FAMILY VIOLENCE AND FOOTBALL: THE EFFECT OF UNEXPECTED EMOTIONAL CUES ON VIOLENT BEHAVIOR*

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We study the link between family violence and the emotional cues associated with wins and losses by professional football teams. We hypothesize that the risk of violence is affected by the "gain-loss" utility of game outcomes around a rationally expected reference point. Our empirical analysis uses police reports of violent incidents on Sundays during the professional football season. Controlling for the pregame point spread and the size of the local viewing audience, we find that upset losses (defeats when the home team was predicted to win by four or more points) lead to a 10% increase in the rate of at-home violence by men against their wives and girlfriends. In contrast, losses when the game was expected to be close have small and insignificant effects. Upset wins (victories when the home team was predicted to lose) also have little impact on violence, consistent with asymmetry in the gain-loss utility function. The rise in violence after an upset loss is concentrated in a narrow time window near the end of the game and is larger for more important games. We find no evidence for reference point updating based on the halftime score. *JEL* Codes: D030, J120.

I. INTRODUCTION

Violence by men against members of their own family is one of the most common yet perplexing forms of criminal behavior.[1] One interpretation is that intrafamily violence is instrumental behavior that is used by domineering men to control their partners and children (e.g., Dobash and Dobash 1979).[2] An alternative view is

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1. There are 2.5 to 4.5 million physical assaults inflicted on adult women by their intimate partner per year (Rand and Rennison 2005). About one-third of female homicide victims in the United States were killed by their husband or partner (Fox and Zawitz 2007).

2. Chwe (1990) shows that painful punishment can arise in an agency model when the agent has low outside opportunities, even if punishment is costly for the principal. Bloch and Rao (2002) propose a model in which husbands use violence to signal the quality of their marriage to their wives' families.

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that family violence is expressive behavior that either provides positive utility to some men (e.g., Tauchen, Witte, and Long 1991; Aizer 2010) or arises unintentionally when an argument escalates out of control (e.g., Straus, Gelles, and Steinmetz 1980; Johnson 2009).

An expressive interpretation of family violence suggests a potentially important role for emotional cues (or "visceral factors") in precipitating violence.[3] In this article we study the effects of the emotional cues associated with wins and losses by local professional football teams, using police reports of family violence during the regular season of the National Football League (NFL). Specifically, we hypothesize the risk of violence is affected by the gain-loss utility associated with game outcomes around a rationally expected reference point (Koszegi and Rabin 2006).

Our focus on professional football is motivated by three considerations. First, NFL fans are strongly attached to their local teams. Home games on Sunday afternoons typically attract 25% or more of the local TV audience.[4] Second, the existence of a well-organized betting market allows us to infer the expected outcome of each game and use this as a reference point for gain-loss utility.[5] Conditioning on the pregame point spread also allows us to interpret any differential effect of a win versus a loss as a causal effect of the game outcome. Third, the structure of NFL competition and the availability of detailed game statistics make it easy to identify more or less salient games, and to measure the updated probability of a win by the home team midway through the game.

Two other recent studies have explored the link between football and violence. Gantz, Bradley, and Wang (2006) relate police reports of family violence to the occurrence of NFL games involving the local team and find that game days are associated with higher rates of violence. Rees and Schnepel (2009) document the effects of college football home games on rates of assault,

3. See Loewenstein (2000) for a general discussion and Laibson (2001) and Bernheim and Rangel (2004) for models of the effect of external cues on decision making.

4. In 2008, NFL Sunday football games were the highest rated local programs in 88% of the market-weeks. Nationally, the top ten TV programs for 18–49-year-old men in 2008 were all NFL football games (NFL and Nielsen Media Research, cited in *Ground Report*, January 7, 2009).

5. As discussed in Levitt (2004) for example, football betting uses a point spread to clear the market. See Wolfers and Zitzewitz (2007) on the information-aggregating properties of betting markets.

vandalism, and alcohol-related offenses.[6] We go beyond these studies by examining the effects of wins and losses relative to pregame expectations, controlling for the size of the local viewing audience, studying the interday timing of violent incidents, comparing the effects of more and less salient games, and testing for potential updating of the reference point for game outcomes using the score at halftime.

Our analysis incorporates family violence data for over 750 city and county police agencies in the National Incident Based Reporting System (NIBRS), merged with information on Sunday NFL games played by six teams over a 12-year period. Controlling for the pregame point spread and the size of the local TV viewing audience, we find that "upset losses" by the home team (losses when the team was predicted to win by four points or more) lead to a roughly 10% increase in the number of police reports of at-home male-on-female intimate partner violence. Consistent with reference point behavior, losses when the game was expected to be close have no significant effect on family violence. "Upset wins" (i.e., victories when the home team was expected to lose) also have no significant impact on the rate of violence, suggesting an important asymmetry in the reaction to unanticipated losses and gains.

The increases in violence after an upset loss are concentrated in a narrow time window around the end of the game, as might be expected if the violence is due to transitory emotional shocks. We also find that upset losses in more salient games (those involving a traditional rival, or when the team is still in playoff contention) have a bigger effect on the rate of violence. Finally, we test whether the reference point for emotional cues is revised during the first half of the game, but we find no evidence of updating.

Taken together, our findings suggest that emotional cues based on the outcomes of professional football games exert a relatively strong effect on the occurrence of family violence. The estimated impact of an upset loss, for example, is about one-third as large as the jump in violence on a major holiday like Independence Day. More broadly, our research contributes to a growing body of work on the importance of reference point behavior and provides field-based empirical support for Koszegi and Rabin's (2006)

6. Rees and Schnepel (2009) show that games that involve the upset of a team ranked in the top 25 by the Associated Press (AP) poll have much higher rates of violence. Their definition of "upsets" is substantially different than ours, because a game can only be an upset if a nationally ranked team is playing.

prediction that individuals frame gains and losses around a rationally expected reference point, with stronger reactions to losses than gains.

II. Modeling the Effect of Emotional Cues and Family Violence

This section presents a simplified model of the impact of NFL game outcomes on the occurrence of family violence and describes our empirical framework for measuring the effects of these cues. Our key hypothesis is that wins and losses generate emotional cues that reflect gain-loss utility around a rational reference point. We consider two alternative mechanisms through which cues affect violence. The first builds on the family conflict paradigm in sociology (Straus, Gelles, and Steinmetz 1980) and research on loss of control (e.g., Baumeister and Heatherton 1996; Bernheim and Rangel 2004; Loewenstein and O'Donoghue 2007) and treats violence as an unintended outcome of interactions in conflict-prone families. We assume that men are more likely to lose control when they have been exposed to a negative emotional shock. The second is a family bargaining model in which women endure violence in exchange for interfamily transfers, and men's demand for violence rises after a negative cue.

II.A. *Loss-of-Control Model*

Consider a couple that each period has some risk of a conflictual interaction (i.e., a heated disagreement or argument). With some probability $h \geq 0$, the interaction escalates to violence (i.e., the husband "loses control").[7] The likelihood of losing control is influenced by the emotional cues associated with the outcome y of a professional football game, where $y = 1$ indicates a home team victory and $y = 0$ indicates a loss. Letting $p = \mathrm{E}[y]$ we assume that

$$h = h^0 - \mu(y - p), \tag{1}$$

where μ is the gain-loss utility associated with the game outcome (Koszegi and Rabin 2006). For simplicity we assume that μ is

7. Strictly speaking, our model focuses on the risk of violent *interactions* between partners: the outcome could involve injuries to both partners. In our data about 80% of the victims of intimate partner violence are women, so we assume a male perpetrator.

piecewise linear, with

$$\mu(y-p) = \alpha(y-p),\; y-p<0$$
$$= \beta(y-p),\; y-p>0,$$

for positive constants α and β. Loss aversion implies that $\alpha > \beta$, that is, that the marginal effect of a positive cue is smaller than the marginal effect of a negative cue. Recognizing that y is binary, the implied probabilities of a loss of control are

$$h^L(p) = h^0 + \alpha p \text{ if } y = 0 \text{ (a loss)},$$
$$h^W(p) = h^0 - \beta(1-p) \text{ if } y = 1 \text{ (a win)}. \tag{2}$$

The upper line in Figure I represents $h^L(p)$. When $p = 0$ a home team loss is fully anticipated, and there is no emotional cue, so $h^L = h^0$. When $p > 0$ a loss is "bad news," with a stronger negative cue with a higher p: thus, h^L is increasing in p. The lower line in the figure represents $h^W(p)$. A win when $p = 0$ is the "best possible" news, leading to the lowest probability of loss of control, $h^0 - \beta$. For higher values of p, a win is less of positive shock, so h^W is also increasing in p.

