Does Movie Violence Increase Violent Crime?*

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Abstract

Laboratory experiments in psychology find that media violence increases aggression in the short run. We analyze whether media violence affects violent crime in the field. We exploit variation in the violence of blockbuster movies from 1995 to 2004, and study the effect on same-day assaults. We find that violent crime *decreases* on days with larger theater audiences for violent movies. The effect is partly due to voluntary incapacitation: between 6PM and 12AM, a one million increase in the audience for violent movies reduces violent crime by 1.1 to 1.3 percent. After exposure to the movie, between 12AM and 6AM, violent crime is reduced by an even larger percent. This finding is explained by the self-selection of violent individuals into violent movie attendance, leading to a substitution away from more volatile activities. In particular, movie attendance appears to reduce alcohol consumption. Like the laboratory experiments, we find indirect evidence that movie violence increases violent crime; however, this effect is dominated by the reduction in crime induced by a substitution away from more dangerous activities. Overall, our estimates suggest that in the short-run violent movies deter almost 1,000 assaults on an average weekend. While our design does not allow us to estimate long-run effects, we find no evidence of medium-run effects up to three weeks after initial exposure.

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1 Introduction

Does media violence trigger violent crime? This question is important for both policy and scientific research. In 2000, the Federal Trade Commission issued a report at the request of the President and of Congress, surveying the scientific evidence and warning of negative consequences. In the same year, the American Medical Association, together with five other public-health organizations, issued a joint statement on the risks of exposure to media violence (Joint Statement, 2000).

The evidence cited in these reports, surveyed by Anderson and Buschman (2001) and Anderson et al. (2003), however, does not establish a causal link between media violence and violent crime. The experimental literature exposes subjects in the laboratory (typically children or college students) to short, violent video clips. These experiments find a sharp increase in aggressive behavior immediately after the media exposure, compared to a control group exposed to non-violent clips. This literature provides causal evidence on the short-run impact of media violence on aggressiveness, but not whether this translates into higher levels of violent crime in the field. A second literature (e.g., Johnson et al., 2002) shows that survey respondents who watch more violent media are substantially more likely to be involved in self-reported violence and crime. This second type of evidence, while indeed linking media violence and crime, is plagued by problems of endogeneity and reverse causation.

In this paper, we provide causal evidence on the short-run effect of media violence on violent crime. We exploit the natural experiment induced by time-series variation in the violence of movies shown in the theater. As in the psychology experiments, we estimate the short-run effect of exposure to violence, but unlike in the experiments, the outcome variable is violent crime rather than aggressiveness. Importantly, the laboratory and field setups also differ due to self-selection and to the context of violent media exposure.

Using a violence rating system from *kids-in-mind.com* and daily revenue data, we generate a daily measure of national-level box office audience for strongly violent (e.g., "Hannibal"), mildly violent (e.g., "Spider-Man"), and non-violent movies (e.g., "Runaway Bride"). Since blockbuster movies differ significantly in violence rating, and movie sales are concentrated in the initial weekends after release, there is substantial variation in exposure to movie violence over time. The audience for strongly violent and mildly violent movies, respectively, is as high as 12 million and 25 million people on some weekends, and is close to zero on others (see Figures 1a-1b). We use crime data from the National Incident Based Reporting System (NIBRS) and measure violent crime on a given day as the sum of reported assaults (simple or aggravated) and intimidation.

We find no evidence that exposure to media violence increases violent behavior in the short-run. After controlling flexibly for seasonality, we find that, on days with a high audience for violent movies, violent crime is *lower*. To rule out unobserved factors that contemporaneously increase movie attendance and decrease violence, such as rainy weather, we use two strategies. First, we add controls for weather and days with high TV viewership. Second, we instrument for movie audience using the predicted movie audience based on the following weekend's audience. This instrumental variable strategy exploits the predictability of the weekly decrease in attendance. Adding in controls and instrumenting, the correlation between movie violence and violent crime becomes more negative and remains statistically significant.

The estimated effect of exposure to violent movies is small in the morning or afternoon hours (6AM-6PM), when movie attendance is minimal. In the evening hours (6PM-12AM), instead, we detect a significant negative effect on crime. For each million people watching a strongly or mildly violent movie, respectively, violent crimes decrease by 1.3 and 1.1 percent. The effect is smaller and statistically insignificant for non-violent movies. In the nighttime hours following the movie showing (12AM-6AM), the delayed effect of exposure to movie violence is even more negative. For each million people watching a strongly or mildly violent movie, respectively, violent crime decreases by 1.9 and 2.1 percent. Non-violent movies have no statistically significant impact. Unlike in the psychology experiments, therefore, media violence appears to decrease violent behavior in the immediate aftermath of exposure, with large aggregate effects. The total net effect of violent movies is to decrease assaults by roughly 1,000 occurrences per weekend, for an annual total of about 52,000 weekend assaults prevented.

We also examine the delayed impact of exposure to movie violence on violent crime. While our research design (like the laboratory designs) cannot test for a long-run impact, we can examine the medium-run impact in the days and weeks following exposure. We find no impact on violent crime on Monday and Tuesday following weekend movie exposure. We also find no impact one, two, and three weeks after initial exposure, controlling for current exposure. This implies that the same-day decrease in crime is unlikely to be due to intertemporal substitution of crime from the following days.

To test the robustness of our results, we disaggregate the effects by individual violence levels ranging from 0 to 10, and by one-hour time blocks. We explore other specifications (including Poisson regression), alternative instrument sets, and an alternative measure of movie violence. The results are all consistent with the baseline analysis. Additionally, we generate a placebo data set to test for uncontrolled seasonal factors in movie releases, and find no effect with the placebo treatment. A final set of results exploits the variation in movie violence from rentals of DVDs and VHSs. These estimates are broadly consistent with our main estimates using the box office data, although the standard errors are larger.

In order to interpret the results, we develop a simple model where utility maximizing consumers choose between violent movies, non-violent movies, and an alternative activity. These options generate violent crime at different rates. The model provides three main insights. First, in the reduced form implied by the model, the estimates of exposure to violent movies capture the impact for the self-selected population that chooses to attend violent movies, and not the population at large. In particular, the violent sub-population is likely to self-select more into more violent movies, magnifying any effects of exposure. Second, the reduced-form estimates capture the net effect of watching a violent movie and not participating in the next-best alternative activity. A blockbuster violent movie has a direct effect on crime as more individuals are exposed to screen violence. But there is also an indirect effect as people are drawn away from the alternative activity (such as drinking at a bar) and its associated level of violence. Third, it is in principle possible to identify the direct effect of strongly violent movies if one can account for self-selection.

We interpret the first empirical result, that exposure to violent movies lowers same-day violent crime in the evening (6PM to 12AM), as voluntary incapacitation. On evenings with high attendance at violent movies, potential criminals choose to be in the movie theater, and hence are incapacitated from committing crimes. The incapacitation effect is increasing in the violence of the movie because potential criminals self-select into violent, rather than non-violent, movies. To document whether the degree of self-selection required is plausible, we use data from the Consumer Expenditure Survey time diaries. We find that demographic groups with higher crime rates, such as young men, select disproportionately into watching violent movies, suggesting that the observed finding is indeed consistent with incapacitation.

The second result is that violent movies lower violent crime in the night after exposure (12AM to 6AM). As the model illustrates, the estimates capture a net effect: they reflect the difference between the direct effect of movie violence on aggression, compared to the violence level associated with an alternative activity. Hence, the reduction in crime associated with violent movies is best understood as movie attendance displacing more volatile alternative activities both during and after movie attendance. Since alcohol is a prominent factor that has been linked to violent crime (Carpenter and Dobkin, 2007), and alcohol is not served in movie theaters, one potential mechanism is a reduction in alcohol consumption associated with movie attendance. Consistent with this mechanism, we find larger decreases for assaults involving alcohol or drugs. We also find a large displacement of assaults taking place in bars and night clubs, although these estimates are imprecise given the relative rarity of such assaults.

This second finding appears to contradict the evidence from laboratory experiments, which find that violent movies increase aggression through an arousal effect. However, the two methodologies estimate different effects. The laboratory experiments estimate the impact of violent movies in partial equilibrium, holding the alternative activities constant. Our natural experiment instead allows individuals to decide in equilibrium between a movie and an alternative activity. Exposure to movie violence can lower violent behavior relative to the foregone alternative activity (the field findings), even if it increases violent behavior relative to exposure to non-violent movies (the laboratory findings). Indeed, the pattern of effects for mildly violent and strongly violent movies provides indirect evidence of arousal effects for strongly violent movies. This arousal effect, however, is of limited magnitude—on net, violent movies still induce substantially less violent behavior than the alternative activity. We also discuss other differences between the laboratory experiments and the field evidence, including the policy implications of each. As such, this paper contributes to the literature on the relationship between laboratory and field evidence in psychology and economics (Levitt and List, 2007).

A common theme to the findings above is the importance of self-selection of potential criminals into more violent movies. We provide separate evidence that selection helps explain other results on the impact of movies. We use the Internet Movie Database ratings by young males to categorize movies highly liked by young males. We find evidence that, even after controlling for movie violence, exposure to movies that attract young men significantly lowers violent crime. In addition, using data which rates movies on other dimensions including sexual content and profanity, we show that the types of movies that do not attract young people do not lower crime substantially.

Our paper is related to a growing literature in economics on the effect of the media. Among others, Besley and Burgess (2002), Green and Gerber (2004), Stromberg (2004), Gentzkow (2006), and DellaVigna and Kaplan (2007) provide evidence that media exposure affects political outcomes. More related, Gentzkow and Shapiro (2008) show that the introduction of television did not have adverse effects on educational outcomes. As in this paper, media exposure did not have a negative impact, though Gentzkow and Shapiro estimate long-term, rather than short-run, elasticities. Finally, Card and Dahl (2007) show that on days of NFL football games, domestic violence spikes, particularly for upset losses involving a local team.

Our paper also complements the evidence on incapacitation, from the effect of school attendance (Jacob and Lefgren, 2003) to the effect of imprisonment (DiIulio and Piehl, 1991; Levitt, 1996; Spelman, 1993). Our paper differs from this literature because the incapacitation is optimally chosen by the consumers, rather than being imposed. Finally, this paper is related to the literature on the impact of emotions such as arousal (Loewenstein and Lerner, 2003; Ariely and Loewenstein, 2005) on economic decisions.

The remainder of the paper is structured as follows. Section 2 presents a simple model of movie attendance choice and its effect on violence. Section 3 describes the data. In Section 4, we present the main empirical results. Sections 5 and 6 provide interpretations, additional evidence, and a comparison to the psychology experiments. Section 7 concludes.

2 Framework

Utility. In this section we model the choice to view a violent movie and the resulting impact on the level of aggregate violence following exposure. We begin by assuming individuals choose among a set of mutually exclusive activities, where for simplicity, we consider four options: watch a strongly violent movie a^v, watch a mildly violent movie a^m, watch a non-violent movie a^n, or participate in an alternative social activity a^s.

Individuals choose to watch a violent movie if it yields more utility than the other options. Holding the violence level of a movie fixed, the utility of a movie increases with its quality. While we could assume a standard multinomial choice model, any choice model implies probabilistic demand functions for each of the activities, leading to demand for movies $P(a^v)$, $P(a^m)$, $P(a^n)$, and demand for the alternative activity $1 - P(a^v) - P(a^m) - P(a^n)$. A higher-quality movie of type j increases the consumption probability $P(a^j)$. We do not make further assumptions about utility since the existence of probabilistic demand functions are sufficient for the derivations in this section.[1]

We allow for a simple form of heterogeneity in the taste for movies. For ease of exposition, we denote the group with high taste for violent movies as young y and the other group as old o. The fraction of the relevant population choosing activity j is denoted as $P(a_i^j)$ for $i = y, o$ and $j = v, m, n, s$. We assume that the young like violent movies relatively more than the old: $P(a_y^v)/P(a_o^v) > P(a_y^m)/P(a_o^m) > P(a_y^n)/P(a_o^n)$. The aggregate demand functions for the young and old are simply these probabilities multiplied by group size N_i, that is, $N_i P(a_i^j)$.

