231***	0.231***	0.231***
	(0.0479)	(0.0482)	(0.0485)	(0.0496)	(0.0401)	(0.0360)
2015	0.139**	0.139**	0.139**	0.139*	0.139**	0.139***
	(0.0642)	(0.0628)	(0.0598)	(0.0736)	(0.0582)	(0.0472)
2016	0.440***	0.440***	0.440***	0.440***	0.440***	0.440***
	(0.0974)	(0.102)	(0.102)	(0.112)	(0.0847)	(0.0855)

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

Regression results with EPL variables (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
Bh-Oth	-0.183***	-0.181***	-0.181***	-0.182***	-0.182***	-0.181***
	(0.0409)	(0.0445)	(0.0475)	(0.0490)	(0.0397)	(0.0482)
Bh-Chris	-0.136	-0.127	-0.123	-0.123	-0.124	-0.123
	(0.0949)	(0.100)	(0.0963)	(0.111)	(0.0869)	(0.112)
matchday	0.0199***					
	(0.00511)					
matchpa		-0.0495				
		(0.155)				
matchcount=1			-0.0303			
			(0.0367)			
matchcount=2			-0.0815			
			(0.0504)			
hometeam				-0.0130		
				(0.0552)		
awayteam				-0.0621		
				(0.110)		
HW					-0.0101	
					(0.0656)	
HD					-0.0325	
					(0.0617)	
HL					-0.00629	
					(0.0692)	
AW					-0.0507	
					(0.0687)	
AD					-0.0932**	
					(0.0408)	
AL					-0.0481	
					(0.0538)	
H-expected						-0.0227
						(0.0445)
H-UW						0.0211
						(0.0529)
H-UL						-0.0120
						(0.308)
A-Expected						-0.0661**
						(0.0330)
A-UW						-0.0736
						(0.0472)
A-UL						0.0475
						(0.0915)
Constant	2.253***	2.265***	2.267***	2.268***	2.268***	2.268***
	(0.291)	(0.284)	(0.314)	(0.331)	(0.300)	(0.375)
Observations	22935	22935	22935	22935	22935	22935

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

Table 3.64: Regression results with variables International Tournaments

	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
Monday	-0.0181	-0.0180	-0.0180	-0.0180	-0.0188	-0.0194
	(0.0272)	(0.0257)	(0.0266)	(0.0316)	(0.0314)	(0.0291)
Tuesday	-0.0346	-0.0348	-0.0351	-0.0344	-0.0345	-0.0345
	(0.0265)	(0.0250)	(0.0238)	(0.0256)	(0.0276)	(0.0274)
Wednesday	0.00198	0.00200	0.00200	0.00211	0.00199	0.00200
	(0.0242)	(0.0244)	(0.0243)	(0.0267)	(0.0263)	(0.0247)
Thursday	0.00817	0.00793	0.00803	0.00830	0.00785	0.00801
	(0.0285)	(0.0242)	(0.0218)	(0.0263)	(0.0279)	(0.0267)
Friday	0.0211	0.0211	0.0211	0.0213	0.0211	0.0211
	(0.0249)	(0.0239)	(0.0228)	(0.0250)	(0.0272)	(0.0241)
Saturday	0.000211	-0.0000879	0.0000273	0.000267	-0.000131	0.000311
	(0.0175)	(0.0151)	(0.0161)	(0.0165)	(0.0146)	(0.0162)
February	0.0775***	0.0775***	0.0775***	0.0775***	0.0775***	0.0776***
	(0.0105)	(0.0110)	(0.0103)	(0.0101)	(0.00983)	(0.00679)
March	0.139***	0.139***	0.139***	0.139***	0.139***	0.139***
	(0.0147)	(0.0169)	(0.0170)	(0.0208)	(0.0153)	(0.0153)
April	0.174***	0.174***	0.174***	0.174***	0.174***	0.174***
	(0.0289)	(0.0291)	(0.0278)	(0.0324)	(0.0330)	(0.0283)
May	0.227***	0.227***	0.227***	0.227***	0.227***	0.227***
	(0.0321)	(0.0282)	(0.0268)	(0.0329)	(0.0313)	(0.0296)
June	0.302***	0.301***	0.301***	0.301***	0.300***	0.300***
	(0.0319)	(0.0270)	(0.0243)	(0.0338)	(0.0267)	(0.0280)
July	0.352***	0.352***	0.352***	0.351***	0.352***	0.352***
	(0.0371)	(0.0304)	(0.0285)	(0.0353)	(0.0285)	(0.0322)
August	0.238***	0.238***	0.238***	0.238***	0.238***	0.238***
	(0.0346)	(0.0307)	(0.0315)	(0.0425)	(0.0375)	(0.0350)
September	0.299***	0.299***	0.299***	0.299***	0.299***	0.299***
	(0.0360)	(0.0290)	(0.0289)	(0.0393)	(0.0371)	(0.0340)
October	0.281***	0.281***	0.281***	0.280***	0.280***	0.280***
	(0.0413)	(0.0384)	(0.0343)	(0.0426)	(0.0415)	(0.0407)
November	0.286***	0.286***	0.286***	0.286***	0.286***	0.286***
	(0.0450)	(0.0455)	(0.0397)	(0.0440)	(0.0448)	(0.0481)