Assuming that the probability of a conflictual interaction is $q \geq 0$, the probability of a violent incident, conditional on watching

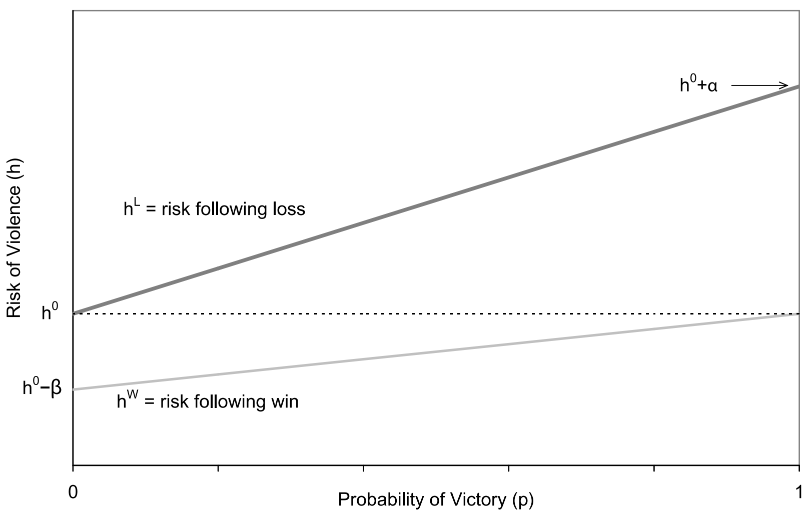

FIGURE I
Risk of Violence Following Loss or Win

the game, is qh. If the husband always watches, the probability of violence is therefore $(h^0 + \alpha p)q$ in the event of a loss and $(h^0 - \beta(1-p))q$ in the event of a win. The differential effect of a loss versus a win on the probability of violence is

$$\Delta(risk|p) = [\beta + (\alpha - \beta)p]q, \tag{3}$$

which is positive and increasing in p, assuming that $\alpha > \beta$.

In Card and Dahl (2009) we present a forward-looking model in which husbands decide in advance whether to watch a game, taking into account the pleasure of watching a win versus a loss and the risk of exposure to the emotional cue if they watch. In this case, the differential effect of a loss versus a win on the probability of violence can be written as

$$\Delta(risk|p) = [\beta + (\alpha - \beta)p] \times E[q|\text{watch}, p] \times \text{Prob}[\text{watch}|p]. \tag{4}$$

A comparison of Equation (4) to Equation (3) shows that discretionary viewing behavior will *reinforce* the effect of an increase in p on the differential effect of a loss versus a win if more people watch a game when p is higher and/or if the composition of the viewing audience shifts toward more conflict-prone men when p is higher.

II.B. An Alternative Model

A simple loss-of-control model is broadly consistent with the literature on situational family violence (e.g., Straus, Gelles, and Steinmetz 1980; Gelles and Straus 1988; Johnson 1995) and with recent economic models of addiction (Bernheim and Rangel 2004) and failure of self-control (Loewenstein and O'Donoghue 2007). In terms of predictions linking emotional cues to violence, however, it is indistinguishable from a family bargaining model in which men value the expression of violence and their preferences are affected by emotional cues from a gain-loss function like $\mu(y-p)$ in Equation (1).[8] A potentially important distinction between these

8. Tauchen, Witte, and Long (1991), Farmer and Tiefenthaler (1997), Bowlus and Seitz (2006), and Aizer (2010) all assume that men value violence and their partners tolerate it in return for higher transfers. An efficient bargain with unrestricted transfers maximizes $E[U(y - c_w, v, h)]$ subject to $E[V(c_w, v)] = V^0$, where y = family income, c_w = consumption of wife, v = violence, h = cue, U is the male's utility, and V is the female's. The optimal choices for v and c_w equate the husband's marginal willingness to pay for violence with his partner's marginal supply price.

models is in the victim's reaction to violence. In a bargaining model the victim is compensated for her injuries, and the optimal choice of violence equates the husband's willingness to pay for violence with his partner's marginal cost. Given that, victims have no incentive to call the police or take other protective action (and in fact outside intervention is inefficient, except for externalities imposed on third parties, such as children).[9] Protective behavior is more easily interpreted in a loss-of-control model in which neither party benefits from violence. Nevertheless, both models imply a similar link between emotional cues and the probability of family violence.

II.C. Evaluating the Effect of Emotional Cues

We test for the predicted effects of positive and negative emotional cues using a Poisson count model for the number of police-reported episodes of family violence in cities and counties in states with a "home" NFL team. As discussed shortly, we classify games based on the Las Vegas point spread into three categories: home team likely to win, opposing team likely to win, or game expected to be close. We then fit models that include a full set of interactions between the ex ante classification and whether the game was a won or lost by the home team ($3 \times 2 = 6$ categories), treating nongame days (i.e., Sundays when the home team has a bye week or is playing on another day of the week) as the base case. As a robustness check, we also fit a model with a polynomial in the point spread, interacted with the game outcome.

Our key identifying assumption is that the outcome of an NFL game is random, conditional on the Las Vegas spread. Conditioning on the pregame spread, we can therefore interpret any difference between the rate of family violence following a win or loss as a causal effect of the outcome of the game. We

Assuming that negative cues increase the willingness to pay for violence, the level of violence demanded by the husband (and supplied by the wife) will respond as in Equation (3). Our reading of the extensive family violence literature outside of economics is that no one thinks a marginal condition like this is true—in other words, the cost of violence to the partner in the "high cue" condition is often far beyond the "price" that is paid by the perpetrator.

9. In the NIBRS data we analyze, we note that it need not be the victim who reports violence to the police.

test for reference point behavior by testing whether the impact of a loss is greater when the home team was expected to win than when the game was expected to be close or the team was expected to lose. We also test for asymmetric reactions to good and bad news by comparing the magnitude of the effects of upset losses and upset wins.

III. Data Sources and Sample Construction

III.A. *Measuring Family Violence: NIBRS Data on Police-Reported Violence*

Our empirical analysis is based on police reports of family violence in the National Incident-Based Reporting System (NIBRS). NIBRS includes *reports* of crime to individual police agencies; the reports are not necessarily associated with an arrest.[10] Each report includes information on the characteristics of the victim (age, gender, etc.), the offender (gender and relationship to the victim), and the incident (date, time of day, location, and injuries).

The NIBRS has two main advantages for our study. First, it includes *all* the family violence incidents recorded by a given agency. Because family violence is relatively rare, a complete count is needed to measure responses to NFL game outcomes on specific days in specific locations. Second, NIBRS includes real-time information on the date and time of day of the incident. Other sources of information on family violence (such as the National Crime Victimization Survey) are based on recall over a multiple-month period and cannot be used to measure occurrences by exact day and time.

One limitation of the NIBRS is that it only includes police-reported family violence.[11] A comparison of the implied rate of violence experienced by women age 18–54 in the NIBRS to the rate in the 1995 National Violence Against Women Survey (NVAWS) suggests that the NIBRS captures a relatively high fraction of serious violence (i.e., episodes that would be classified as

10. About half of family assaults in the NIBRS result in an arrest (Durose et al. 2005; Hirschel 2008). Direct arrests by police officers with no intervening report of a crime are also included in NIBRS. Information on the NIBRS data set is available at the National Archive of Criminal Justice Data, http://www.icpsr.umich.edu/NACJD/NIBRS.

11. Only about half of adult women in the National Crime Victimization Survey who were assaulted by their spouse or partner reported the incident to police (Durose et al. 2005).

assault or intimidation). Specifically, we estimate that the annual risk of intimate partner violence (IPV) is approximately 1.6% per year in the 2000 NIBRS, versus 1.3% per year in the NVAWS (1995–96).[12] A second limitation is that participation by police agencies in NIBRS is voluntary and relatively low. The total fraction of the U.S. population covered by NIBRS was only 4% in 1995, but had risen to 25% by 2006.

As has been noted in other studies (e.g., Vazquez, Stohr, and Purkiss 2005; Gantz, Bradley, and Wang 2006), the rate of family violence varies substantially across the days of the week, with much higher rates on weekends than weekdays. In view of these patterns, and the small number of NFL games on days other than Sunday, we have elected to simplify the analysis by limiting our sample to the 17 Sundays during the regular NFL season. We define IPV as an incident of simple assault, aggravated assault, or intimidation by a spouse, partner, or boyfriend/girlfriend. Our primary focus is on male-on-female IPV occurring at home between noon and midnight Eastern Time.

Table I provides summary statistics for IPV for our estimation sample (Sundays during the regular football season) for the set of NIBRS agencies used in our analysis (all reporting police agencies in the set of states that we match to NFL teams, as described in the next section).[13] In our estimation sample, the overall rate of IPV is 1.28 per 100,000 individuals per day.[14] Panel A shows how the rate of intimate partner violence varies by location and victim-offender relationship. Most of the victims of IPV are women (81%), and most are victimized at home (82%), leading to our focus on

12. To construct a national incidence rate from the NIBRS, we assume that information on the family relationship of the perpetrator is missing at random and inflated the incident rates for the agencies to the national level using relative populations as of 2000.