Violence. We model the production function of violence as follows. Violence, which does not enter individuals' utility functions, depends on the type of movies viewed, as well as participation in the alternative social activity. The level of aggregate log violence, $\ln V$, is a linear function of the group audience size for the different movies and the group size of the alternative social activity, aggregated over young and old:

$$\ln V = \sum_{i=y,o} [\sum_{j=v,m,n} \alpha_i^j N_i P(a_i^j) + \sigma_i N_i (1 - P(a_i^v) - P(a_i^m) - P(a_i^n))]. \quad (1)$$

The key parameters in the production function are α_i^v, α_i^m, α_i^n, and σ_i, which are all (weakly) positive. We illustrate the parameters for the young ($i = y$); a similar interpretation holds for the old. The parameter α_y^v indicates that increasing the young audience size of violent movie by 1, ceteris paribus, will result in roughly a α_y^v percent increase in violence (for small α_y^v). The parameter α_y^v thus will be *larger* if movie violence triggers violence, and *smaller* if movie violence has a cathartic effect. A similar interpretation holds for α_y^m and α_y^n , as applied, respectively, to mildly violent and non-violent movies. Finally, σ_y indicates that increasing the number of young people undertaking the alternative activity by 1 will result in a σ_y percent increase in violence. The parameter σ_y is likely to be large if the alternative social activity, such as drinking at a bar, brings potential criminals together or otherwise triggers violence.

[1] For example, if each consumer can participate in only one activity, it is natural to assume that utility depends on the quality of that activity and the quantity of other goods consumed. Normalizing the price of other goods to be \$1, assuming additive separability for the error term, and using a linear utility function we can write the utility of the alternatives as $U^j = \delta(I - p^j) + \theta q^j + e^j$ for $j = v, m, n, s$ where p^j, q^j, and e^j are the price, quality, and error term associated with the activities and I is income. Assuming an extreme value distribution for the error terms, the structural parameters δ and θ could be estimated using a multinomial logit, as could the probabilities of each choice, $Pr(a^j) = exp(\delta(I - p^j) + \theta q^j) / \sum_{k=v,m,n,s} exp(\delta(I - p^k) + \theta q^k)$ for $j = v, m, n, s$. This is just an example; we do not impose the multinomial logit setup in our empirical work.

Since individual-level consumption data for movie attendance for each movie is not readily available, aggregate data must be used. (In the empirical section, we discuss ways to estimate audience share by consumer type with auxiliary data.) Given this limitation, we rewrite equation (1) in terms of aggregate movie attendance by type of movie. Letting A^j denote aggregate movie attendance (for young and old combined) and letting x^j denote the young audience share for movie j, log violence can be expressed as

$$\ln V = (\sigma_y N_y + \sigma_o N_o) + \sum_{j=v,m,n} \left[x^j(\alpha_y^j - \sigma_y) + (1 - x^j)(\alpha_o^j - \sigma_o) \right] A^j \tag{2}$$

where $A^j = N_y P(a_y^j) + N_o P(a_o^j)$ and $x^j = N_y P(a_y^j)/(N_y P(a_y^j) + N_o P(a_o^j))$. Equation (2) makes clear that the effect of total audience size on log violence is a weighted average of the effects for the young and old subgroups.

Empirical strategy. Equation (2) motivates the approach we take in our empirical work. The estimating equation which follows directly from equation (2) is

$$\ln V = \beta_0 + \beta^v A^v + \beta^m A^m + \beta^n A^n + \varepsilon. \tag{3}$$

where ε is an additively separable error term. This equation closely parallels the one used in Section 4, which differs only in that there we introduce time subscripts and include control variables.[2] Comparing equation (3) and equation (2), we can write the coefficients as

$$\beta^j = x^j(\alpha_y^j - \sigma_y) + (1 - x^j)(\alpha_o^j - \sigma_o) \text{ for } j = v, m, n. \tag{4}$$

Notice the parameter β^j is constant only if the young audience share x^j is constant in response to changes in movie quality. In what follows, we assume that this is approximately the case, i.e., that when movie quality changes, demand by young and old roughly rises and falls proportionately with each other.[3]

Expression (4) illustrates two important points. First, the impact of a violent movie β^v is the sum of two effects: a direct effect, captured by α_i^v, and an indirect effect, captured by σ_i. The direct effect is the impact of violent movies on violence for group i. This impact can be large, in the case of arousal or imitation, as suggested by the experiments, or small, if exposure to media violence has a cathartic effect. The indirect effect is due to the fact that the violent movie displaces alternative social activities; to the extent these activities, such as drinking at

[2]This formulation is very similar to that of a Poisson count model. We have opted for the current formulation, treating violence as a continuous variable, as the daily violent crime counts are large (and never zero). Empirically, the Poisson and the log-linear OLS regressions give very similar marginal effects.

[3]This is true for the example given in footnote 1 when utility is modified to account for age differences. Adding age-specific constants for violent and nonviolent movies to the utility functions, and assuming probabilistic demand for any single movie is relatively small (i.e., aggregate demand is less than 10% of the population), the multinomial logit setup yields an approximately constant ratio of young to old demand within each movie type.

bars, trigger crime ($\sigma_i > 0$), this can make the net effect β^v negative. Second, heavy movie-goers contribute most to the identification of β^v. To the extent the young like violent movies more than the old, they will be over-represented in the audience for violent movies, and hence x^v will be larger than $N_y/(N_y + N_o)$. These two points apply also to the exposure to mildly violent movies (β^m) and to non-violent movies (β^n).

To illustrate the interpretation of expression (4) further, consider a simplified example. Assume the old do not commit violent acts under any circumstance ($\alpha_o^v = \alpha_o^m = \alpha_o^n = \sigma_o = 0$). Then the coefficient for exposure to movies with violence level j, $\hat{\beta}^j$, is $x^j(\alpha_y^j - \sigma_y)$.

To start, suppose also that the direct effect of movie exposure is the same for all types of movies ($\alpha^n = \alpha^m = \alpha^v = \alpha$). In this case, the qualitative impact of exposure to any type of movie is the same, and it depends on the sign of $\alpha_y - \sigma_y$, which can be positive or negative. To the extent that the aftermath of movie attendance is more dangerous that the alternative activity ($\alpha_y - \sigma_y > 0$), then movie attendance increases crime: $\beta^j > 0$ for all j. This is the case, for example, if movies provide a meeting point for potential criminals. To the extent, instead, that movie attendance is less dangerous than the alternative activity ($\alpha_y - \sigma_y < 0$), movie-going decreases crime: $\beta^j < 0$ for all j. This is the case, for example, if movie attendance leads to earlier bed times and lower alcohol consumption, compared to, say, bar attendance.

Even in the absence of a differential direct effect of violent movies, the level of violence in a movie can affect crime. This is because more violent movies are more likely to attract the violent sub-population (i.e., $x^v > x^m > x^n$). (We provide empirical support for this type of selection below.) Selection into violent movies implies the effect of exposure to movies is increasing in the violence level of the movie: $|\beta^v| > |\beta^m| > |\beta^n|$. The two solid lines in Figure 2 illustrate the two cases where movies are more ($\beta^j > 0$) and less ($\beta^j < 0$) conducive to crime than the alternative activity. To match the level of detail in our data, in the figure we allow the violence level of a movie to vary from 0 to 10. We have graphed the case where the share of violent people watching a movie increases linearly in the violence level; more generally, all that is required is that the share of violent people increases in the violence level.

Now consider what happens when there can be a differential direct impact of violent movies relative to non-violent movies. We distinguish two cases. The first case is that violent movies trigger additional violence through imitation or arousal ($\alpha_y^v > \alpha_y^m > \alpha_y^n$), as the psychology experiments suggest. The two dotted lines in Figure 2 display the effects in this case, assuming arousal effects do not start until violence level 5. Imitation and arousal effects cause the net effect of movie exposure to become more positive as violent content increases. We point out that it may be difficult to detect this effect if movies are *more* dangerous than the alternative activity ($\beta^j > 0$), since the arousal effect is hard to distinguish from stronger selection (much higher x^v relative to x^n). It is easier, instead, to detect arousal or imitation when movies are *less* dangerous than the alternative activity ($\beta^j < 0$), as the arousal effect works in the opposite direction of selection. The second case is that exposure to violent movies has a cathartic effect and hence lowers the incidence of violence ($\alpha_y^v < \alpha_y^m < \alpha_y^n$). This case, captured by the dashed lines in Figure 2, is symmetric to the arousal case. It is easier to detect if movies are *more* dangerous than the alternative activity ($\beta^j > 0$).

This discussion and Figure 2 make clear that, while an estimate of β^v answers the important question of how violent crime responds to movie exposure, it is not simple to separate the direct effect operating through α_y^v from the indirect effect operating through σ_y. We can, however, attempt to compare the direct impact of violent movies α_y^v relative to the impact of mildly violent α_y^n and non-violent movies α_y^n. We also point out a difference between the effect of movies in the aftermath of exposure (the delayed effect), as we have discussed so far, versus during the movie showing (the contemporaneous effect). When interpreting the contemporaneous effect, the direct effect equals zero for all levels of movie violence (insofar as there are mechanically no crimes while in the movie theater). Hence, qualitatively the effect of exposure while physically in the movie theater should roughly equal $\beta^j = -x^j\sigma_y$, which is captured by the solid lines in Figure 2.

Before continuing, a brief comparison to the psychology experiments is in order. In the experiments, exposure to violent and non-violent movies is manipulated as part of the treatment. The subjects do not optimally choose relative to a comparison activity a^s. Within our empirical specification, the estimate of β^v in the laboratory experiment would yield

$$\beta_{lab}^v = \frac{N_y}{N_y + N_o}\alpha_y^v + (1 - \frac{N_y}{N_y + N_o})\alpha_o^v.$$

Comparing this estimate to the estimate on field data (4), two differences are apparent. First, the impact of media violence does not include the indirect effect of σ which operates through the alternative activity. By virtue of experimental control, the indirect effect is 'shut down.' Second, the weights on the young and old coefficients are different (compare $N_y/(N_y + N_o)$ to x^v). The laboratory experiments capture the reaction to media violence of a representative sample, while the field evidence assigns more weight to the parameter of the individuals that sort into the violent movies (the 'young'). Hence, the laboratory setting is not representative of exposure to movie violence in most field settings, where consumers choose what media to watch. However, it is representative of instances of unexpected exposure, as in the case of a violent advertisement or a trailer placed within family programming.

3 Data

In this section we introduce our various data sets, provide summary statistics, and describe general patterns of movie attendance and violent crime.

Movie data. The data on box-office revenue is from *www.the-numbers.com*, which uses the studios and *Exhibitor Relations* as data sources. Information on weekend (Friday through

Sunday) box-office sales is available for the top 50 movies consistently from January 1995 on. Daily revenue is available for the top 10 movies from mid-August 1997 on. In our analysis, we focus on daily data for Friday, Saturday, and Sunday. We do this because movie attendance, and therefore the identifying variation used in our analysis, is concentrated on weekends (see Table 1). To estimate the number of people in the movie theater audience, we deflate both the weekend and the daily box office sales by the average price of a ticket.

For the period January 1995 to mid-August 1997 and for all movies that do not make the daily top 10 list, we impute daily box office revenue using the weekend sales for the same movie in the previous weekend. The imputation procedure, described in detail in Appendix A, takes advantage of the regularity in the within-week pattern of sales. Ticket sales peak on Saturday, Friday, and Sunday (in decreasing order) and are lowest on Tuesday through Thursday (Table 1). The accuracy of the imputation is high. In the sub-sample for which both the daily and the weekend data are available, a regression of predicted daily revenue on actual daily revenue yields a slope coefficient of 0.9559 and has an R^2 of 0.9590.