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

Regression results with variables International Tournaments (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Public order offence						
December	0.230***	0.230***	0.230***	0.230***	0.230***	0.230***
	(0.0464)	(0.0477)	(0.0371)	(0.0474)	(0.0429)	(0.0470)
2015	0.139**	0.139**	0.139**	0.139**	0.139**	0.139**
	(0.0632)	(0.0582)	(0.0563)	(0.0692)	(0.0639)	(0.0678)
2016	0.440***	0.440***	0.440***	0.439***	0.439***	0.439***
	(0.101)	(0.107)	(0.0851)	(0.0977)	(0.0917)	(0.0979)
Bh-Oth	-0.181***	-0.182***	-0.182***	-0.182***	-0.181***	-0.181***
	(0.0417)	(0.0353)	(0.0477)	(0.0478)	(0.0481)	(0.0362)
Bh-Chris	-0.130*	-0.130	-0.130	-0.130	-0.130*	-0.130
	(0.0770)	(0.0943)	(0.104)	(0.0851)	(0.0762)	(0.102)
fifa-matchday	-0.00140					
	(0.0188)					
fifa-england		0.0406				
		(0.0312)				
England Draw (fifa)			0.0722			
			(0.0956)			
England Lose (fifa)			0.0250			
			(0.0360)			
euro-matchday				0.00525		
				(0.0288)		
euro-england					0.0306	
					(0.0379)	
England Lose (uefa)						0.125**
						(0.0577)
England Draw (uefa)						-0.0101
						(0.0509)
England Win (uefa)						0.0165
						(0.0666)
Constant	2.264***	2.264***	2.264***	2.264***	2.265***	2.265***
	(0.319)	(0.313)	(0.254)	(0.273)	(0.278)	(0.309)
Observations	22935	22935	22935	22935	22935	22935

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

Table 3.65: Regression results with Domestic (EPL) and international tournaments variables

	(1)	(2)	(3)
Public order offence			
Monday	-0.0123	-0.0203	-0.0211
	(0.0258)	(0.0277)	(0.0293)
Tuesday	-0.0252	-0.0364	-0.0366
	(0.0242)	(0.0240)	(0.0257)
Wednesday	0.0113	0.000471	0.000403
	(0.0245)	(0.0213)	(0.0244)
Thursday	0.0197	0.00552	0.00575
	(0.0248)	(0.0237)	(0.0267)
Friday	0.0328	0.0190	0.0190
	(0.0237)	(0.0185)	(0.0224)
Saturday	0.000616	0.00295	0.00340
	(0.0175)	(0.0133)	(0.0167)
February	0.0769***	0.0778***	0.0778***
	(0.00927)	(0.00918)	(0.0119)
March	0.138***	0.140***	0.139***
	(0.0152)	(0.0210)	(0.0186)
April	0.170***	0.175***	0.174***
	(0.0266)	(0.0337)	(0.0273)
May	0.227***	0.227***	0.227***
	(0.0265)	(0.0366)	(0.0283)
June	0.305***	0.297***	0.297***
	(0.0265)	(0.0355)	(0.0273)
July	0.356***	0.350***	0.350***
	(0.0314)	(0.0348)	(0.0307)
August	0.237***	0.238***	0.238***
	(0.0295)	(0.0419)	(0.0327)
September	0.298***	0.299***	0.299***
	(0.0305)	(0.0395)	(0.0311)
October	0.280***	0.280***	0.280***
	(0.0318)	(0.0438)	(0.0406)
November	0.285***	0.286***	0.286***
	(0.0344)	(0.0480)	(0.0480)
December	0.227***	0.230***	0.231***
	(0.0362)	(0.0529)	(0.0453)
2015	0.139***	0.139**	0.139**
	(0.0524)	(0.0666)	(0.0592)
2016	0.439***	0.439***	0.440***
	(0.0780)	(0.115)	(0.102)