13. We include incidents reported by city and county agencies but exclude state police, college police, and special agencies. We limit the sample to agencies that report data on any crime (not just IPV) for at least 13 out of 17 Sundays in a season. Copies of the programs that we used to process the publicly available NIBRS data are available from the authors on request.

14. We refer to the hours between noon and midnight ET as a day; these hours account for roughly 60% of at-home male-on-female IPV. Ideally the rate of IPV would be expressed relative to the number of intimate partner couples. In 2000 there were approximately 21 intimate partnerships per 100 people in the U.S. population; thus, the rate per couple is approximately 4.8 times the rate per person. Our models include agency fixed effects and therefore control flexibly for most of the variation in the size of the at-risk population.

TABLE I
SUMMARY STATISTICS FOR INTIMATE PARTNER VIOLENCE, NIBRS DATA, 1995–2006

Intimate partner violence	Daily rate for the hours of noon to 11:59 PM per 100,000 population	Fraction in category or subcategory
A. Sundays during regular football season		
Location and victim-offender relationship		
All intimate partner violence	1.28	1.00
Male on female	1.04	0.81
Occurring at home	0.85	0.82
Against wife	0.46	0.54
Against girlfriend	0.39	0.46
Occurring away from home	0.19	0.18
Female on male	0.24	0.19
Occurring at home	0.19	0.79
Occurring away from home	0.05	0.21
B. Sundays during regular football season, male on female, occurring at home		
Time of day (all times eastern time)		
noon to 2:59 PM	0.16	0.19
3–5:59 PM	0.18	0.22
6–8:59 PM	0.25	0.29
9–11:59 PM	0.25	0.30

TABLE I
(CONTINUED)

Intimate partner violence	Daily rate for the hours of noon to 11:59 PM per 100,000 population	Fraction in category or subcategory
Alcohol use and assault severity		
Alcohol involved	0.17	0.20
Minor assault	0.41	0.48
Serious assault	0.44	0.52
Agency size		
Smaller cities or counties (pop < 50K)	0.89	0.47
Larger cities or counties (pop $\geq$ 50K)	0.73	0.53
Age		
Younger offenders (age < 30)	0.32	0.38
Older offenders (age $\leq$ 30)	0.52	0.61

Notes. Data are reports of intimate partner violence to local police agencies in the National Incident-Based Reporting System (NIBRS) for the states and years listed in Table II. Intimate partner is defined as a spouse (including common law and ex-spouse) or a boyfriend/girlfriend. Violence is defined as aggravated assault, simple assault, or intimidation. Alcohol involved indicates the reporting officer noted that either alcohol or drugs were a contributing factor. Minor assault is simple assault or intimidation without injury; serious assault is aggravated assault or any assault with a physical injury. Category fractions for agency size are weighted by the average population in smaller versus larger cities and counties.

at-home male-on-female incidents.[15] Within this class, violence by husbands against their wives and violence by men against unmarried partners account for roughly equal shares.

Panel B narrows the focus to male-on-female violence occurring at home. To crudely characterize the severity of an incident, we classified aggravated assaults and other incidents involving physical injury as “serious assaults,” and the remaining forms of IPV as “minor assaults.”[16] Using this classification, just over half of male-on-female at-home IPV incidents are serious assaults.

Alcohol use is widely believed to contribute to family violence (Klosterman and Fals-Stewart 2006) and may amplify the effects of emotional cues (Exum 2002). Unfortunately, alcohol use information in the NIBRS is limited to a single variable indicating whether the offender was suspected of using alcohol (or drugs) during or shortly before the offense. Overall, about 20% of at-home male-on-female incidents of IPV list alcohol or drugs as a contributing factor.

III.B. Matching NFL Team Data to NIBRS Violence Data

We link the NIBRS data to the team records for “local” NFL franchises. Because NIBRS data are unavailable for many larger cities, relatively few NFL teams can be matched to crime rates in the city (or county) that hosts their home stadium. As an alternative, we focus on cities and counties in *states* where there is a single NFL team (or nearby team), assigning all jurisdictions within a state to that team. Using this approach, and requiring that at least four years of crime data are available for a given team, we were able to match six NFL teams to 763 NIBRS agencies.

15. The relative fraction of female victims of IPV is controversial because some data sources (in particular, behavioral checklists that collect incidents of slapping and pushing as well as more serious violence) find that men and women are equally likely to be victimized (e.g., Straus, Gelles, and Steinmetz 1980). Police reports and victimization surveys suggest that women are more likely to be the victims of relatively serious violence (see Hamby 2005, table I).

16. The NIBRS uses the FBI’s definition of aggravated assault, which is an unlawful attack where the offender wields a weapon or the victim suffers obvious severe or aggravated injury. Simple assault is also an unlawful attack, but does not involve a weapon or obvious severe or aggravated bodily injury. Intimidation is the act of placing a person in reasonable fear of bodily harm without a weapon or physical attack.

Table II shows the six football teams in our sample, with the associated NIBRS states listed in parentheses.[17] For each team we also show the win-loss record in the sample years for which NIBRS data are available and the number of reporting agencies in the state in that year. Three teams (the Carolina Panthers, Detroit Lions, and New England Patriots) have NIBRS data available for all 12 years, starting in 1995 and continuing to 2006. The three remaining teams (the Denver Broncos, Kansas City Chiefs, and Tennessee Titans) enter the NIBRS sample in later years. Within a state, the number of reporting agencies in the NIBRS tends to rise over time, though there are some downward fluctuations as certain agencies leave the program.

The win-loss records reported in Table II display wide variation across teams. Detroit had a weak record over most of the sample period, whereas Denver and New England were relatively successful. Even for a given team, however, there are swings from year to year. For example, Denver had a 14-2 win-loss record in the 1998 season (and won the Superbowl), but had a losing season in 1999. Because predicted game outcomes tend to be based on recent past performance, these patterns hint at the prevalence of both upset losses (e.g., during the Denver Broncos' 1999 season) and upset wins (e.g., during the Kansas City Chiefs' 2003 season). We characterize upset losses and upset wins more formally using the Las Vegas point spread in the next subsection.

In all, the six teams in our sample can be matched to 993 regular season football games and 53 playoff games. The characteristics of these games are shown in the upper panel of Table III. The vast majority (87%) of the regular season games were played on Sundays. As noted earlier, given the seasonal and intraweek variation in family violence rates, we elected to simplify our empirical design by focusing on regular season Sunday games. The characteristics of these games and their associated local TV market are summarized in panels B and C of Table III.

III.C. Expected Outcomes from Betting Markets

Betting on NFL game outcomes is organized through Las Vegas bookmakers, who equilibrate the market using a point spread.

17. Kansas City is in Missouri, but we assume fans in Kansas also follow the team. The NIBRS has no data for Missouri agencies until 2006, the last year of our sample period.

TABLE II
NFL FOOTBALL TEAMS MATCHED TO NIBRS AGENCIES

	Season											
	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Carolina Panthers (SC)												
Regular season w-l record	7-9	12-4*	7-9	4-12	8-8	7-9	1-15	7-9	11-5*	7-9	11-5*	8-8
# Of reporting agencies	22	64	75	73	76	82	65	76	80	74	80	84
Pop. coverage (thousands)	795	2174	2614	2740	2559	2588	2436	2847	3051	2861	2726	2776
Denver Broncos (CO)												
Regular season w-l record			12-4*	14-2*	6-10	11-5*	8-8	9-7	10-6*	10-6*	13-3*	9-7
# Of reporting agencies			28	29	25	27	25	28	33	30	38	41
Pop. coverage (thousands)			1626	1733	1502	1642	1435	1699	1776	1935	2757	3052
Detroit Lions (MI)												
Regular season w-l record	10-6*	5-11	9-7*	5-11	8-8*	9-7	2-14	3-13	5-11	6-10	5-11	3-13
# Of reporting agencies	63	108	141	141	145	159	158	168	168	164	173	180
Pop. coverage (thousands)	1799	3142	4451	4606	4951	5895	5872	6211	6370	6611	7801	7883
Kansas City Chiefs (KS)												
Regular season w-l record						7-9	6-10	8-8	13-3*	7-9	10-6	9-7*
# Of reporting agencies						39	43	47	44	41	38	45
Pop. coverage (thousands)						794	791	1291	1225	1140	1149	1246

TABLE II
(CONTINUED)

	Season											
	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
New England Patriots (MA, NH, VT)												
Regular season w-l record	6-10	11-5*	10-6*	9-7*	8-8	5-11	11-5*	9-7	14-2*	14-2*	10-6*	12-4*
# Of reporting agencies	32	32	37	55	58	70	81	94	105	112	127	124
Pop. coverage (thousands)	768	986	1068	1387	1491	1960	2162	2643	2954	3416	3861	3846
Tennessee Titans (TN)												
Regular season w-l record				8-8	13-3*	13-3*	7-9	11-5*	12-4*	5-11	4-12	8-8
# Of reporting agencies				45	112	134	131	140	135	137	147	149
Pop. coverage (thousands)				922	2748	4882	4835	5039	5017	5133	5288	5313

Notes. An asterisk (*) next to a regular season record indicates that the team played in the postseason. Reporting agencies can be either cities or counties within the state indicated in parentheses.