We match the box office data to violence ratings from *www.kids-in-mind.com*, a site recognized by *Time Magazine* in 2006 as one of the "Fifty Coolest Websites." Since 1992, this non-profit organization has assigned a 0 to 10 point violence rating to almost all movies with substantial sales. The ratings are performed by trained volunteers who, after watching a movie, follow guidelines to assign a violence rating. In Appendix Table 1, we illustrate the rating system by listing the three movies with the highest weekend audiences within each rating category. For most of the analysis, we group movies into three categories: strongly violent, mildly violent, and non-violent. Movies with ratings between 0 and 4 such as "Toy Story"and "Runaway Bride" have very little violence; their *MPAA* ratings range from G to R (for sexual content or profanity). Movies with ratings between 5 and 7 contain a fair amount of violence, with some variability across titles ("Spider Man" versus "Mummy Returns"). These movies are typically rated PG-13 or R. Movies with a rating of 8 and above are violent and almost uniformly rated R. Examples are "Hannibal" and "Saving Private Ryan". Compared to other movies, violent movies are disproportionately more likely to be in the "Action/Adventure" and "Horror" genres and are very unlikely to be in the "Comedy" genre. For a very small number of movies, typically with limited audiences, a rating is not available.[4]

Movie violence measures. We define the number of people (in millions) exposed to movies of violence level k on day t as $A_t^k = \sum_{j \in J} d^{j \epsilon k} a_{j,t}$, where $a_{j,t}$ is the audience of movie j on day t, $d^{j \epsilon k}$ is an indicator for film j belonging to violence level k, and J is the set of all movies. The violence level varies between 0 and 10. To deal with the small number of movies with missing violence ratings, we assume ratings are missing at random with respect to the level of violence in a movie, and inflate each day's exposure variables A_t^k accordingly. The

[4]The re-releases of Star Wars V and VI in 1997 were not rated because the original movie pre-dates *kids-in-mind*. We assigned them the violence rating 5, the same rating as for the other Star Wars movies.

average share of missing ratings is 4.1 percent across days.

We define three summary measures of exposure to movies with differing levels of violence. The measure of exposure to strongly violent movies on day t is the audience for movies with violence levels between 8 and 10, $A_t^v = \sum_{k=8}^{10} A_t^k$. Similarly, exposure to mildly violent A_t^m and non-violent A_t^n movies on day t are defined as the aggregated audiences for movies with a violence level between 5-7 and 0-4, respectively.

Figure 1a plots the measure of strong movie violence, A_t^v, over the sample period 1995 to 2004. To improve readability, we plot the weekend audience (the sum from Friday to Sunday) instead of the daily audience. In the graph, we label the top 10 weekends with the name of the movie responsible for the spike. The series exhibits sharp fluctuations. Several weekends have close to zero violent movie audience. On other weekends, over 12 million people watch violent movies. The spikes in the violent movie series are distributed fairly uniformly across the years, and decay within 2-3 weeks of the release of a violent blockbuster.

Figure 1b plots the corresponding information for the measure of mild movie violence, A_t^m. Since more movies are included in this category, the average weekend audience for mildly violent movies is higher than for strongly violent movies, with peaks of up to 25 million people. There is some seasonality in the release of violent movies, with generally lower exposure to movie violence between February and May. This seasonality is less pronounced for the strongly violent movies compared to the mildly violent movies.

To put audience size into perspective, note that blockbuster movies are viewed by a sizeable fraction of the U.S. population. Over a weekend, strongly violent and mildly violent blockbusters attract up to 4% and 8%, respectively, of the U.S. population (roughly 300 million). This extensive exposure provides the identifying variation of our setup.

Violent crime data. Our source for violent crime data is the National Incident Based Reporting System (NIBRS). This data set is uniquely suited for the present study along two important dimensions. First, it reports violent acts known to police, such as verbal intimidation or fistfights, which do not necessarily result in an arrest. Second, it reports the date and time of the crime, allowing us to match movie attendance and violent crime at the daily level. Alternative large-scale data sets on crime do not contain this same type of information. For example, the Uniform Crime Report only includes data for arrests and is aggregated at the monthly level. The National Crime Victimization Survey, while incident-based like the NIBRS, is subject to recall bias and also aggregates at the monthly level.

The NIBRS data collection effort is a part of the Uniform Crime Reporting Program which is a Federal law enforcement program. Currently, submission of NIBRS data is still voluntary at the city, county, and state level. Between 1995 (the first year of NIBRS data) and 2004, the number of reporting agencies has increased substantially. In 1995, only 4% of the U.S. population was covered by a NIBRS reporting agency. As of August 2005, there were 29 states certified to report NIBRS data to the FBI, for a coverage rate of 22% of the U.S. population (reporting is not always 100% within a state). This 22% coverage represents 17% of the nation's reported crime, which reflects the fact that NIBRS coverage is more heavily weighted towards smaller cities and counties (where crime rates are lower).

We use data from 1995 to 2004 for NIBRS city and county reporting agencies, which includes local police forces and county sheriff offices. Since not all agencies report consistently, we limit our sample each year to agencies which do not have large reporting gaps. More specifically, in each year we exclude agencies which have missing data on crime (not just assaults) for more than seven consecutive days, where a report of 0 counts as non-missing data. This filter eliminates 12.5 percent of reported assaults. If no crime is reported on a given day after this filter, we set that day's assault count to zero. Our main violence measure is the total number of assaults, defined as the sum of aggravated assault, simple assault, and intimidation.[5], across all agencies on day t, V_t. In some specifications, we separate assaults into 4 time blocks: 6AM-12PM, 12PM-6PM, 6PM-12AM, and 12AM-6AM. We assign assaults occurring in the night hours (12AM-6AM) to the previous calendar day to match them to movies played on day t.

Figure 1c plots the log of weekend assaults V_t over time. The number of assaults increases over time as a result of increased coverage in NIBRS. The series is also highly seasonal, with troughs in assaults in the winter and peaks in the summer. The figure also reports the top 10 weekends for strongly violent movies and the top 10 weekends for mildly violent movies. No obvious relationship between the assaults series and the violent movies series is apparent.

The seasonality in the assault series may well mask important variation in the data. For this reason, in the regressions below, we include an extensive set of indicator variables for year, month, day-of-week, day-of-year, and holidays; in addition, we also control for weather and TV audience. To illustrate what variation is left after controlling for these variables, we generate the residual of a regression of ln(violence) on the full set of controls (excluding the movie audience measures). Figure 1d plots this residual, aggregated to the weekend level (i.e., the average of the Friday through Sunday residuals) to enhance readability. Unlike the original series, this residual behaves approximately like white noise. Only 44 weekends differ from the mean by more than 0.05 log points, and just one differs by more than 0.10 log points.

Figure 1d also labels the top 10 weekends for the audience of strongly violent and mildly violent movies. Interestingly, not only does the figure offer no indication of a positive relationship between violent movies and crime, but it offers an indication of a *negative* relationship. For both mildly violent and strongly violent movies, 7 out of the top 10 weekends have residuals below the median for ln(assaults). (One of the positive residuals is for "Passion of the Christ", an atypical violent movie, both for its target audience and its potential effect on crime.) In

[5]Aggravated assault is an unlawful attack by one person upon another wherein the offender uses a weapon or displays it in a threatening manner, 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 placing a person in reasonable fear of bodily harm without a weapon or physical attack.

addition, out of 20 weekends with a residual more negative than -0.05 log points, 2 are among the top 10 weekends for strongly violent movies, and 2 are among the top 10 weekends for mildly violent movies. This evidence, hence, suggests a negative relationship between violent movies and violent crime. We examine this relationship in detail in the next section.

Summary statistics. After matching the assaults and the movie violence data, the resulting data set includes 1,563 weekend (Friday through Sunday) observations, covering the time period from January 1995 to December 2004. The data set covers a total of 2,272,999 assaults and a total of 1,781 reporting agencies. Table 1 reports summary statistics. The average number of assaults on any given weekend day in our sample is 1,454. The assaults occur mostly in the evening (6PM-12AM), but are also common in the afternoon (12PM-6PM) and in the night (12AM-6AM). Assaults are highest on Friday and Saturday, and lower on Sundays and other weekdays. Across demographic characteristics, assaults are three times larger for males than for females, and are decreasing in the age of the offender (for ages above 18). The share of assaults where the offender is suspected of using alcohol or drugs is 17.0 percent over the whole day, and assaults taking place at a bar involving alcohol or drug are 1.4 percent. The incidence of alcohol-related assaults is several times larger in the night hours.

Table 1 also reports summary statistics for the movie audience. The average daily movie audience on a weekend day is 6.29 million people, with a peak on Saturday. The audience for strongly and mildly violent movies is respectively 0.87 million and 2.43 million. The table also presents information on movie rentals and movies rated by sexual content, profanity, and an alternative classification system for violence, which we discuss below in Sections 4 and 5.

4 Empirical Results

4.1 Theater Audience – Daily

To test for the short-run effects of exposure to violent movies, we focus on same-day exposure,[6] a short time horizon similar to the one considered in the psychology experiments. The outcome variable of interest is V_t, the number of assaults on day t. While the number of assaults V_t is a count variable, specifying explicitly the count process (as in a Poisson regression) is not key since the number of daily assaults is sufficiently large. Hence, we adopt an OLS specification, which allows us to more easily instrument for movie exposure later in the paper. The benchmark specification which follows from the model developed in Section 2 is

$$\ln V_t = \beta^v A_t^v + \beta^m A_t^m + \beta^n A_t^n + \Gamma X_t + \varepsilon_t. \quad (5)$$

The number of assaults depends on the exposure to strongly violent movies A_t^v, mildly

[6] We define day t to run from 6AM of day t to 6AM of day $t+1$. This assigns hours following movie exposure to the same day.

violent movies A_t^m, and non-violent movies A_t^n. The coefficient β^v can be interpreted as the percent increase in assaults for each million people watching strongly violent movies on day t, and similarly for coefficients β^m and β^n. Identification of the parameters relies on time-series variation in the violence content of movies at the theater (see Figures 1a and 1b). By comparing the estimates of β^v and β^m to the estimate of β^n, one can obtain a difference-in-difference estimate of the effect of violent movies versus non-violent movies.

The variables X_t are a set of seasonal control variables: indicators for year, month, day-of-week, day-of-year, holidays, weather, and TV audience. Since new movie releases and movie attendance are concentrated on weekends, we restrict the sample to Friday, Saturday, and Sunday. All standard errors are robust and clustered by week, to allow for arbitrary correlation of errors across the three observations on the same weekend.

In column 1 of Table 2 we begin by estimating equation (5) with only year controls included. The year controls are necessary since the cities and counties in the sample vary year-to-year. In this specification, exposure to media violence appears to increase crime. However, we also obtain the puzzling result that exposure to non-violent movies increases crime significantly, suggesting that at least part of this correlation is due to omitted variables. Einav (2007) documents seasonality in movie release dates and underlying demand, with the biggest ticket sales in the beginning of the summer and during holidays. Since assaults are also elevated during summers and holidays, it is important to control for seasonal factors. In columns 2 and 3, we include indicators for month-of-year and for day-of-week. While introducing these coarse seasonal variables increases the R^2 substantially, from 0.9344 to 0.9846, these variables do not control for additional effects such as the Christmas season in the second half of December or for holidays such as Independence Day. We therefore add 365 day-of-year indicators (column 4) and holiday indicators (column 5), raising the R^2 further to 0.9912.[7] (The full set of holiday indicators is described in Appendix A.) As we add these variables, the coefficients β^v and β^m on the violent movie measures flip sign and become *negative*, significantly so in column 5. This suggests that the seasonality in movie releases and in crime biases the estimates upward.

This negative correlation, however, may still be due to an unobserved variable that contemporaneously increases violent movie attendance and decreases violence ε_t. For example, on rainy days assaults are lower, but movie attendance is higher.[8] To address this possibility, we use two strategies. First, we add a set of weather controls to account for hot and cold temperatures, humidity, high winds, snow, and rain. We also control for distractors that could affect both crime and movie attendance by controlling for the day of the Superbowl and for the other days with TV shows having an audience in excess of 15 million households according to Nielsen Media Research. (These controls are described in Appendix A.) Adding these controls makes the estimates more negative (Column 6).

[7]To guarantee the 365 day-of-year dummies are comparable across years, we drop February 29 in leap years.

[8]Some of these variables imply an opposite bias: on hot days assaults and movie attendance are both high.

Second, we instrument for movie audience on day t using information on the following weekend's audience for the same movie. This instrumental variable strategy exploits the predictability of the weekly decrease in attendance. At the same time, it removes the effect of any shocks that affect violence and attendance in week $w(t)$, but are not present in week $w(t)+1$. Examples include one-time TV events or transient weather shocks that are not already captured in our TV and weather controls. This procedure, detailed in Appendix B, generates predictors for the audience of strongly violent, mildly violent, and non-violent movies on day t. Panel B in Table 3 shows that these predictors are strongly correlated with the actual audience numbers they are instrumenting for. In the first stage for the audience of strongly violent movies (column 1), the coefficient on the predicted audience for strongly violent movies is highly significant and close to one (0.9145), as predicted. The other two coefficients in this regression are close to zero, though also significant. We obtain similar first stages for the audience of mildly violent movies (column 2) and non-violent movies (column 3).