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

Regression results with Domestic (EPL) and international tournaments variables (Continued)

	(1)	(2)	(3)
Public order offence			
Bh-Oth	-0.183***	-0.181***	-0.181***
	(0.0388)	(0.0392)	(0.0434)
Bh-Chris	-0.136*	-0.124	-0.124
	(0.0731)	(0.0805)	(0.0933)
fifa-matchday	-0.0000133		
	(0.0133)		
euro-matchday	0.00665		
	(0.0277)		
matchday	0.0200***		
	(0.00659)		
fifa-england		0.0412	
		(0.0449)	
euro-england		0.0313	
		(0.0389)	
hometeam		-0.0130	
		(0.0317)	
awayteam		-0.0620*	
		(0.0362)	
England Draw (fifa)			0.0741
			(0.0901)
England Lose (fifa)			0.0247
			(0.0365)
England Lose (uefa)			0.126**
			(0.0592)
England Draw (uefa)			-0.0108
			(0.0544)
England Win (uefa)			0.0187
			(0.0553)
HW			-0.0103
			(0.0555)
HD			-0.0326
			(0.148)
HL			-0.00646
			(0.0755)
AW			-0.0508
			(0.139)
AD			-0.0933
			(0.148)
AL			-0.0482
			(0.107)
Constant	2.253***	2.268***	2.268***
	(0.269)	(0.296)	(0.283)
Observations	22935	22935	22935

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

Conclusion

In this thesis we approached competition from two broad perspectives. First, we considered competition as a motivator of performance as in chapter one and chapter two of this thesis. Then, we considered competition as a source of emotional stimulus as in chapter three.

In chapter one, we studied the role of leadership in teams facing a game with a complex strategy space. Teams of three members faced an instance of a team dispatching problem, in which the members jointly devised then separately implemented a plan to visit a set of locations on a map. Some teams had one member designated as a "leader", although this role did not confer any distinct responsibility or capability in the game. We compared the performance of teams with elected leaders, appointed leaders, and no leaders. We found that teams with leaders performed better than those without, while teams with elected leaders and teams with appointed leaders performed similarly. Our results indicate that electing a leader serves as a device to coordinate team activity, and is valuable primarily when a team needs to be able to deliver well immediately.

In chapter two, we studied experimentally the effects of individual skill in a real-performance task and the responsiveness of individual skill to various incentive schemes. Participants faced instances of the Truck Dispatch Problem, in which they devised three journeys which visit a set of locations on a map. Some participants were remunerated under a rank order tournament incentive scheme, some participants were informed of their performance ranking and were given a fixed rate whilst some participants were remunerated under a fixed rate incentive scheme. We found evidence for individual skill differences in the task, but that the distribution of these differences does not depend on the incentive treatment

In chapter three, we studied empirically the effects of domestic and international football tournaments on domestic abuse in England and Wales and how these effects vary with people's expectations of the football match outcomes. We found in our analysis, that the existence of an EPL fixture is associated with a 1% percent increase in domestic abuse while the existence of a FIFA World Cup fixture is associated with a 3% increase in domestic violence in England and Wales. Our results, also suggest that expected match outcomes have strong effects on domestic abuse in England and Wales.

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