TABLE III
SUMMARY STATISTICS FOR NFL FOOTBALL GAMES AND NIELSEN TELEVISION RATINGS

	Number of games	Fraction in category or subcategory
A. All NFL football games, 1995–2006		
Day of week and season/postseason		
Regular season games	993	0.95
Sunday games	866	0.87
Monday Night Football	68	0.07
Thursday, Friday, or Saturday games	59	0.06
Postseason games (36 on Sunday, 17 on Saturday)	53	0.05
B. Sunday regular season NFL games, 1995–2006		
Outcome		
Loss	414	0.48
Win	452	0.52
Predicted and actual outcomes based on pregame point spread		
Predicted win: point spread ≤ 4	283	0.33
Actual loss (*upset loss*)	79	0.28
Predicted close: $-4 <$ point spread < 4	377	0.44
Actual loss (*close loss*)	194	0.49
Predicted loss: point spread ≥ 4	206	0.24
Actual win (*upset win*)	65	0.32

TABLE III
(CONTINUED)

	Number of games	Fraction in category or subcategory
Predicted and actual outcomes based on halftime point spread		
Predicted win: halftime point spread ≤ 4	338	0.39
Actual loss (*halftime upset loss*)	61	0.18
Predicted close: –4 < halftime point spread < 4	240	0.28
Actual loss (*halftime close loss*)	126	0.53
Predicted loss: halftime point spread ≥ 4	288	0.33
Actual win (*halftime upset win*)	61	0.21
No Sunday game		
Played on another day of the week	127	0.67
Bye week	62	0.33
By time of day		
1 PM ET start time	587	0.68
4 PM ET start time	224	0.26
8 PM ET start time	55	0.06
Salient games		
(a) Still in playoff contention	589	0.68
(b) Against a traditional rival	201	0.23
(c) Sacks ≥ 4, turnovers ≥ 4, or penalties > 80 yards	341	0.39
(d) Highly salient: (a) and [(b) or (c)]	321	0.37

TABLE III
(CONTINUED)

	Number of games	Fraction in category or subcategory
C. Nielsen media research local television ratings, 1997–2006		
Percent of local TV households watching game	Average (%)	Max (%)
Local team playing	24.3	47.9
1 PM game		
Local team playing	23.1	47.2
Local team not playing that Sunday	8.1	17.7
4 PM game		
Local team playing	29.4	47.9
Local team not playing that Sunday	12.3	22.2
8 PM game (ESPN/TNT games only)		
Local team playing	10.1	19.0
Local team not playing that Sunday	8.3	21.4

Notes. Sample covers the teams and years listed in Table II. Starting times of games are approximate. See notes to Table VI for definitions of salient games. Nielsen ratings begin in 1997 for Carolina, Denver, Detroit, and New England; 1998 for Tennessee; and 2000 for Kansas. Ratings for the 8 PM games do not include the 2006 season, as the broadcasts switched from cable/satellite (ESPN/TNT) to an over the air network (NBC) in 2006. Average ratings for 8 PMgames in 2006 are 33.9% and 9.1% when the local team is playing and not playing, respectively.

If the point spread is –3 for one team against another, the team must win by more than 3 points for a bet on that team to pay off. The market assessment of the outcome of a game is contained in the closing value of the point spread (the so-called closing line).

Previous research has suggested that the point spread is an unbiased predictor of game outcomes in the NFL (e.g., Pankoff 1968; Gandar et al. 1988). To verify this conclusion, we collected data on point spreads and final scores for all 3,725 NFL football games played during the 1995–2006 seasons. Figure II shows the relationship between the actual and predicted point spread in each game. The actual spread is "noisier" than the predicted spread, but the two are highly correlated. In fact, a regression of the actual on the predicted spread yields a coefficient of 1.01 (standard error = 0.03). Thus, there is no evidence against the null hypothesis of an efficient prediction. Moreover, the R^2 of the relationship is relatively strong (0.20), suggesting that the closing line is an informative predictor of game outcomes.

The vertical lines in Figure II divide the predicted spreads into three regions, depending on whether the home team is predicted to win by at least four points, predicted to lose by at least four points, or predicted to have a close game. About 45% of games

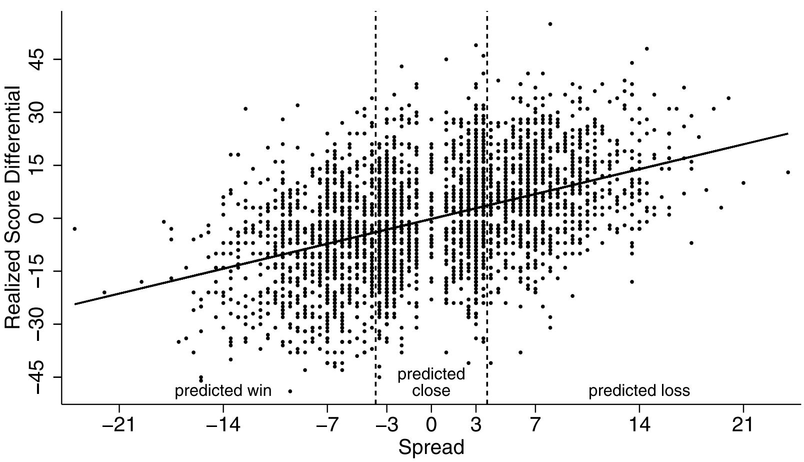

FIGURE II

Final Score Differential versus the Pregame Point Spread

Realized score differential is opponent's minus local team's final score. The plotted regression line has an intercept of −0.17 (s.e. = 0.21) and a slope of 1.01 (s.e. = 0.03).

are expected to be close: the remaining games are equally divided in the two tails. In our empirical analysis we use these three categories to classify games as predicted wins, predicted close games, and predicted losses for the home team.

Our model is written in terms of the ex ante probability of a home team win, rather than the point spread. The mapping between the two is shown in Figure III. To derive this relationship, we regressed the probability of a victory by the home team on a third-order polynomial in the spread. The fitted relationship follows the expected inverse S-curve shape and is symmetric. For spreads of ± 14 points (a range that includes 98% of games) the probability of a win is very close to linear, with each one-point increase in the spread translating into a 3% decrease in the probability of a win. For games with a spread of -4 points or less (predicted wins) the probability of a home team victory is 63% or greater. For predicted losses (spread ≥ 4) the probability of a win is 37% or less.

Panel B of Table III summarizes the predicted outcomes of the 866 regular season Sunday games in our IPV analysis sample. Of these games, 283 (33%) were predicted wins for the home team, 206 (24%) were predicted losses, and 377 (44%) were predicted

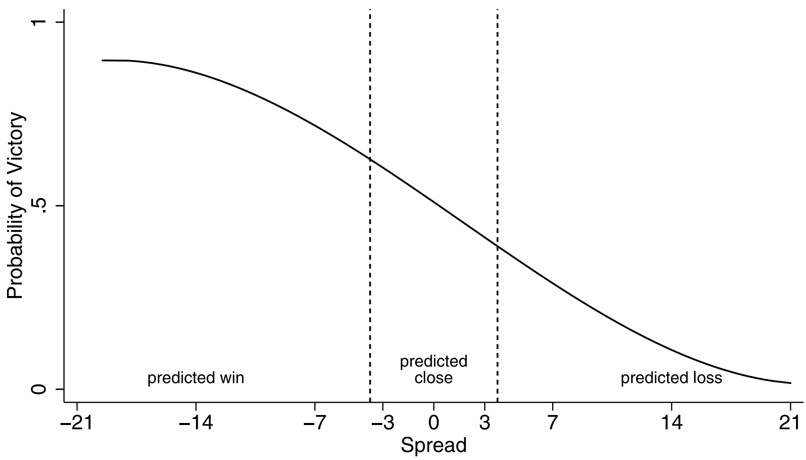

FIGURE III

Probability of Victory as a Function of the Spread

Curve is fit from a regression of the probability of victory for the local team on a third-order polynomial in the spread.

close games. The greater number of predicted wins than losses in our sample reflects the inclusion of two relatively successful teams (Denver and New England). We also report the actual outcomes of the games: the home team lost relatively few (28%) of the games they were favored to win by four or more points and won relatively few (32%) of the games they were predicted to lose by four or more points. Among predicted close games the home team victory rate was approximately 50%.

As discussed shortly in the section on Extensions and Robustness Checks, we present some analyses of game outcomes relative to the actual point spread at halftime (which we call the "halftime spread"—note that this is not an updated predicted spread from betting markets but the observed point difference at halftime). Like the final score, the halftime spread is more variable than the pregame spread: by the midpoint of the game only 28% of games are closer than four points, and 44% are within the same range using the pregame spread. The halftime spread is also a better predictor of the final game outcome. For example, among games where the home team led by four points or more at halftime, the fraction of losses was 18% (versus 28% using the same classification of the pregame spread).