Column 7 in Table 2 presents the IV estimates, where we have instrumented for the movie audience variables with their predicted values. Instrumenting makes the correlation between movie violence and violent crime become more negative. An increase of one million in the audience for violent movies decreases violent crime by 1.06 percent (strongly violent movies) and 1.02 percent (mildly violent movies), substantial effects on violence. Non-violent movies have a smaller (marginally significant) negative effect on assaults. The IV estimates do not noticeably change if the weather controls are excluded (not reported), suggesting that the instruments are taking care of temporary shocks, such as those due to weather.

4.2 Theater Audience – Time of Day

After controlling flexibly for seasonal patterns and for weather, and after instrumenting for movie attendance, exposure to violent movies appears to diminish crime in the short-run. To clarify this potentially puzzling result (relative to the findings in the laboratory experiments), we separately examine the effect of violent movies on violent crime by time of day. In these and all subsequent specifications, we include the full set of controls X_t and instrument for the actual audiences A_t^v, A_t^m, and A_t^n using the predicted audiences.

In Table 3, we present our baseline estimates by time of day: assaults committed in the morning (6AM-12PM), afternoon (12PM-6PM), evening (6PM-12AM), and nighttime (12AM-6AM). Since movie audiences are unlikely to watch movies in the morning and in the afternoon, and especially so for violent movies, we expect to find little or no effect of exposure to violent movies in the first two time blocks. There are small negative effects for assaults in the morning hours which are not very significant. This appears to be due to a spillover from the previous day's movie exposure (which is highly correlated with today's movie exposure). Exposure to violent movies has no differential impact on assaults in the afternoon (column 2). Since we consistently find similar effects for these two time periods (small negative effects in the early morning and no effect in the afternoon), we pool them in subsequent tables to save space.

During the evening hours (column 3), we find, instead, a significant negative effect of exposure to violent movies. An increase in the audience of mildly violent movies of one million decreases violent crime by 1.09 percent. Exposure to strongly violent movies has a slightly larger effect. Exposure of one million additional people reduces assaults by 1.30 percent. Exposure to non-violent movies is negatively correlated with violent crime, but the point estimate is smaller than for violent movies, and not significant. Over the night hours following exposure to a movie (column 4), violent movies have an even stronger negative impact on violent crime. Exposure to strongly violent movies for one million people decreases violent crimes by 1.92 percent. Exposure of one million people to mildly violent movies reduces assaults by 2.05 percent. In this specification as well, the impact of non-violent movies is also negative but substantially smaller and not significantly different from zero.

To put these estimates into perspective, consider that on a cold day (20-32 degrees Fahrenheit), assaults go down by 11 percent in the evening hours and 8 percent in the night hours. (These are coefficients from the baseline IV regression, which includes the other weather, holiday, and seasonality controls. The omitted temperature group is 33-79 degrees Fahrenheit.) In comparison, the blockbuster strongly violent movie "Hannibal" (with an audience size of 10.1 million on opening weekend) is predicted to account for a 4.4 percent reduction in assaults in the evening hours and a 6.5 percent reduction in the night hours (see footnote 26 for details on this calculation). In Section 5, we provide interpretations of these findings.

4.3 Theater Audience – Timing of Effects

So far, we have estimated the impact of exposure to movie violence on same-day violent crimes. We now estimate whether there is a delayed impact at various time intervals. If violent movies increase violent crime in the medium-run, or if violent movies simply lead to intertemporal substitution of crime (as in the case of weather shocks in Jacob, Lefgren, and Moretti, 2007), violent crime is likely to be higher in the period following movie exposure.

Monday and Tuesday. In columns 1-2 of Table 4, we estimate the impact of average weekend movie audience on violent crime for the Tuesday and Monday following the weekend. Since the movie audience on these weekdays is limited, to a first approximation this specification captures the delayed effect of movie exposure one to three days later. We find no evidence of an increase in violent crime due to either imitation or intertemporal substitution. Most coefficients are close to zero, and the only marginally significant coefficient indicates a delayed negative impact of mildly violent movies.

One Week, Two Weeks, and Three Weeks Later. In the next specifications, we estimate the impact one, two, and three weeks after the original exposure, controlling for contemporaneous exposure. Separate identification is made possible by new releases occurring after the initial exposure. Lagged movie attendance is instrumented using a similar methodology as for the other movie attendance variables, except for the one-week lag (Columns 3-4). In this specification, we report the OLS results, since the instrument for lagged exposure would be essentially collinear with contemporaneous exposure. Across the three specifications (Columns 3-8), we find no evidence of a delayed effect of movie exposure. Of eighteen coefficients for lagged exposure, only one is significant (negative) at the 5 percent level. At the same time, we find strong evidence of a negative impact of contemporaneous exposure to violent movies, as in our benchmark specifications.[9] These results suggest there is no medium-run effect of exposure to movie violence due to either imitation or intertemporal substitution.

4.4 Theater Audience – Robustness

Unlike the psychology experiments, media violence does not induce more violent behavior in the immediate aftermath of exposure; to the contrary, it appears to decrease it. Before we discuss interpretations of this result, we assess the robustness of our baseline estimates.

Alternative Instruments, Specifications, and Samples. In Appendix Table 2, we first document the robustness of our findings to the use of different instruments. For space reasons, we pool the morning and afternoon periods (Panel A), and then present results for the evening (Panel B) and night (Panel C). The benchmark instruments form a predictor of the audience in week $w(t)$ using the information on the audience in week $w(t)+1$ and allowing for different weekly decay rates for different types of movies (see Appendix B). A coarser, but simpler approach is to use as instruments the audience in week $w(t)+1$ of all movies in a category (strongly, mildly, and non-violent). The results (Column 2) are very similar to the results with the benchmark instrument (reproduced in Column 1), though the standard errors are 10 to 20 percent higher, reflecting some loss in precision due to the neglect of movie-type specific decay rates.

An alternative instrument uses information on the production budget and the number of theaters in which a movie is playing in week $w(t)$, instead of information on audience size (see Appendix B for details.) Production budgets are decided far in advance, while the number of screens is finalized one or two weeks in advance (Moretti, 2007). These instruments, like our baseline instruments, should purge the estimates of short-term shocks affecting both theater attendance and crime. However, these instruments do not predict well the overall movie audience, since the total number of theaters is essentially fixed in any given week and production budgets do not provide much identifying variation.[10] Hence, we supplement these

[9] The estimates for contemporaneous exposure in Columns 3-4 should be compared with the OLS estimates in Column (7) of Appendix Table 2.

[10] The joint F-tests for the first stages of this instrument set range from 280 to 378, with most of the power coming from the variables for the number of theaters.

instruments with an additional instrument for total movie audience size based on our standard procedure. The results (column 3) are remarkably similar to the benchmark results.

To clarify the identifying variation behind the benchmark results, we use the standard instrument, but include the audience only for movies in their first week of release (column 4). We get similar point estimates (somewhat lower in the night hours) and comparable standard errors, indicating that new releases contribute substantially to identification.

Next, we estimate the results using our standard instrument, but including in the sample all seven days of the week instead of just the weekend (column 5). The point estimates for the effect of movie violence in the evening and night (Panels B and C) become more negative, but so does the estimate for non-violent movies, which is now significant.[11] The latter finding may reflect an impact of non-violent movies, for example by incapacitating potential criminals. An alternative possibility, however, is that the instrument, which is based on next weekend's audience, does not completely remove the impact of short-term shocks for weekdays (especially Wednesdays and Thursdays, which fall immediately before next weekend).

We next explore the role of the controls. One may worry the model is over-specified by the inclusion of 365 indicators for each day-of-year. In column 6, we replace these controls with indicators for the 52 weeks of the year, leaving all other controls in place. The results are similar, indicating that the benchmark model does not appear to be over-specified.

Finally, we estimate two specifications that do not instrument for movie audience: an OLS specification (column 7) and a Poisson regression (column 8). In these specifications, exposure to all types of movies in the morning and afternoon has a negative (significant) effect on violent crime, unlike in the benchmark specification. The effect in the evening and night hours is similar to the effect in the benchmark specification, although with smaller point estimates. The results for the morning and afternoon are likely due to omitted variables that are correlated with overall movie audience and crime. Indeed, if one considers the differential impact of violent versus non-violent movies, the results mirror the IV results: no differential effect in the morning and afternoon, and large negative effects in the evening and night.

Individual Movie Violence Level. We also present more disaggregated evidence on the effect of movies using different violence categories. We estimate the regression

$$\ln V_t = \sum_{k=0}^{10} \beta^k A_t^k + \Gamma X_t + \varepsilon_t,$$

using the same sample, control variables, and IV approach as in the benchmark specification. That is, we estimate separately the effect on assaults of exposure to movies of violence level k, with $k = 0, 1, ..., 10$. In Figure 3, we plot the coefficients β^k for evening assaults and for nighttime assaults. Over the evening hours (6PM-12AM), the decrease in assaults is fairly

[11] The standard errors are only slightly smaller relative to the benchmark sample, despite a more than doubling of the number of observations. This reflects the fact that the movie audience on non-weekends is limited.

monotonic in the violence level of the movie. The impact of movie exposure on violent crime is close to zero for non-violent movies, becomes more negative for more violent movies, and peaks at movie violence 9. Over the night hours (12AM-6AM), the effect of exposure to movie violence becomes more negative with violence until violence level 5, and then remains about flat. In both time periods, no single violence group appears to be driving the results.

One-Hour Time Blocks. To provide additional evidence on the timing of the effect of violent movies, we re-run specification (5) separately by one-hour time blocks (Figure 4). The time stamp is supposed to indicate the time of the assault, but it might also reflect the time of the police report. As such, the crime is likely to have occurred in the indicated time block or in the previous one-hour block. We plot the coefficients for strongly violent, mildly violent, and non-violent movies. The size of the points is inversely proportional to the estimated variance of the coefficient estimates. The horizontal lines within each 6-hour time block are the weighted average of the estimated coefficients within a violence category, where the weights are the inverse of the estimated variances.

In the morning hours (6AM-12PM), we find some negative impact of exposure to violent movies, especially for the early hours, though the estimates are noisy due to the small number of crimes in the morning. This negative impact likely reflects a carry-over from exposure in the previous night. In the afternoon hours (12PM-6PM) we find no impact on assaults. In the evening hours (6PM-12AM), the impact of movie exposure is negative from 7PM on, and more so for violent movies. The timing of these effects lines up with the timing of movie attendance. In the nighttime hours (12AM-6AM), we find even stronger negative impacts, especially for the hours of 4AM and 5AM; however, these coefficients are very imprecisely estimated.

Alternative Movie Violence Measure. We next cross-validate our results using an alternative measure of movie violence. In addition to rating movies ("R", "PG", etc.), the *MPAA* summarizes in one sentence the reason for the rating, including the violence of the movie. We characterize as mildly violent movies those for which the *MPAA* rating contains the word "Violence" or "Violent", with two exceptions. If the reference to violence is qualified by "Brief", "Mild", or "Some", we classify the movie as non-violent. If the word violence is qualified as either "Bloody", "Brutal", "Disturbing", "Graphic", "Grisly", "Gruesome", or "Strong", we classify the movie as strongly violent. We then construct a daily measure of mild and strong movie violence along similar lines to the procedure *used* for the benchmark measures.[12] The *MPAA*-based mild violence measure averages 2.19 million in audience, compared to 2.43 million for the *kids-in-mind*-based mild violence measure (Table 1), with a correlation of 0.68 between the two measures. The *MPAA*-based measure of strong violence is more restrictive than the *kids-in-mind*-based measure, averaging an audience of 0.48 million, compared to 0.87

[12] In the first weeks of 1995, the *MPAA* rating is missing for a number of movies; we set the *MPAA* violence measure missing for the 10 weeks in which the rating is available for less than 70 percent of the movie audience.

million. The correlation between these two measures is 0.66.[13] The correlation is also apparent in Appendix Table 1, which lists the *MPAA* violence rating for blockbuster movies.

In columns 1-2 of Appendix Table 3 we replicate the regressions of Table 3 using the *MPAA*-based measure of movie violence, and find similar results. In both the evening (6PM-12PM) and in the night (12AM-6AM), exposure to movie violence lowers the incidence of violent crime, with similar magnitudes. When we include both measures of violence (columns 3-4), however, we find that the effects on assaults load almost exclusively on the *kids-in-mind* measures. Overall, while the *MPAA* measure of movie violence produces comparable results to the *kids-in-mind* measure, the latter measure appears to be more accurate. This is not surprising given that the *kids-in-mind* raters refine the *MPAA* rating into a 0-10 scale.

4.5 Theater Audience – Placebo Tests

Although we have included an exhaustive set of seasonal control variables, it is still possible that the remaining seasonality in movie releases and assaults could bias our estimates. We estimate placebo treatments to test whether our findings are due to unobserved seasonal factors.

Day-Of-Year / Day-Of-Week Placebo. We generate a placebo data set by re-assigning the movie audience variables to the other date in the sample that falls on both the same day-of-year and the same day-of-week (if such date exists).[14] To the extent that the negative correlation between movie violence and assaults is due to unobserved seasonality, we would expect a negative correlation also in this placebo data set. If, instead, the effect is a causal one due to violent movie attendance, we should not find an effect in the placebo treatment. This correspondence is complicated slightly by leap years. For example, all dates between January 1 and February 28 of 1996 are matched to the corresponding date in 2001 (and vice versa). All dates between March 1 and December 31 in 1996, instead, are matched to the corresponding date in 2002 (and vice versa). This data set includes 1,200 observations (out of 1,563).

In columns 1-3 of Table 5, then, we estimate equation (5), with movie audiences from the placebo-matched year as additional controls. We find a significant impact of the real audience of violent movies, as in the benchmark specification, and no evidence of an impact of the placebo movie audience. Out of 9 placebo variables, none is significant.

Lead Placebo. While the placebo specification in columns 1-2 tests for the impact of seasonality, it does not test for the possibility that the estimated effect of violent movies may be due to slow-moving omitted variables that affect both movie attendance and violent crime. While our instrumental strategy is designed to address this issue, in columns 4-9 we provide additional evidence by examining the effect of movie exposure two or three weeks into the

[13]These are the correlations of the residuals from OLS regressions on the standard set of control variables appearing in column (6) of Table 2, excluding the movies violence measures.

[14]This procedure takes into account that the amount of violence on, for example, July 4 varies substantially depending on whether it falls on a Friday, Saturday, or Sunday.

future, controlling for current exposure. To the extent that our estimates capture an omitted variable that is relatively long-lasting, we expect to find similar (negative) impacts of exposure to future movie attendance. If, instead, our estimates are due to a causal effect, future movie attendance should have no impact.

We estimate this placebo test using movie attendance two weeks ahead (columns 4-6) and three weeks later (columns 7-9).[15] In both specifications, we find the expected effect of contemporaneous exposure, but no significant pattern of future exposure. Of eighteen coefficients on placebo exposure, two are significant at the 5 percent level, and two more at the ten percent level. While this is somewhat more than one would expect to occur by chance, we find no pattern in such coefficients, two of which are positive and two negative.

4.6 DVD and VHS Rental Audience

While this paper mostly focuses on the effect of movies shown in theaters, a similar design exploits the releases of movie rentals on VHS and DVD. Given the differences between the home and theater settings, estimating the impact of rentals is of independent interest. These releases occur several months after the theatrical release, and rentals of newly released VHSs and DVDs peak in the first week of release and decay quickly in the following weeks. Moreover, the top 1-2 movies capture a substantial share of the rental revenue.

We use data on weekly DVD and VHS rental revenue from *Video Store Magazine* covering the top 25 movies over the period January 1995-December 2004.[16] The average number of rentals on a weekend day is 3.92 million (Table 1), with peaks on Saturday and Friday. Weekly rentals of strongly violent (mildly violent) movies are 0.64 (1.56) million. While rentals are 30 to 40 percent smaller than the theater attendance, these numbers underestimate the audience reached since multiple people often view a single rented movie. The audience reached by DVD and VHS rentals, therefore, is roughly comparable to the audience reached at the theaters. The violent audience size for DVD and VHS rentals are positively correlated to the box office measure in the corresponding week: the conditional correlation between the two measures of strong (mild) violence is 0.15 (0.39) (see footnote 13).

In columns 1-3 of Table 6, we estimate specification (5) using DVD and VHS rentals instead of box office audience. We include the full set of controls and instrument using the predictor based on next week's rental. We find, as might be expected, no effect of exposure to violent movies in the morning and afternoon hours (column 1). In the evening hours (column 2),

[15] We do not report the results for one-week later, since our standard instrument is based on next week's movie attendance. Using an OLS specification for the one-week lead, we find no effect of the placebo variables.

[16] To convert revenue data into an estimated number of rentals, we deflate rental revenue by the average price of a rental estimated using the *Consumer Expenditure Survey.* We impute daily rentals using the within-week distribution of rentals in the *Consumer Expenditure Survey.* Finally, as with the box office data, we focus on weekend rentals. Data are missing for 20 weeks in which the magazine did not publish the relevant numbers.

we find a large negative impact of exposure to mildly violent movies (a 1.48 percent decrease in assaults per million rental), and a smaller, insignificant impact of strongly violent movies. In the night hours (column 3), we find large negative effects of exposure to rentals of violent movies, but also a significant negative effect of the rental audience of non-violent movies. These estimates are less precise than the estimates for box-office releases, with standard errors about 30 percent larger. When we also control for box office movie audience in the regressions, the results are similar although with larger standard errors (columns 4-6).

The results on DVD and VHS releases are consistent with a negative impact of violent movies on violent crime, especially over the evening hours. The similarity with the results from theater releases is interesting in the light of differences in setting (e.g., alcohol consumption is possible at home but not at the theater) and in the activities displaced. However, the DVD/VHS results are less precisely estimated compared to the effect of box office releases.

5 Interpretation and Additional Evidence

We can summarize the findings so far as follows: (i) exposure to violent movies lowers same-day violent crime in the evening; (ii) violent movies lower violent crime in the night after exposure; (iii) strongly violent movies have somewhat larger negative effects compared to mildly violent movies in the evening, but *not* after exposure; (iv) nighttime hours have larger negative effects compared to evening hours; (v) there is no lagged effect of exposure in the weeks following movie attendance. We now provide interpretations and additional evidence for the first four of these findings (the fifth finding is straightforward to interpret).

5.1 Lower Crime in the Evening - Voluntary Incapacitation and Sorting

We interpret the first finding, that violent movie exposure lowers crime in the evening hours, as *voluntary incapacitation*. When people choose to attend the movie theater, they are removing themselves from other activities and situations more conducive to crime. Since it is virtually impossible to commit an assault while in the theater, as movie attendance rises, violent acts fall relative to the counterfactual. Interestingly, as simple as this explanation is, incapacitation has largely been ignored in discussions on the effect of movie violence. This voluntary incapacitation differs from the standard incapacitation in the literature because it is optimally chosen by the consumers, rather than being imposed, as in the case of school closings (Jacob and Lefgren, 2003) or incarceration (DiIulio and Piehl, 1991; Levitt, 1996; Spelman, 1993).

While the qualitative findings are consistent with incapacitation, are the magnitudes also consistent with this interpretation? Suppose watching a movie (including time spent buying tickets, waiting in the lobby, and traveling to and from the theater) occupies roughly one half of the 6PM-12AM time period and fully incapacitates individuals. For the rest of the time block, for simplicity, assume that crime rates are the same as for the alternative activity.[17] Using the framework of Section 2, these assumptions imply $\beta^j = -0.5x^j\sigma_y$. If criminals were equally represented in the audience of a movie with 1 million viewers, about 1/300th (i.e., 1 million out of a total population of 300 million) of the criminals would be incapacitated, leading to $\beta^v_{equal} = -0.5 * (1/300) \approx -0.0017$, compared to the observed values $\hat{\beta}^v = -0.0130$ and $\hat{\beta}^m = -0.0109$. This implies violent individuals are over-represented by about $0.0130/0.0017 = 7.6$ times in strongly violent movies and $0.0109/0.0017 = 6.4$ times in mildly violent movies.

While this is a substantial amount of selection, it is not implausibly large. To provide evidence on the sorting of more violent individuals into more violent movies, we turn to data from the Consumer Expenditure Survey (*CEX*). We take advantage of the fact that the *CEX* diaries record all expenditures of surveyed households day-by-day for a period of one or two weeks, including also demographic information about the households that purchase movie tickets, which our primary movie attendance data set does not.

For each day t in the years 1995-2004, we compute the share of interviewed households that watch a movie at the theater, $share^{CEX}_t$.[18] We regress this share on shares of population attending movies of different violence levels according to our primary movie attendance data[19]:

$$share^{CEX}_t = \alpha + \beta^v \frac{A^v_t}{Pop_t} + \beta^m \frac{A^m_t}{Pop_t} + \beta^n \frac{A^n_t}{Pop_t} + \Gamma X_t + \varepsilon_t \tag{6}$$

where Pop_t is the U.S. population in year t (Table 7). Since $share^{CEX}_t$ and A^j_t/Pop_t are both measures of the share of the population attending a movie on day t, we expect the regression coefficients β^j to be close to 1 when we include all demographic groups (column 1). Indeed, the estimated coefficients (0.9469, 0.7736, 0.7614) are all statistically indistinguishable from 1 (but significantly different from zero). Our measures of movie audience, therefore, are validated by the corresponding measures constructed using the *CEX* data.

In columns 2-5 we examine sorting by demographics into violent and non-violent movies. While different types of movies should have the same impact — and hence similar βs — on overall attendance (column 1), we expect different patterns when we split the data by demographics. For demographic groups that attend the movies more regularly, we should find larger coefficients. More importantly, for those demographic groups with a higher taste for movie violence, we should see a larger effect for violent movies — larger β^v and β^m compared to β^n — and the opposite for groups with a lower taste.

[17] If, for the rest of the time block, crime rates were as in the night (12AM-6AM), the amount of selection needed to explain our results would be lower, since the net effect of violent movies β^v is negative in the night.

[18] We obtain similar results when using an individual-level measure obtained by dividing the total number of movie visits by the total number of individuals in the households, where the total number of movie visits is imputed as the amount spent on movies divided by the average price of a ticket.

[19] The regressions include Friday, Saturday, and Sunday and are weighted by the number of households reporting consumption expenditures for day t, which averages 157.88. We include the standard set of controls X_t. We obtain similar, but less precisely estimated, results if we instrument for movie attendance.

In columns 2-4 we separate households by the age of the household head. Younger households (heads aged 18 to 29) have larger estimated coefficients, indicating that they attend the movies more often than older people. More interestingly, younger households select disproportionately into violent movies: they are $2.094/0.9469 = 2.2$ times over-sampled in strongly violent movies and $1.4642/0.7736 = 1.9$ times over-sampled in mildly violent movies, while they are only $1.0786/0.7614 = 1.4$ times over-sampled in non-violent movies. Middle-aged households (heads aged 30 to 44) and especially older households (heads over 45) attend the movie theater less and display a flatter attendance pattern with respect to the violence content of movies. The age groups with higher crime rates (Table 1), therefore, select disproportionately into watching violent movies, a result consistent with selective incapacitation.

Since men also have higher assault rates compared to women (Table 1), it would be useful to differentiate by gender. While this is generally problematic in the *CEX* data (which only reports purchases at the household level), we can consider singles aged 18-29. In this group (column 5), we find even greater evidence of selection. Single young males are $2.7751/0.9469 = 2.9$ times over-sampled in strongly violent movies and $2.7825/0.7736 = 3.6$ times over-sampled in mildly violent movies. While the estimates for this small group should be taken with caution given the large standard errors, they indicate substantial sorting into violent movies.[20]

Overall, we find substantial sorting even using relatively poor correlates of criminal behavior, age and gender. In addition to between-group sorting, we expect substantial within-group sorting.[21] The combination of between- and within-group sorting can plausibly generate over-representation of potential criminals by a factor of 6 or 7, as implied by the effect on assaults.

5.2 Lower Crime after Exposure - Sobriety

The second result is that exposure to movie violence lowers violent crime also in the night hours. To interpret this result, we compare the observed patterns in Figure 3 to the possible patterns predicted by the model in Figure 2. In the night hours, since movie theaters are closed, the net effect on crime captures the difference between the direct impact on aggression of exposure to movies (α^v), compared to the counterfactual scenario (σ). The negative estimates for non-violent, mildly violent, and strongly violent movies all imply that an evening spent at the movies leads to less dangerous activities in the night hours following exposure. This pattern corresponds to the bottom set of lines in Figure 2. Apparently, by the time a potential criminal exits the movie theater, the situational opportunities to engage in violent crime are diminished.