Table III, panel B also shows two other important characteristics of NFL games that we explore in later analyses: the starting time and the likely emotional salience of a game. The largest share of games (68%) in our sample had a 1 PM starting time. Most of the others (26%) had a 4 PM start time, and only 6% were night games. We consider three measures of emotional salience: whether the home team was still in playoff contention, whether the game was played against a traditional "rival" team, and whether the game involved an unusually high number of sacks, turnovers, or penalty yards.[18] Most regular season games (68%) are played when the team is still in playoff contention, about one-fifth are played against a traditional rival, and about 40% involve a high number of sacks, turnovers, or penalty yards. We define "highly salient" games as those in which the home team was still in playoff contention *and* either played against a traditional rival or had

18. We classify a team as out of contention once the predicted probability of making the playoffs (based on the historical record for teams with a similar win-loss record at the same point in the season) is under 10%. We identified traditional rivalries using information from "Rivalries in the National Football League" on Wikipedia. A list of the rival team pairs we use is available on request.

an unusual number of sacks, turnovers, or penalty yards. These games represent 37% of our sample.

III.D. *Measures of Viewership*

We purchased data from Nielsen Media Research (Nielsen) for the six TV markets corresponding to the teams in our matched NIBRS-NFL sample. Nielsen uses information from metering devices installed in a sample of homes to estimate the fraction of all "television households" that are watching a given program at a given time. Panel C of Table III shows the Nielsen ratings for the regular season Sunday football games in our estimation sample (each Nielsen point represents 1% of local TV households). On average, 24% of all households watch their local team play on a typical Sunday. In contrast, the Sunday afternoon TV audience when the local team is not playing is only one-fourth as large.

Figure IV plots the fraction of households watching a game (deviated from the average viewership in the same media market on Sunday game-days) against the pre-game spread. The estimated regression line in the graph shows that the expected audience falls by about 1 percentage point as the spread rises from −4 (a predicted win by the home team) to +4 (a predicted loss). This is not a large effect, and we infer that any differential reaction to the outcomes of predicted wins versus predicted losses is unlikely to be attributable to changes in viewership.

IV. Econometric Model and Main Estimation Results

IV.A. *Econometric Model*

Given the incident-based nature of NIBRS data, we specify a Poisson regression model for the number of incidents of IPV reported by a given police agency on a given Sunday of the regular NFL season. Specifically we assume that

$$\log(\mu_{jt}) = \theta_j + X_{jt}\gamma + \mathrm{f}(p_{jt}, y_{jt}; \lambda), \tag{5}$$

where μ_{jt} represents the expected number of incidents of IPV reported by agency j in time period t, θ_j represents a fixed effect for the agency (which controls for the size and overall characteristics of the population served by the agency), X_{jt} represents a set of time-varying controls (e.g., controls for season and weather),

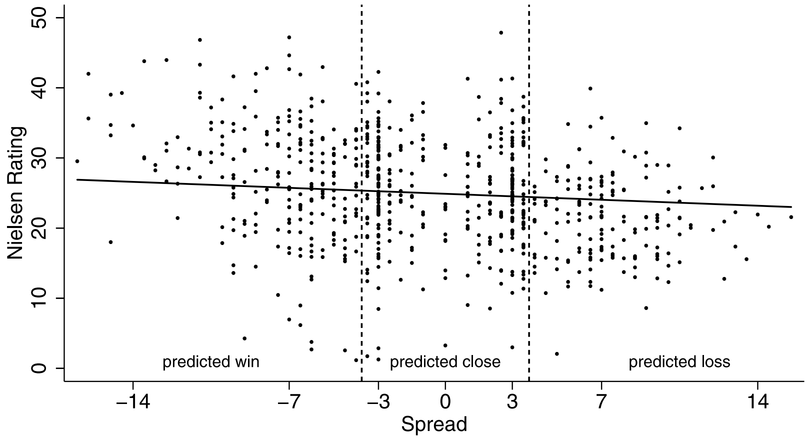

FIGURE IV

Television Audience for Local Games and the Spread

Each rating point equals 1% of the total number of television households in the local market. The plotted regression line controls for team fixed effects and has an intercept of 24.89 (s.e. = 0.20) and a slope of –0.12 (s.e. = 0.03).

and $f(p_{jt}, y_{jt}; \lambda)$ is a general function of p_{jt}, the probability of a victory by the home team for a game played on date t, and y_{jt}, the actual game outcome, with parameters λ. We assume that $p_{jt} = p(S_{jt})$ where S_{jt} is the observed pregame point spread, allowing us to write

$$\log(\mu_{jt}) = \theta_j + X_{jt}\gamma + g(S_{jt}, y_{jt}; \lambda). \tag{5'}$$

Our primary interest is in the effect of a loss or win by the home team, controlling for the spread. Assuming that the Las Vegas betting market provides efficient forecasts of NFL game outcomes, the actual outcome of a game is "as good as random" when we control for the spread, and a specification like (5′) yields unbiased estimates of the causal effect of a loss relative to a win.[19]

An advantage of a Poisson specification is that fixed effects can be included without creating an incidental parameters problem (see Cameron and Trivedi 1998). This is potentially

19. Formally, for a binary random variable y with mean p, $E[y|p, Z] = E[y|p]$ for any Z, so conditioning on p, y is independent of Z. Assuming the mapping $p(S)$ from the spread to p is invertible and does not depend on Z, $E[y|S, Z] = E[y|p, Z] = E[y|p]$, so y is independent of Z conditioning on S.

important in the NIBRS context because there are many small police agencies with relatively low counts of family violence incidents. A second useful property of a Poisson specification is that consistency of the maximum likelihood estimates of the parameters associated with the time-varying covariates (in particular, the parameters λ) only requires that we have correctly specified the conditional mean for $\log(\mu_{jt})$ (Cameron and Trivedi 1986). Consistency does *not* require that the arrival process for IPV incidents is actually Poisson.

IV.B. Baseline Empirical Results

Table IV presents results for our baseline Poisson regressions for at-home male-on-female IPV occurring between the hours of noon and midnight on Sundays of the NFL regular season. In these models we assume that

$$\begin{aligned} g(S_{jt}, y_{jt}, \lambda) = {} & \lambda_1 \cdot 1(S_{jt} \leq -4) + \lambda_2 \cdot 1(S_{jt} \leq -4)\, 1(y_{jt} = 0) \\ & + \lambda_3 \cdot 1(-4 < S_{jt} < 4) + \lambda_4 \cdot 1(-4 < S_{jt} < 4)\, 1(y_{jt} = 0) \\ & + \lambda_5 \cdot 1(S_{jt} \geq 4) + \lambda_6 \cdot 1(S_{jt} \geq 4)\, 1(y_{jt} = 1), \end{aligned}$$

that is, we include dummies for three ranges of the spread and interactions of these dummies with a game outcome indicator. The main coefficients of interest are λ_2, λ_4, and λ_6, which measure the effects of an upset loss, a close loss, and an upset win, respectively. The coefficients associated with the range of the spread (λ_1, λ_3, λ_5) are also potentially interesting but less easily interpreted, because variation in S may be correlated with other factors that affect the likelihood of IPV.

The basic model in column (1) of Table IV includes the spread indicators and the interactions with the win or loss variables, as well as a set of agency fixed effects. Columns (2–5) add in three sets of time-varying covariates: season, week of season, and holiday dummies; local weather conditions on the day of the game; and the Nielsen rating for the local NFL game broadcast. The Nielsen data are only available for the 90% of the game days in our sample that occur in 1997 or later. To check the sensitivity of our results to the sample, column (4) presents a specification identical to the one in column (3) (with agency fixed effects and date and weather controls) but fit to the subsample with Nielsen data.