[20] When we split households by income (results not shown), we find strong evidence of selection into more violent movies by lower-income households, a selection pattern consistent with research that documents the poor are more likely to be victims of aggravated assaults.

[21] For example, in a laboratory setting Bushman (1995) offers subjects (college students) the choice whether to watch a violent or non-violent movie, and observes that subjects that rank high in self-reported aggressiveness are more likely to choose a violent movie.

This could be because a visit to the movie theater involves less alcohol consumption, disrupts and alters an evening's activities, or places potential criminals in relatively safer environments once the movie is over. This is not a trivial finding, since attendance at movie theaters could have provided a meeting point for potential criminals, leading to an increase in crime.

Alcohol is one prominent factor that has been linked to violent crimes, and assaults in particular (Carpenter and Dobkin, 2007). In the U.S., alcohol is banned in almost all movie theaters, so the mechanism for reduced crime in the night-time could well be due to a reduction in alcohol consumption. To test the importance of sobriety as part of the explanation, we examine whether the displacement of violent crimes is larger for crimes involving alcohol or drug consumption (columns 1 and 2 of Table 8) than for crimes not involving such consumption (columns 3 and 4). Indeed, while the negative impact of movie violence on assaults is present in both samples, the estimates are on average 1.5 times larger for assaults involving alcohol or drugs, consistent with sobriety playing an important role. To further test the impact of alcohol, in columns 5 and 6 we estimate the impact on assaults in bars and night clubs, where consumption of alcohol is very likely. We find large displacement in the night hours, although these estimates are imprecise given the relative rarity of these assaults. Additionally, in column 7 we estimate the impact of violent movies on arrests for drunkenness (i.e., arrests for drunk and disorderly conduct or intoxication). We find a large negative, and marginally significant, effect for strongly violent movies, but no effect for mild and non-violent movies.[22]

To provide direct evidence that movie attendance lowers alcohol consumption, we use data from the *CEX* time diaries (see Table 8). We examine whether exposure to violent movies reduces the share of respondents consuming alcohol away from home. We find suggestive evidence that violent movies (and particularly strongly violent ones) may have reduced alcohol consumption, though the estimates are not significantly different from zero.

To further evaluate the channels of the substitution effect, we estimate the impact for different types of crimes in Appendix Table 4. We find a similar impact for assaults at home (Columns 1-2) and for assaults away from home (Columns 3-4), suggesting that movie attendance substitutes for violent behavior in both locations. The impact in the night hours is three times larger for assaults of a person known to the offender (Columns 5-6) than for assaults of a stranger (Columns 7-8), suggesting that the alternative activity displaced by movie attendance likely also involved friends or family. Finally, exposure to movie violence has less of an impact on non-violent crimes such as theft and burglary (Columns 9-10). This is consistent with Carpenter and Dobkin (2007), who find that alcohol consumption leads to larger increases in violent crimes than in non-violent crimes.

Overall, these findings provide suggestive evidence that a decrease in alcohol consumption plays a role in explaining the decrease in violent behavior after movie attendance.

[22] Although not shown, we find no effect for driving under the influence arrests. We also note the arrest data does not contain information on time of day, and hence does not allowed for as precise a test.

5.3 Non-monotonicity in Violent Content - Arousal

The third finding is that the negative effect in the night hours is not monotonic: the effect of strongly violent movies is slightly smaller than the effect of mildly violent movies ($\hat{\beta}^v = -0.0192$ versus $\hat{\beta}^m = -0.0205$). This at first seems puzzling, since strongly violent movies attract more of the potential criminals, and the additional selection should render the effect more negative. As Figure 2 illustrates, however, violent movies can also have catharsis or arousal effects. Consider the case in which violent movies induce crime through arousal or imitation (that is, $\alpha^v > \alpha^m$). In Figure 2, this case is captured by the dotted downward sloping line. Since the arousal effect counteracts the selection effect (rendering the effect less negative), the overall effect of movie exposure can be non-monotonic in movie violence. Indeed, the observed patterns in Figure 3 for the night hours closely resemble the arousal case portrayed in Figure 2.

This pattern could also be observed in the absence of arousal if the sorting of potential criminals into movies was about the same for mildly violent and strongly violent movies. To establish more convincingly that arousal is the explanation for Figure 3, we document the sorting of more violent individuals into more violent movies. The *CEX* data used in Table 7 indicates substantial selection: young households (with a head age 18-29) select into strongly violent movies at a rate which is 43 percent higher compared to mildly violent movies.

To produce additional evidence on sorting, we turn to an auxiliary source of data, the *Internet Movie Database* (*IMDB*). *IMDB* maintains a popular website for movie-goers which invites its users to rate movies. A typical blockbuster movie is rated by tens of thousands of viewers. *IMDB* displays, for each movie, statistics on the rating for each combination of gender (male, female) and four age groups (under 18, 18 to 29, 30 to 44, and over 45). As a measure of the attractiveness of a movie to potential criminals, we use the share of raters that are male and are aged 18 to 29, a group disproportionately likely to commit crimes (see Table 1).

Figure 5 shows that the share of young male reviewers is remarkably linear in the 0 to 10 violence ratings for movies from *kids-in-mind*. The extent of selection is substantial: while only 36 percent of movies with a violence rating of 0 are rated by young men, this number increases to 54 percent for the most violent movies with a rating of 10. This strong and linear pattern of selection suggests that, in the absence of catharsis or arousal effects, the effect of movies should also be trending downward in the violence content of movies (see Figure 2). The observed non-monotonicity, hence, supports the interpretation that violent movies increase crime by arousal or imitation. This finding also provides evidence against a cathartic effect of violent movies, which would have made the effect of strongly violent movies even more negative.

5.4 Larger Nighttime Estimates - Compositional Effects

The fourth finding is that, in the night hours following the movie exposure (12AM-6AM), the impact of movie violence on assaults is higher than in the evening hours (6PM-12AM). This finding is at first puzzling, since the highest decrease in crime should occur when potential criminals are in the movie theater, when committing crimes is nearly impossible.

However, the composition of crimes in the two time periods is different, making a direct comparison of the size of the effects tricky. For example, assaults involving alcohol or drugs are much more common in the night hours (29 percent) than in the evening hours (18.5 percent) (Table 1). As previously noted, alcohol-related assaults respond more to violent movie exposure (Table 8). We find a similar pattern for assaults taking place at bars. Hence, the decrease in alcohol consumption, a primary mechanism for the effects, is likely to prevent a higher fraction of violent crimes in the night (when inebriation would have the most impact) compared to the evening. In the model, this implies a larger parameter σ at night; that is, the activities prevented by movie attendance in the night hours are more dangerous than the activities prevented in the evening hours. This is consistent with a larger effect for crimes at night.

Broadly speaking, we obtain similar compositional differences in the pattern of assaults by demographics. In Table 9 we present estimates by gender and age of the offender. The impact of exposure to violent movies is larger (i.e., more negative) for male offenders than for female offenders, especially in the night hours when the difference is very large (Panel A). Since male offenders also commit a higher share of the assaults at night than in the evening hours (Table 1), this contributes to explaining the finding. When we separate the offenders by age group, we find a relatively monotonic decrease of the effect sizes by age, with the exception of the 45-54 age group (Panel B). This compositional pattern also contributes to explaining the findings, since the younger age group also contributes disproportionately to assaults (Table 1).

5.5 Additional Evidence on Selection

In both the evening hours and the night hours, the effect of violent movies on crime is more negative than the effect of non-violent movies. Our explanation of these facts relies on selection: violent movies are more likely to attract potential criminals. We now provide separate evidence that this form of sorting helps explain other results on the impact of movies. In particular, we test whether (i) movies that attract young men tend to decrease violent crime, even if the movies are not violent; (ii) movies that do not attract young people do not lower crime substantially. We present one example in the first category—movies with high *IMDB* ratings by young males, and three examples in the second category—violent movies using the *MPAA* movie rating, high-sexual-content movies, and high-profanity movies.

IMDB Data. We divide movies into thirds based on the fraction of young men rating a movie in IMDB (see Figure 5). We denote the bottom third as not liked by young males, the middle third of movies as liked by young males, and the top third as highly liked by young males. Table 10 reports information on the blockbusters within the three categories, holding constant the *kids-in-mind* violence rating. Among the non-violent movies, "Runaway Bride" is in the category not liked by young makes, while "Austin Powers in Goldmember" is in the category of movies highly liked by young males. Within the mildly violent movies, "Save The Last Dance" and "Spiderman" are best-sellers respectively in the not-liked category and in the highly-liked category. Within the strongly violent movies, there are essentially no blockbuster movies that are not liked by young males, since movie violence and liking by young males are highly correlated. However, the *IMDB* information distinguishes between movies in the middle group such as "Passion of the Christ" and movies in the top group such as "Hannibal."

To estimate the impact of movie attendance on violence within each of the nine cells, we estimate $\ln V_t = \sum_{j=1}^{9} \beta^j A_t^j + \Gamma X_t + \varepsilon_t$, where $j = 1, ..., 9$ denotes the nine cells. We adopt the full set of controls and use the baseline instrument. Table 10 reports within each cell j the coefficients β^j for the evening time block and for the night time block. Moving down within a column shows that more violent movies are generally associated with lower crime, even holding constant the liking by young males (except for movies not liked by young males, where the violent movie category is very sparse and hence the estimates very noisy). For example, among the movies highly liked by young males, the estimated parameters $\hat{\beta}^j$ are -0.0090 (non-violent), -0.0111 (mild violence), and -0.0140 (strong violence) for the evening hours, and -0.0079 (non-violent), -0.0179 (mild violence), and -0.0150 (strong violence) for the night hours. These patterns are broadly consistent with the interpretations discussed in Sections 5.1 to 5.4.

More importantly for a test of selection, moving along a row the coefficients also generally become more negative. In 9 out of 12 pairwise comparisons, the estimates become more negative as the liking by males increases (7 out of 10 if we exclude the bottom-left group, which is very sparse). For example, among the mildly violent movies, the estimated parameters $\hat{\beta}^j$ are 0.0049 (not liked by young males), -0.0099 (liked), and -0.0111 (strongly liked) for the evening hours, and -0.0268 (not liked), -0.0177 (liked), and -0.0179 (strongly liked) for the night hours. Movies that attract more young males, therefore, appear to lower the incidence of violent crimes more, even holding constant the level of violence in a movie.

MPAA Violence. In Column (5) of Appendix Table 3 we document the selection of young people into movies with varying *MPAA* ratings of violence using the *CEX* diaries. Young respondents are somewhat more likely to sort into mildly violent movies, and much more likely to sort into strongly violent movies—a sorting pattern consistent with the negative impact of violent movies on crime (columns 1 and 2). When we include in the sorting specification both the *MPAA* and the *kids-in-mind* measures of violence (column 6), the *kids-in-mind* violence variables are strongly predictive of attendance by young households, while the *MPAA* measures are not any more (if anything predicting sorting the other way). These patterns are strikingly in line with the finding that, when we include both sets of movie violence measures, only exposure to the *kids-in-mind* measures lowers the incidence of violence (Columns 3 and 4).

Sex and Profanity. Finally, we examine the impact of high-sexual content movies and high-profanity movies. *Kids-in-mind*, in addition to rating movies on violent content, rates them also on sexual content and on profanity, both using a 0 to 10 scale. We report these ratings for the movies listed in Appendix Table 1. "Scary Movie" is an example of a movie high in sexual content, while "Erin Brockovich" and "Bad Boys 2" are movies high in profanity. We use the same scale as for violence to define measures of mild sexual content and profanity (5-7) and strong sexual content and profanity (8-10). The audience for movies high in sexual content is much lower than for the corresponding category of violence, while movies high in profanity reach about the same share of the audience as violent movies (Table 1).

The impact of these types of movies has been debated, in particular the impact of high sexual content movies on sexual assaults (Ariely and Loewenstein, 2005; Kendall, 2007). The selection explanation suggests the most important dimension is the extent to which these movies attract potential criminals. In columns 1-3 of Table 11 we examine the extent to which movies high in sexual content or profanity attract a more violent demographic, young people, using the *CEX* data. We find that the young audiences sort disproportionately into movies with mild and high sexual content (column 1) and some evidence that they select into movies with higher profanity (column 2). However, after controlling for the audience of violent movies (column 3), there is no remaining evidence of selection on profanity, weaker evidence of selection on sexual content, and strong evidence of selection on movie violence.

We then consider the impact on assaults. When we consider the impact separately (columns 4-7), we find that movies with mild sexual content and with strong sexual content both lower the incidence of assaults, with smaller effects for movies with no sexual content (columns 4-5). We find similar results, with smaller magnitudes, for the impact of movies with mild or strong profanity (columns 6-7). When we control for the audience of movies of different violent content (columns 8-9), however, the impact of either profanity or sexual content is no longer significant, while the impact of movie violence is similar to the impact in the benchmark specification. These findings are fully consistent with the selection patterns documented in columns 1-3. When considered on their own, sexual content and profanity attract young audiences, but this is no longer true once one controls for movie violence.

The results for the *IMDB* measures, for *MPAA* violence, and for sexual content and profanity underscore the importance of selection. Exposure to movies that attract more violent groups (along observable lines) is associated with lower rates of violent crime.

6 Laboratory and Field Findings

We now compare our findings to the experimental evidence from the psychology literature.[23] Table 12 summarizes the results of representative experiments. The first experiments (Lovaas,

[23]In sociology there is a small literature that uses natural experiments in media programming. The most relevant studies consider the impact of television boxing prizefights on homicides and the effect of suicide episodes in soap operas on suicides (Phillips, 1982 and 1983).

1961; Bandura, Ross, and Ross, 1963), dating to the 1960s, were run mostly on small samples of children, while the more recent studies (Bushman, 1995; Josephson, 1997) are run with larger samples and on more varied populations. The treatment usually consists in exposure to a 5 to 15 minute video of violent scenes from a violent movie. The control group usually watches a video of comparable length with non-violent scenes. The measures of violence vary from aggressive play with dolls for the children (Lovaas, 1961; Bandura, Ross, and Ross, 1963) to the imposition of electric shocks or noxious noises on other subjects (Geen and O'Neill, 1969; Bushman, 1995), and to aggressive play during a hockey game (Josephson, 1987). In all cases except for Leyens (1975), the violence proxies are measured within an hour of the treatment. The effect of the exposure to movie violence is large. In four out of first five experiments of Table 12, exposure to the violent movie doubles the incidence of violence.[24]

Leyens et al. (1975) stands out because it studies aggression and violence in a more realistic context. Young people in a juvenile detention facility in Belgium are exposed to 5 consecutive days of commercial violent movies (the treatment) or commercial non-violent movies (the control). Therefore, unlike in the other experiments, subjects are exposed to full-length movies. The violence measure is a record of the percent of subjects that engage in acts of physical aggression in a monitoring period. Interestingly, exposure to violent movies significantly increases aggression in the evening, right after the movies are shown, but not at noon, after a night's sleep. The effects of media violence, though large, appear to be short-lived.[25]

In contrast to the experimental studies, we find a significant negative short-run effect of exposure to media violence on violent behavior. Reconciling these findings is important not only to better understand the effect of media violence on violence, but also more generally to understand the relationship between experimental and field evidence (Levitt and List, 2007).

We discuss three factors that differ between the laboratory experiments and the field evidence. The first and most important is the comparison group. In the laboratory, the control group is exposed to a non-violent movie; hence, the treatment effects are estimated as the difference between the effect of violent versus non-violent movies (in the model, $\alpha^v - \alpha^n$). In the field, the implicit control group instead chooses the next-best alternative activity, for example, going to a bar. Hence, the effect of exposure is measured as the difference between the effect of movie violence and the effect of the alternative activity (in the model, $\alpha^v - \sigma$). In light of

[24]This summary masks some heterogeneity. In the Geen and O'Neal (1969) study, for example, the effect of the violent movie is significant only for the group that was exposed to a frustration manipulation (2 minutes of loud white noise). (In fact, most of the experiments embed a frustration manipulation.)

[25]A second set of evidence in Psychology comes from cross-sectional or longitudinal surveys. In these studies, self-reported measures of media exposure are correlated with measures of aggressiveness and violence. Johnson et al. (2002), for example, finds that the share of people committing assaults that can cause injury at age 16-22 is four times larger for people that (at age 14) watched at least 3 hours of television a day, as opposed to less than an hour. These studies, which generally imply very large effects of the media, are plagued by problems of endogeneity and reverse causation.

this difference, the two sets of findings are not necessarily contradictory. Exposure to violent movies may be more dangerous than exposure to non-violent movies ($\alpha^v > \alpha^n$, the laboratory finding), but still less dangerous than the alternative activity ($\alpha^v < \sigma$, the field finding).

The second factor is selection. Subjects in the laboratory are a representative sample of the (student) population, while movie-goers in the field are a self-selected sample. The sorting of violent individuals into violent movies, which results in large displacement effects in the field, is not present in the lab. Finally, the third factor is the type of violence. The clips used in the experiments typically consist of 5-10 minutes of selected sequences of extreme violence. In the field, instead, media violence also includes meaningful acts of reconciliation, apprehension of criminals, and non-violent sequences. The exposure to random acts of violence may induce different effects from the exposure to acts of violence viewed in a broader context.

Given these differences, it is interesting that in the field we detect suggestive evidence of arousal effects, in line with the experimental findings. After accounting for selection, strongly violent movies appear to generate an increase in assaults relative to mildly violent movies (Section 5.3). This may occur for the same reasons as in the laboratory—an emotional effect of arousal, or short-term imitation of violent acts. Again as in the laboratory, we find no evidence of a cathartic effect. Importantly, the field evidence allows us to benchmark this arousal effect against other determinants of crime. The arousal effect is of a limited magnitude, compared to the foregone violence associated with the alternative activity.

The field findings are important to evaluate policies that would restrict access to violent movies, as such policies would lead to substitution toward alternative activities. In the short-run these policies would be likely to increase crime. The relevant impact is the one estimated in this paper, as opposed to the one in the laboratory. The results of the laboratory experiments, however, are useful to evaluate different policies. The laboratory experiments evaluate the impact of unexpected exposure, as in the case of a violent advertisement or a trailer placed within family programming. In addition, the differences between laboratory and field can be altered by changes in the laboratory design. For instance, the laboratory experiments can incorporate sorting into a violent movie (Lazear, Malmendier, and Weber, 2005) to replicate the selection in the field, or can change the exposure to a full length movie.

7 Conclusion

We have provided causal evidence on the short-run effect of exposure to media violence on violent crime. We exploit the natural experiment induced by the time-series variation in the violence of movies at the box office. We show that exposure to violent movies has three main effects on violent crime: (i) it reduces significantly violent crime in the evening on the day of exposure; (ii) by an even larger percent, it reduces violent crime during the night hours following exposure; (iii) it has no significant impact in the days and weeks following the exposure.

We interpret the first finding as voluntary incapacitation: potential criminals that choose to attend the movie theater forego other activities which have higher crime rates. As simple as this finding is, it has been neglected in the literature, despite its quantitative importance. We interpret the second finding as substitution away from a night of more volatile activities, in particular, reducing alcohol consumption. The third finding implies that the same-day impact on crime is not offset by intertemporal substitution of crime. An important component of these interpretations is the sorting of more violent individuals into violent movie attendance.

These findings appear to contradict the evidence from laboratory experiments documenting an increase in violent behavior following exposure to movie violence. However, the field and the laboratory findings are not necessarily contradictory. Exposure to movie violence can lower violent behavior relative to the foregone alternative activity (the field findings), even if it increases violent behavior relative to exposure to non-violent movies (the laboratory findings). In fact, despite other differences with the psychology experiments, we document suggestive evidence that violent movies induce more violent crime relative to non-violent movies, consistent with an arousal effect. This arousal effect, however, is of limited magnitude—on net, violent movies still induce substantially less violent behavior than the alternative activity.

We can calculate the change in assaults that would occur if the audience of violent movies did not go to the movies, but instead engaged in their next best alternative. The total number of evening and nighttime assaults prevented is 997 assaults per weekend, adding up to almost 52,000 weekend assaults prevented yearly.[26] Our estimates imply that a strongly violent blockbuster movie like "Hannibal" (with 10.1 million viewers on opening weekend) reduced assaults by 1,056 on its opening weekend, which amounts to a 5.2% decrease in assaults, about half the impact of the reduction in crime due to a cold day. This short-term impact of violent movies has been overlooked by the previous literature, yet it is substantial.

In the paper, we find no impact of violent movies in the days and weeks following exposure. Still, our design (like the laboratory experiments) cannot address the important question about the long-run effect of exposure to movie violence. As such, this paper should not be used to inform policy on the long-term effects of limiting the level of violence allowed in the media. However, it does indicate that in the short-run these policies will likely increase violent crime, as they induce substitution toward more dangerous activities. Other activities with a controlled, alcohol-free environment that attract young men, like Midnight Basketball, should also reduce crime in the short run. Additional forms of entertainment targeted at young men, including video games and television, may also have the same effect, a topic left for future research.

[26] We assume: (i) no impact of media violence on assaults beyond the evening and night of the media exposure, (ii) no substitution towards other movies, and (iii) effects for the whole population being the same as for the set of cities in the NIBRS sample. We calculate the effect separately for each time block (evening and night) and level of violence (strong and mild). We multiply the estimated baseline coefficient by the assault rate in NIBRS data times the US population (300 million), times average violent movie attendance.

A Appendix A - Data

Imputation of daily box-office audience. The daily box-office movie revenue is available starting from September 1997, and it covers the 10 highest-selling movies on that day. To expand the coverage to the period January 1995-August 1997 and to the movies that do not make the daily top 10 list, we exploit the availability of the weekend revenue throughout the whole sample for the 50 highest-selling movies. We take advantage of the regularity in the within-week pattern of sales (Table 1) and impute the daily data, whenever missing, using the weekend box-office data for the same movie in the same week. We use the following model. Denote by $a_{j,t}$ the daily audience of movie j on date t, and by $a^w_{j,w(t)}$ the weekend audience of movie j on weekend $w(t)$ corresponding to date t. (Since most movies are released on Friday, the function $w(t)$ assigns the days from Monday through Thursday to the previous weekend.) We assume that the daily audience is a share s of the weekend audience, where the share allowed to depend on a set of controls Y, $s(Y)$: $a_{j,t} = s(Y)\, a^w_{j,w(t)}$. After taking logs, the model can be written as $\ln(a_{j,t}) = \ln(s(Y)) + \ln(a^w_{j,w(t)})$. The most important control for the share $\ln(s(Y))$ is the set of day-of-week indicators d^d_t, since different days of the week capture a different share of the overall revenue (Table 1). In addition, we use the following set of controls $X_{j,t}$ for the weekday share: month indicators (in the summer the Monday-Thursday audience is larger), a linear time trend, indicators for the level of violence (non-violent versus mildly violent versus strongly violent), indicators for rating type (G/PG/PG-13/R/NC-17/Unrated/Missing Rating), indicators for week-of-release (up to week 26), and indicators for audience size in week $w(t)$ (audience $< .5m$, $\geq .5m$ and $< 1m$, $\geq 1m$ and $< 2m$, $\geq 2m$ and $< 5m$, $\geq 5m$). This set of controls X is interacted with the day-of-week dummies, as well as present in levels. Finally, we control for a set of holidays H_t, described below. We estimate

$$\ln(a_{j,t}) - \ln(a^w_{j,w(t)}) = \sum_{d \in D} \beta^d d^d_t + \sum_{d \in D} \Gamma^{d,X} d^d_t X_{j,t} + \Gamma X_{j,t} + \Phi H_t + \varepsilon_{j,t}$$

over the set of movie-day observations (j,t) for which we observe both the daily audience $a_{j,t}$ and the weekend audience $a^w_{j,w(t)}$. We use the predicted values from the regressions, $\widehat{\ln(a_{j,t}) - \ln}(a^w_{j,w(t)})$, to obtain the predicted daily audience $\hat{a}_{j,t}$, as follows: $\hat{a}_{j,t} = \exp[\ln(a^w_{j,w(t)})$ $+\widehat{\ln(a_{j,t}) - \ln}(a^w_{j,w(t)})]$. The final daily box-office audience is defined as the actual box-office data $a_{j,t}$ whenever available, and the predicted value otherwise. To test the accuracy of the imputation, we regress actual daily revenue $a_{j,t}$ on predicted daily revenue $\hat{a}_{j,t}$ over the sample of weekend days (for consistency with the main specification) for which we have both measures. The regression yields a slope coefficient of 1.0023 with an R^2 of 0.9801.