TABLE IV

UNEXPECTED EMOTIONAL SHOCKS FROM FOOTBALL GAMES AND MALE-ON-FEMALE INTIMATE PARTNER VIOLENCE OCCURRING AT HOME

	Poisson regression intimate partner violence, male on female, at home baseline model				
	(1)	(2)	(3)	(4)	(5)
(a) Loss × predicted win *(upset loss)*	0.112	0.099	0.100	0.096	0.100
	(0.034)	(0.032)	(0.032)	(0.031)	(0.031)
Loss × predicted close *(close loss)*	0.031	0.030	0.032	0.025	0.026
	(0.026)	(0.024)	(0.024)	(0.024)	(0.024)
(b) Win × predicted loss *(upset win)*	0.001	0.007	0.016	0.010	0.007
	(0.037)	(0.027)	(0.027)	(0.029)	(0.029)
Predicted win	–0.014	–0.019	–0.018	–0.009	–0.081
	(0.028)	(0.025)	(0.025)	(0.024)	(0.035)
Predicted close	–0.022	–0.012	–0.013	–0.010	–0.080
	(0.025)	(0.030)	(0.028)	(0.030)	(0.043)
Predicted loss	–0.016	–0.007	–0.016	0.006	–0.071
	(0.023)	(0.021)	(0.021)	(0.021)	(0.039)
Nongame day	—	—	—	—	—
Nielsen rating					0.003
					(0.001)
Agency fixed effects	X	X	X	X	X
Season, week of season, and holiday variables		X	X	X	X
Weather variables			X	X	X
Nielsen data subsample				X	X

TABLE IV
(CONTINUED)

	Poisson regression intimate partner violence, male on female, at home baseline model				
	(1)	(2)	(3)	(4)	(5)
Loss aversion test:					
p-value for row (a) = – row (b)	0.02	0.01	0.00	0.01	0.01
Number of agencies	764	764	764	747	747
Observations	79,386	79,386	79,386	73,522	73,522

Notes. Standard errors in parentheses, clustered by team × season (62 groups). Predicted win indicates a point spread of –4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between –4 and +4 exclusive; predicted loss indicates a spread of +4 or more. Sample is limited to Sundays during the regular NFL football season. Agencies are NIBRS law enforcement units reporting crime for a city or county; agencies are matched to the corresponding local NFL team for their state. The unit of observation is an agency – day (where a day runs from noon to 11:59 PM ET). There are 12 football seasons included in the sample and 17 weeks in each season. The holiday variables include indicators for Christmas Eve, Christmas Day, New Year's Eve, New Year's Day, Halloween, as well as Thanksgiving, Labor Day, Columbus Day, and Veterans Day weekends. Weather variables include indicators for hot, high heat index, cold, windy, rainy, and snowy days. The Nielsen data subsample is limited to observations with available TV ratings; for earlier seasons, not all local markets were tracked by Nielsen Media Research (see note to Table III).

Focusing on the coefficients associated with the game outcome (in the first three rows of the table) notice that the estimates are quite stable across specifications, as would be anticipated if the game outcome is orthogonal to the other covariates, conditional on the spread.[20] The estimates show that an upset loss leads to an approximately 10% increase in the rate of male-on-female at-home IPV. In contrast, the estimated effects of a loss when the game was predicted to be close are only about one-fourth to one-third as large in magnitude and are never significant. The difference provides direct support for reference point behavior of fans. Even more surprising, perhaps, is that upset wins appear to have little or no protective effect. Indeed, the estimated effects of an upset win are all positive, rather than negative, as would be expected if the reaction to wins and losses is symmetric. Formal tests for symmetry (comparing the effect of an upset loss to the negative of the effect for an upset win) are shown in the third-to-last row of the table and indicate substantial evidence of loss aversion.[21]

In column (5) we explore the effect of controlling for the number of households tuned in to watch a local game. The Nielsen audience ratings are a significant factor in game day violence (t = 2.2), with IPV rising by about 0.3% for each percentage point increase in the number of households watching the game. Importantly, however, the addition of this proxy for the number of couples at home together during a game has no effect on the estimated effects of the game outcomes. This suggests that the asymmetric reaction to upset losses and upset wins *cannot* be attributed to the lower number of viewers for expected losses.

V. Extensions and Robustness Checks

V.A. *Intraday Timing of Violence Reports*

Our baseline specifications examine the effect of NFL game outcomes on incidents of IPV in the 12-hour period starting

20. Estimates of the complete set of coefficients for the baseline model in column (3) of Table IV are presented in Appendix Table 5 of the online appendix.

21. As a robustness check, we explored whether violence is not due to upset losses per se but to game outcomes where the home team failed to "beat the spread." Specifically, we added a dummy equal to 1 if the actual point spread was less than the Las Vegas spread. In a model like the one in Table IV, column (3), the estimated effect is relatively small and insignificantly different from 0 (estimate = −0.013, s.e. = 0.020).

at noon. Using NIBRS information on the timing of incident reports (which is coded to the hour of the day), we can refine these models and check whether the pattern is consistent with a causal effect of the game outcome. Specifically, we fit separate models for incidents in various three-hour time windows, allowing separate coefficients for games starting at 1 PM (68% of Sunday games) and 4 PM (26% of Sunday games).[22] The models (presented in Table V) include the Nielsen rating for the number of households watching a game, although the key coefficients are very similar when this variable is excluded.

Each column of Table V shows the effects of game outcomes on violence in a different time window. For the noon to 3 PM window (column [1]) there is no significant effect of any game outcomes. Because the final outcomes of the 1 PM and 4 PM games are still unknown at 3 PM, this is consistent with the assumption that it is the game outcome that matters. By comparison, for the 3–6 PM window (column [2]) there is a significant upset loss effect for 1 PM games, but no significant effect for the 4 PM games. The 1 PM games end in this interval, and the 4 PM games are still going on, so again the pattern is consistent with a causal effect of the game outcome. Between 6 and 9 PM (column [3]) there is no significant effect of an upset loss for the 1 PM games but a sizable effect (a significant 31% increase in violence) for the 4 PM games. Finally, during the 9 PM to midnight interval (column [4]), neither of the two upset loss coefficients is statistically significant. In sum, although the standard errors are fairly large, especially for the less numerous 4 PM games (which include only 16 upset losses and 13 upset wins), the data suggest that the spike in violence after an upset loss is concentrated in a narrow time window surrounding the end of the game.

V.B. Emotionally Salient Games

Assuming that the link between NFL game outcomes and violence arises through emotional cues, one might expect more emotionally salient games to have larger effects. The models in Table VI explore the relative effects of game outcomes for more salient games (upper panel) and less salient games (lower panel)

22. We do not try to fit separate coefficients for games starting at 8 PM, because there are very few of these games (6% of the sample), and until 2006 they were only shown on cable or satellite.

TABLE V
TIMING OF SHOCKS AND VIOLENCE

	Poisson regression intimate partner violence, male on female, at home assaults occurring between (Eastern standard time)			
	Noon to 3 PM	3 to 6 PM	6 to 9 PM	9 to 12 PM
	(1)	(2)	(3)	(4)
Games starting at 1 PM				
Loss × predicted win *(upset loss)*	0.075	0.200	0.036	0.075
	(0.075)	(0.057)	(0.071)	(0.073)
Loss × predicted close *(close loss)*	0.012	–0.002	–0.013	0.077
	(0.058)	(0.065)	(0.056)	(0.050)
Win × predicted loss *(upset win)*	0.017	–0.071	–0.006	0.036
	(0.073)	(0.067)	(0.057)	(0.050)
Predicted win	–0.007	–0.140	0.070	–0.191
	(0.105)	(0.103)	(0.090)	(0.095)
Predicted close	0.024	–0.075	0.049	–0.154
	(0.097)	(0.097)	(0.083)	(0.097)
Predicted loss	–0.075	–0.039	0.029	–0.117
	(0.087)	(0.099)	(0.079)	(0.085)
Nielsen rating	0.001	0.005	–0.002	0.006
	(0.004)	(0.004)	(0.003)	(0.003)
Games starting at 4 PM				
Loss × predicted win *(upset loss)*	0.033	0.235	0.307	0.137
	(0.182)	(0.216)	(0.167)	(0.170)
Loss × predicted close *(close loss)*	0.064	0.211	0.016	–0.042
	(0.113)	(0.110)	(0.091)	(0.103)
Win × predicted loss *(upset win)*	0.115	0.121	–0.282	0.024
	(0.203)	(0.157)	(0.124)	(0.121)
Predicted win	–0.188	0.035	–0.100	–0.040
	(0.240)	(0.177)	(0.160)	(0.160)
Predicted close	–0.263	–0.117	–0.124	–0.083
	(0.213)	(0.154)	(0.129)	(0.126)
Predicted loss	–0.073	–0.022	–0.096	–0.101
	(0.206)	(0.133)	(0.123)	(0.128)
Nielsen rating	0.006	–0.002	0.006	0.004
	(0.007)	(0.006)	(0.005)	(0.005)
Nongame day	—	—	—	—
Number of agencies	563	591	619	620
Observations	63,875	65,285	67,426	67,308

Notes. Standard errors in parentheses, clustered by team × season. Regressions include agency fixed effects, season dummies, week of season dummies, and the holiday and weather variables described in the note to Table IV. Estimated models are comparable to the baseline model in column (3) of Table IV. See notes to Table IV for details. Each column is a single regression for a given three-hour period and allows for separate coefficients for games starting at 1 PM versus 4 PM.

TABLE VI
SHOCKS FROM EMOTIONALLY SALIENT GAMES

	Poisson regression intimate partner violence, male on female, at home			
	Game type = still in playoff contention (1)	Game type = traditional rivals (2)	Game type = sacks ≥ 4, turnovers ≥ 4, or penalties > 80 yards (3)	Game type = highly salient: (1) and [(2) or (3)] (4)
More salient games (game type = 1)				
(a) Loss × predicted win *(upset loss)*	0.126	0.197	0.151	0.172
	(0.034)	(0.046)	(0.048)	(0.045)
Loss × predicted close *(close loss)*	0.054	0.011	0.027	0.082
	(0.031)	(0.053)	(0.038)	(0.046)
Win × predicted loss *(upset win)*	0.027	0.156	0.083	0.063
	(0.048)	(0.080)	(0.040)	(0.059)
Predicted win	–0.021	–0.042	–0.055	–0.042
	(0.028)	(0.036)	(0.035)	(0.029)
Predicted close	–0.040	–0.021	0.019	–0.068
	(0.034)	(0.051)	(0.038)	(0.044)
Predicted loss	–0.023	–0.042	–0.024	0.010
	(0.033)	(0.055)	(0.026)	(0.038)
Less salient games (game type = 0)				
(b) Loss × predicted win *(upset loss)*	–0.016	0.080	0.070	0.028
	(0.080)	(0.034)	(0.037)	(0.041)

TABLE VI
(CONTINUED)

	Poisson regression intimate partner violence, male on female, at home			
	Game type = still in playoff contention (1)	Game type = traditional rivals (2)	Game type = sacks ≥ 4, turnovers ≥ 4, or penalties > 80 yards (3)	Game type = highly salient: (1) and [(2) or (3)] (4)
Loss × predicted close *(close loss)*	–0.003	0.035	0.042	0.018
	(0.030)	(0.026)	(0.034)	(0.028)
Win × predicted loss *(upset win)*	0.002	–0.011	–0.024	–0.004
	(0.039)	(0.030)	(0.033)	(0.027)
Predicted win	–0.013	–0.014	–0.009	–0.010
	(0.055)	(0.027)	(0.028)	(0.030)
Predicted close	0.032	–0.012	–0.012	0.004
	(0.032)	(0.029)	(0.032)	(0.029)
Predicted loss	–0.008	–0.012	0.006	–0.023
	(0.028)	(0.020)	(0.027)	(0.021)
Nongame day	—	—	—	—
Salience test:				
p-value for row (a) = row (b)	0.11	0.01	0.17	0.01
Number of agencies	764	764	764	764
Observations	79,386	79,386	79,386	79,386

Notes. Standard errors in parentheses, clustered by team × season. Regressions include agency fixed effects, season dummies, week of season dummies, and the holiday and weather variables described in the note to Table IV. Estimated models are comparable to the baseline model in column (3) of Table IV. See notes to Table IV for details. Each column is a single regression that allows for separate coefficients by game type. Still in playoff contention indicates that a team has a greater than 10% chance of making the playoffs given their current win-loss record, based on the probability that any NFL team made the playoffs with such a win-loss record between 1995 and 2006. Traditional rivals indicates a game between traditional rivals, as defined by “Rivalries in the National Football League” on Wikipedia.

using the salience classifications introduced in Table III.[23] In column (1), we define salience by whether the home team is still in playoff contention (based on having at least a 10% chance of making the playoffs). Among such games the effect of an upset loss rises to 13%, whereas the effect of a close loss rises to 5% and is marginally significant ($t = 1.8$). In contrast, when the home team is no longer in playoff contention, the effect of an upset loss is small and statistically insignificant. The effects of upset losses in the two types of games are statistically different from each other at the 11% level (third-to-last row of the table).

Column (2) looks at games against a traditional rival team. The effect of an upset loss is about twice as large for a rivalry game compared to a nonrivalry game (20% versus 8%, p-value for test of equality = .01). There is also a marginally significant *increase* in violence following an upset win against a rival ($t = 2.0$), a pattern that is inconsistent with our simple emotional cuing model.

Upset losses in games that are particularly frustrating for fans could also generate a larger emotional response. In column (3) we look at the effects of three potentially frustrating occurrences: four or more sacks, four or more turnovers, or 80 or more penalty yards. At least one of these events happens in about 40% of the games in our sample. For frustrating games defined in this manner, the estimated effect of an upset loss is 15%, compared with an estimated 7% increase in violence for upset losses in nonfrustrating games.

In the final column of Table VI, we narrow the focus to the 37% of games where the home team is still in playoff contention *and* is either playing a traditional rival or the game involved an unusual number of sacks, turnovers, or penalties. The effect of an upset loss is now a 17% increase in IPV, compared to a 13% increase for all playoff contention games in column (1). Moreover, the effect of an upset loss is very close to 0 for games that do not fit these criteria. (In fact, none of the spread or outcome interaction coefficients are large or significant for these games). These patterns suggest that the overall rise in IPV following an upset loss is driven entirely by losses in games that "matter" the most to fans.[24]

23. We fit the models in each column with a full set of interactions between the salience indicator and the six dummies representing the pregame spread and its interaction with the game outcome.

24. It is also possible that conditional on the point spread, more violent men are more likely to watch pivotal games (although the amount of selection would have to be sizable).

V.C. Alternative Parameterization

The models in Tables IV–VI all control for the pregame point spread using a simple set of indicators for three ranges of the spread. As an alternative, we fit a set of models with a second-order polynomial in the point spread and an interaction between the polynomial and a dummy for a home team loss. Consistent with our baseline specifications, the results show that the effect of a home team loss on IPV is large and positive when the home team is expected to win, and declines steadily as the expected likelihood of a home team victory increases. This pattern is also present when we limit attention to "highly salient" games, defined as in column (4) of Table VI. Figure V shows the estimated interaction effects for highly salient games, along with the associated (pointwise) 95% confidence intervals. For highly salient games with pregame point spreads less than –2 or so, the effect of a loss is positive and significantly different from 0. For predicted close games and predicted losses, the effects of a loss are insignificantly different from 0.

V.D. Updating the Reference Point for Game Outcomes

So far we have assumed that family violence is related to the gap between actual game outcomes and fans' *pregame* expectations. Over the roughly three hours that a game actually occurs, however, fans receive new information about the likelihood of final victory, and it is interesting to ask whether the reference point for the emotional cue of the final outcome adjusts accordingly. Some stickiness would seem to be required to generate the pattern of effects in Table V, which shows little or no reaction while a game is in progress but a rise in violence following an upset loss. Because many of these losses would be predictable midway through the game, if fans actually updated their reference point the final score would *not* be a surprise. To address the question more formally, we use information on the score at halftime to form an updated spread and ask whether the rise in violence following a loss is better explained by pregame expectations, or those as of halftime.

To proceed, let p_0 denote the probability of a home team victory based on the pregame spread, and let p_1 denote the point spread at half-time (i.e., the actual point difference at halftime). Assume that the emotional cue generated by the game outcome (y) is based on the deviation from an updated reference point:

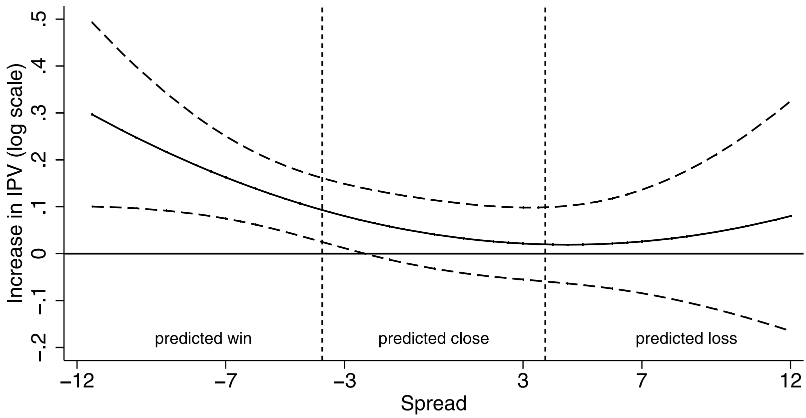

FIGURE V

Differential Increase in Violence for a Loss versus a Win, as a Function of the Spread, for Highly Salient Games

Dashed lines are pointwise 95% confidence intervals. Highly salient games include games in which the local team is still in playoff contention and also is playing against a traditional rival or has an unusually large number of sacks, turnovers, or penalties (see Table VI).

$$p^* = \delta p_1 + (1 - \delta) p_0.$$

With fully rational updating δ would be equal to the coefficient of the halftime spread in a regression of the probability of ultimate victory on the pregame and halftime spreads (which is approximately 0.6), whereas with rigid expectations $\delta = 0$.[25] Substituting this expression into Equation (3), the predicted difference in the risk of violence after a loss versus a win becomes

$$\Delta(risk\,|\,p) = [\beta + (\alpha - \beta)\,\delta p_1 + (\alpha - \beta)(1 - \delta) p_0] q. \quad (3)$$

Consideration of this expression suggests that we extend our basic model by including a second set of indicators for upset loss, upset win, and so on, based on the halftime spread.

25. Appendix Table 1 presents a series of models that relate the probability of a home team win to the pregame spread and the halftime spread. Both are highly significant predictors: the relative magnitude of the halftime spread compared to the pregame spread is approximately 0.6. We also fit models that divide the pregame and halftime spread into three ranges (with cutoffs at −4 and 4 points). In these models the relative magnitudes of the halftime dummies are also about 60% of the combined magnitude.

Estimation results from two alterative variants of this extended specification are presented in Table VII. Because of perfect collinearity, we cannot simply replicate our baseline models by adding dummies for the three ranges of the halftime spread, and a full set of interactions with a loss or win dummy.[26] One estimable specification, which drops the main effects for the range of the halftime spread, is presented in the first column of the table. In this specification the estimated interactions with the predicted outcomes based on the *pregame* spread are all very similar to the estimates from our baseline model, whereas the interactions with the predicted outcomes based on the *halftime* spread are all small and insignificant (individually and jointly). Results from an alternative, and more parsimonious specification are presented in columns (2) and (3). Here, we include a linear control for the spread and a dummy for nongame days, rather than dummies for the range of the spread. As a check on the validity of this simpler specification, the model in column (2) excludes all the halftime variables. As in our baseline models, this simple specification shows a roughly 10% effect of upset losses, and small and insignificant effects of upset wins and close loses. Column (3) extends this model by adding dummies for upset win, upset loss, and close loss, based on predictions using the halftime spread. As in column (1), the halftime variables are jointly insignificant ($p = .50$) though the point estimates are somewhat larger in magnitude. Based on the results from these two specifications, we conclude that fans' emotional reactions to game outcomes appear to be driven by the game outcome relative to expectations *at the start of the game*, with little or no updating using information as of halftime.

V.E. *Other Forms of Family Violence, Alcohol and Drug Use, Severity of Violence*

As noted in Table I, the most common family violence incidents are those committed at home by men against their wives and girlfriends. Although our main results concern these types of incidents, we also examined the effects of NFL game outcomes on

26. Our baseline model includes dummies for three ranges of the pregame spread (S_1, S_2, S_3), and interactions of these with a loss dummy (L), treating nongame days as the base case. Call the additional indicators for the halftime spread (H_1, H_2, H_3). Since $S_1 + S_2 + S_3 = H_1 + H_2 + H_3 = 1$, the set of 12 variables (S_1, S_2, S_3), (H_1, H_2, H_3), ($S_1 \times L, S_2 \times L, S_3 \times L$), ($H_1 \times L, H_2 \times L, H_3 \times L$) has only 9 degrees of freedom.

TABLE VII
UPDATING BASED ON THE HALFTIME SCORE DIFFERENTIAL

	Poisson regression intimate partner violence, male on female, at home		
	(1)	(2)	(3)
Loss × predicted win *(upset loss)*	0.116	0.105	0.142
	(0.033)	(0.028)	(0.033)
Loss × predicted close *(close loss)*	0.046	0.035	0.059
	(0.024)	(0.020)	(0.026)
Win × predicted loss *(upset win)*	0.006	0.007	–0.015
	(0.029)	(0.025)	(0.030)
Loss × halftime predicted win *(halftime upset loss)*	–0.010		–0.030
	(0.031)		(0.035)
Loss × halftime predicted close (*halftime close loss*)	–0.036		–0.047
	(0.021)		(0.026)
Win × halftime predicted loss (*halftime upset win*)	0.004		0.023
	(0.037)		(0.042)
Predicted win	–0.018		
	(0.026)		
Predicted close	–0.014		
	(0.028)		
Predicted loss	–0.006		
	(0.022)		
Spread		0.001	0.003
		(0.002)	(0.002)
Halftime spread			–0.001
			(0.001)
Nongame day		0.016	0.015
		(0.019)	(0.020)
Joint significance of halftime variables p-value	.36		.50
Number of agencies	764	764	764
Observations	79,386	79,386	79,386

Notes. Standard errors in parentheses, clustered by team × season. Regressions include agency fixed effects, season dummies, week of season dummies, and the holiday and weather variables described in the note to Table IV. Estimated models are comparable to the baseline model in column (3) of Table IV. See notes to Table IV for details. Predicted win, predicted close, and predicted loss are based on the pregame point spread (negative spreads indicate the number of points a team is expected to win by). Predicted win indicates a point spread of –4 or less; predicted close indicates a point spread between –4 and +4 exclusive; predicted loss indicates a spread of +4 or more. Halftime predicted win, halftime predicted close, and halftime predicted loss are based on the halftime point spread, which is the observed point difference at halftime (where a negative halftime spread indicates the number of points a team is actually winning by at halftime). Predicted halftime win indicates a halftime spread of –4 or less; predicted halftime close indicates a halftime spread between –4 and +4 exclusive; predicted halftime loss indicates a halftime spread of +4 or more. For an analysis of the relative predictive power of these measures, see the online Appendix Table 1.

family violence committed in different places and involving different combinations of victims and offenders. The results are summarized in Appendix Table 2 (available in the online appendix).

We find that upset losses have no significant effect on away-from-home violence. As a result, the effect on *total* male-on-female violence (combining at-home and away-from-home) is somewhat smaller than the effect on at-home violence (around 7%). We also find that NFL game outcomes have no large or significant effect on the rate of intimate partner violence committed by women. On the other hand, violence by men against wives and girlfriends both respond about equally to upset losses. Rates of violence against family members other than an intimate partner (e.g., a child, sibling, or parent) also show no significant relationship with the outcomes of local NFL games, whereas there is some indication of an effect on rates of violence at home against friends.

To gain some insights into the kinds of incidents that are most affected by the emotional cues of NFL game outcomes, we fit separate Poisson models for incidents with alcohol and/or drugs involved, and for serious versus minor assaults.[27] The results, summarized in Appendix Table 3 of the online appendix, suggest that all forms of IPV rise following an upset loss, with no significant difference in the rise in alcohol-related and non–alcohol-related offenses. We also looked at incidents occurring in larger and smaller places (populations over and under 50,000 as of 2000) and incidents committed by younger and older offenders (less than age 30 versus 30 or older), and found insignificantly different effects of upset losses.

V.F. *Other Robustness Tests*

Finally, we conducted a number of additional specification checks to judge the robustness of our main results. These are summarized in Appendix Table 4 of the online appendix. The specification checks include the use of a negative binomial model instead of a Poisson, estimation of models with date fixed effects, and inclusion of separate linear time trends for each of the individual teams in our sample. None of these changes has much impact on our main results. We also investigated different ways of dealing with the presence of days with no reported crime in the NIBRS data. Reassuringly, our main results are very similar, regardless of whether we treat these "no crime" days as missing or true zeros.

27. Recall that in about 20% of incidents the reporting officer notes that alcohol or drugs were a contributing factor in the incident—these are the incidents with "alcohol involved." Serious assaults include aggravated assaults and all other incidents in which the victim was physically injured.

VI. Discussion

Our empirical results show a roughly 10% effect of an upset loss by the local NFL team on the rate of male-on-female at-home IPV. To provide some context for the magnitude of this effect, we estimated a set of Poisson models for the rate of IPV on *all* days of the year for the six states of our estimation sample. These models included agency fixed effects; an expanded set of holiday dummies; dummies for the day of the week, the month, and the sample year; and the same set of weather controls included in our main models.[28] The resulting estimates show large and precisely estimated effects of major holidays on the rate of IPV: for example, Christmas Day +18%, Thanksgiving +20%, Memorial Day +30%, New Year's Day +31%, New Year's Eve +22%, and July 4 +29%. They also show a significant positive effect of hotter weather: relative to a day with a maximum temperature less than 80°F, IPV is 8% higher when the maximum temperature is over 80. Thus, an upset loss is comparable to the effect of a hot day, or about one-third of the effect of a holiday like Memorial Day or Independence Day. We view the magnitude of the cuing effect attributable to an upset loss as rather large, considering that only a fraction of the population are serious football fans and our sample largely excludes the cities in which the NFL teams are located.

Our findings add to the literature on the impact of media on violence and the well-being of women. Television has been shown to influence a variety of behaviors and attitudes, including fertility choices, women's status, and the acceptability of intimate partner violence (La Ferrara et al., 2008; Jensen and Oster 2009). As emphasized by Dahl and DellaVigna (2009), media (particularly violent movies) affects behavior not only via content but also because it changes time spent in alternative activities. In our case, NFL football games are likely to bring couples together, and the emotional cues associated with televised games place women at an elevated risk of abuse.

From a broader perspective, our analysis contributes to the growing literature on the importance of reference points in observed behavior (see DellaVigna 2009 for a review; Crawford and Meng 2009 for a recent empirical contribution; Abeler, Falk, Gotte, and Huffman 2009 for a recent laboratory experiment). A key

28. These models, like our main results in Table IV, were fit using data on male-on-female at-home incidents from noon to midnight only.

advantage of our setting is that the "rational" reference points for NFL game outcomes are readily observable and vary widely across games. Our finding that upset losses have a large effect on family violence, whereas losses in games that were expected to be close have small and insignificant effects, provides confirmation of rational reference point formation. In comparison to the large and systematic effects of upset losses, we also find very small effects from upset wins, suggesting that gains and losses have asymmetric behavioral effects.

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Supplementary Material

Supplementary material is available at *The Quarterly Journal of Economics* online.

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