Holiday controls. We define an extensive set of holiday indicators to take into account that (i) holidays generally increase movie attendance; (ii) the effect of different holidays on attendance is quite different (attendance on Labor Day is much higher than on Memorial Day); (iii) attendance increases also in the days preceding a Holiday, and for major holidays in the week surrounding. Taking into account these facts, we include separate indicators for Martin Luther King Day, President's Day, Memorial Day, Labor Day, and Columbus Day, separate indicators for the Friday, Saturday, and Sunday preceding each of these holidays (that is, three separate indicators for each holiday) and a separate indicator for the Tuesday following these holidays. We also include an indicator for Independence Day, Veteran's Day, three Easter indicators (Friday, Saturday, and Sunday), three Thanksgiving indicators (Wednesday, Thursday, and Thanksgiving weekend), four Christmas indicators (December 20-23, December 24, December 25, and December 26-30), and three New Year indicators (December 31, January 1, and January 2-3). In addition, we include an indicator for holidays if they fall on a weekend (Independence Day, Veteran's Day, Christmas, New Year, and Valentine's Day). Finally, we include an indicator for St. Patrick's Day, Valentine's Day, Halloween, Cinco de Mayo, and Mother's Day. (Notice that several holiday indicators drop out in the benchmark sample which includes only Friday through Sunday).

TV Audience controls. We include two controls for TV audience: (i) an indicator for the date of the Superbowl; (ii) the TV audience for TV programs with an audience above 15 million viewers, and 0 otherwise. The latter variable was constructed using Nielsen data on top shows of the year listed in *Time Almanac*; the variable is zero for the season 2000-2001, for which we could not locate the data.

Weather controls. The source for the weather variables is the "Global Surface Summary of Day Data" produced by the National Climatic Data Center and available from ftp://ftp.ncdc.noaa.gov/pub/data/gsod.

Weather information is collected for the capital of each state in our sample (except for Kentucky, where Lexington rather than Frankfort is used due to data issues). An average of the weather variables is taken, using as weights the covered NIBRS population. These weights are specific to a state and year due to the changing NIBRS coverage over time.

The variables used are maximum and minimum daily temperature measured in Fahrenheit, the heat index (which combines air temperature and relative humidity to determine an apparent temperature for how hot it actually feels), wind speed measured in knots (categorized using the Beaufort scale), rainfall, and snow. Before averaging, the variables are categorized as dummy variables for the maximum daily temperature falling in one of three categories (> 80 and ≤ 90, > 90 and ≤ 100, > 100), the minimum daily temperature falling in one of three categories (≤ 10, > 10 and ≤ 20, > 20 and ≤ 32), the heat index falling in one of three categories (> 100 and ≤ 115, > 115 and ≤ 130, > 130), the windspeed falling in one of two categories (> 17 and ≤ 21, > 21), any rain, and any snow.

B Appendix B - Instruments

Benchmark Instrument. Our set of instruments uses information on the following weekend's audience for the same movie to predict movie attendance, and then aggregates these predictors across all movies of a given violence level. The procedure is related to the imputation procedure, and we use the same notation (Appendix A). We assume the daily audience $a_{j,t}$ on day t is a share s of the weekend audience in the same week $w(t)$, where the share allowed to depend on a set of controls Y^j, $s(Y^j)$: $a_{j,t} = s(Y^j)\, a^w_{j,w(t)}$. In addition, we assume that the weekend audience decays at rate $d(Y)$ each week: $a^w_{j,w(t)+1} = d(Y^j)\, a^w_{j,w(t)}$. Combining the two expressions and taking logs, we obtain $\ln(a_{j,t}) - \ln(a^w_{j,w(t)+1}) = \ln(s(Y^j)) - \ln(d(Y^j))$. The most important control for the term $\ln(s(Y^j)) - \ln(d(Y^j))$ is the set of day-of-week indicators d^d_t: different days of the week capture a different share of the overall revenue (Table 1). In addition, we use the same set of controls $X_{j,t}$ as for the imputation procedure (Appendix A), with only two differences: (i) the indicators for audience size refer to week $w(t)+1$ (as opposed to week $w(t)$), and (ii) we add indicators for slow releases (indicators for the cases in which the weekend audience for week $w(t)$ is less than 3 (respectively, 5) times smaller than in week $w(t)+1$. This set of controls $X_{j,t}$ is interacted with the day-of-week dummies, as well as present in levels. This allows the decay rate to vary by weekday and differentially so for different types of movies. Finally, we include the holiday controls H_t, described above, and 365 day-of-year indicators $\eta_{d(t)}$. We estimate

$$\ln(a_{j,t}) - \ln(a^w_{j,w(t)+1}) = \sum_{d\in D} \beta^d d^d_t + \sum_{d\in D} \Gamma^{d,X} d^d_t X_{j,t} + \Gamma X_{j,t} + \Phi H_t + \eta_{d(t)} + \varepsilon_{j,t} \qquad (7)$$

over the set of movie-day observations (j,t) for which we observe both the daily (not imputed) audience $a_{j,t}$ and the audience $a^w_{j,w(t)+1}$ for the next weekend. The regression is weighted by the next weekend's audience $a^w_{j,w(t)+1}$. We use the predicted values from the regressions, $\ln(a_{j,t}) - \widehat{\ln}(a^w_{j,w(t)+1})$, to obtain the predicted daily audience $\hat{a}_{j,t}$: $\hat{a}_{j,t} = \exp[\ln(a^w_{j,w(t)+1}) + \ln(a_{j,t}) - \widehat{\ln}(a^w_{j,w(t)+1})]$. Finally, to generate the predicted audiences $\hat{A}^n_t$, $\hat{A}^m_t$, and $\hat{A}^v_t$, we simply aggregate across the movies in the relevant violence category. For example, $\hat{A}^v_t = \sum_{v=8}^{10}\sum_{j\in J} d^{j\epsilon v}\hat{a}_{j,t}$, where $d^{j\epsilon v}$ is an indicator for film j belonging to violence level v. The instruments for the audience measures by sexual content, profanity, and *MPAA*-based violence ratings differ only in the final aggregation by categories of movies.

Instrument for DVD/VHS Rentals. The instrument for DVD and VHS rentals is constructed similarly to the benchmark instrument, except that *Video Store Magazine* only publishes the DVD and VHS rental at the weekly level. Hence, we estimate the equivalent of the predictive specification (7) for rentals in week $w(t)$:

$$\ln\left(a_{j,w(t)}\right) - \ln(a^w_{j,w(t)+1}) = \Gamma Y_{j,w(t)} + \Phi H_{w(t)} + \eta_{d(t)} + \varepsilon_{j,t}.$$

The regression is weighted by the next week's rentals $a^w_{j,w(t)+1}$. The set of controls $Y_{j,w(t)}$, as for the standard instrument, includes month indicators, a linear time trend, indicators for the level of violence, indicators for rating type, and indicators for rentals in week $w(t)+1$. The holiday controls H_t indicate separate indicators for whether the week $w(t)$ includes any of the holidays described in Appendix A, and whether the week $w(t)+1$ includes any of these holidays. The predicted values from the regressions are used to generate the predicted weekly rentals $\hat{a}_{j,t}$. These predicted rentals are then approportioned to each day of week using the within-week shares of rentals from the *CEX* time diaries.

Theaters and Budget Instrument. The estimates in column 3 of Appendix Table 2 use an instrument based on the number of theaters and on the production budget. The number of theater screens in which a movie plays in a given week is a good predictor of its audience (Moretti, 2007). We use the data on number of screens for week $w(t)$ from *www.the-numbers.com* (the same source of the revenue data), and renormalize it by the 90th percentile of the number of screens in that year, obtaining variable $ns_{j,w(t)}$. We obtain the production budget from the same source, and also renormalize it by the 90th percentile of the budget in that year. To obtain the final variable we take logs: $\log(b_j)$. An indicator variable indicates movies for which the production budget is missing, in which case $\log(b_j)$ is set to zero. We denote the vector of these variables as $NB_{j,w(t)}$. Since the predictability of audience using number of screens and budget varies with both the weekday and the number of weeks a movie has been out, we interact the variables $NB_{j,w(t)}$ with a day-of-week indicators d^d_t as well indicators for number of weeks out $d^{nw}_{j,w(t)}$ (0 weeks, 1 week, 2-4 weeks, 5-9 weeks, 10-19 weeks, 20-26 weeks, >26). We estimate

$$\begin{aligned}\ln(a_{j,t}) \quad = \quad & \sum_{nw\in NW}\beta^{nw}d^{nw}_{j,w(t)} + \sum_{nw\in NW}\Gamma^{nw,NB}d^{nw}_{j,w(t)}NB_{j,w(t)} + \sum_{d\in D}\beta^d d^d_t + \\ & \sum_{d\in D}\Gamma^{d,NB}d^d_t NB_{j,w(t)} + \Gamma^{NB}NB_{j,t} + \sum_{d\in D}\Gamma^{d,Y}d^d_t Y_{j,t} + \Gamma Y_{j,t} + \Phi H_t + \eta_{d(t)} + \varepsilon_{j,t}\end{aligned}$$

over the set of movie-day observations (j,t) for which we observe the daily (not imputed) audience $a_{j,t}$. The regression is weighted by the number of movies screens next week $n_{j,w(t)+1}$. The set of controls $Y_{j,t}$ is the same as for the standard instrument, except that we do not use information on the audience next week.

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Figure 1a. Weekend Theater Audience of Strongly Violent Movies

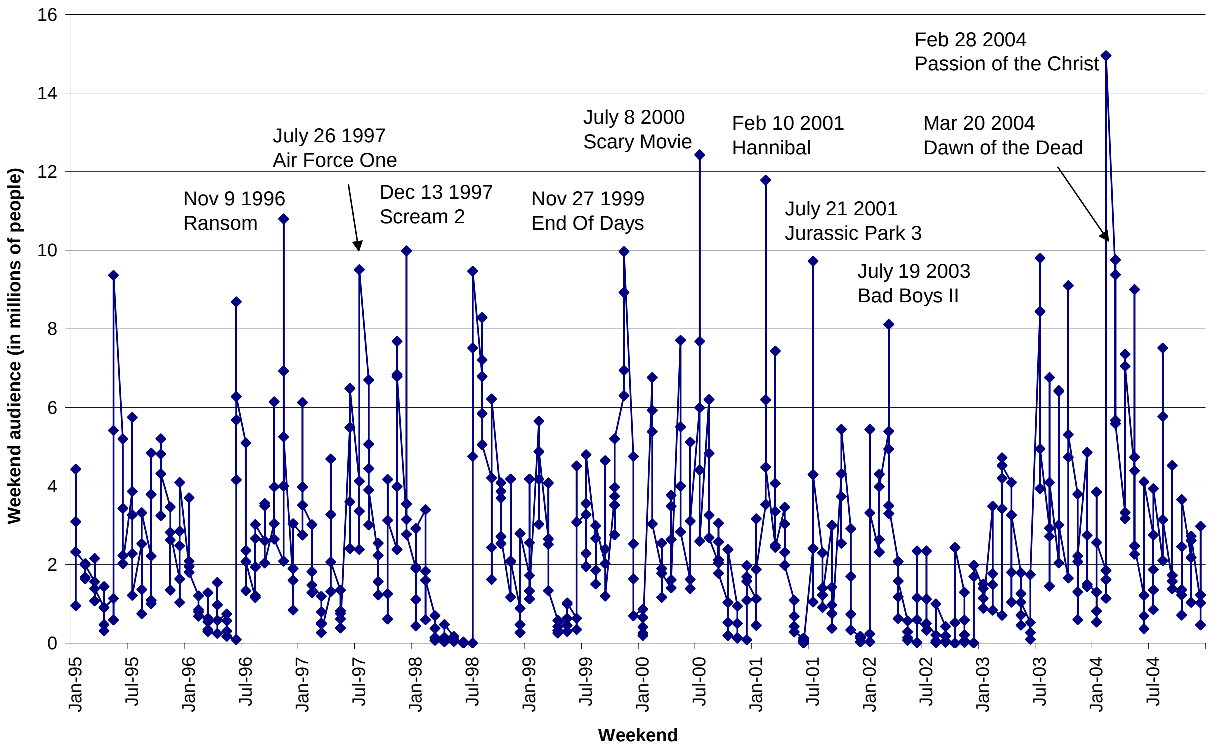
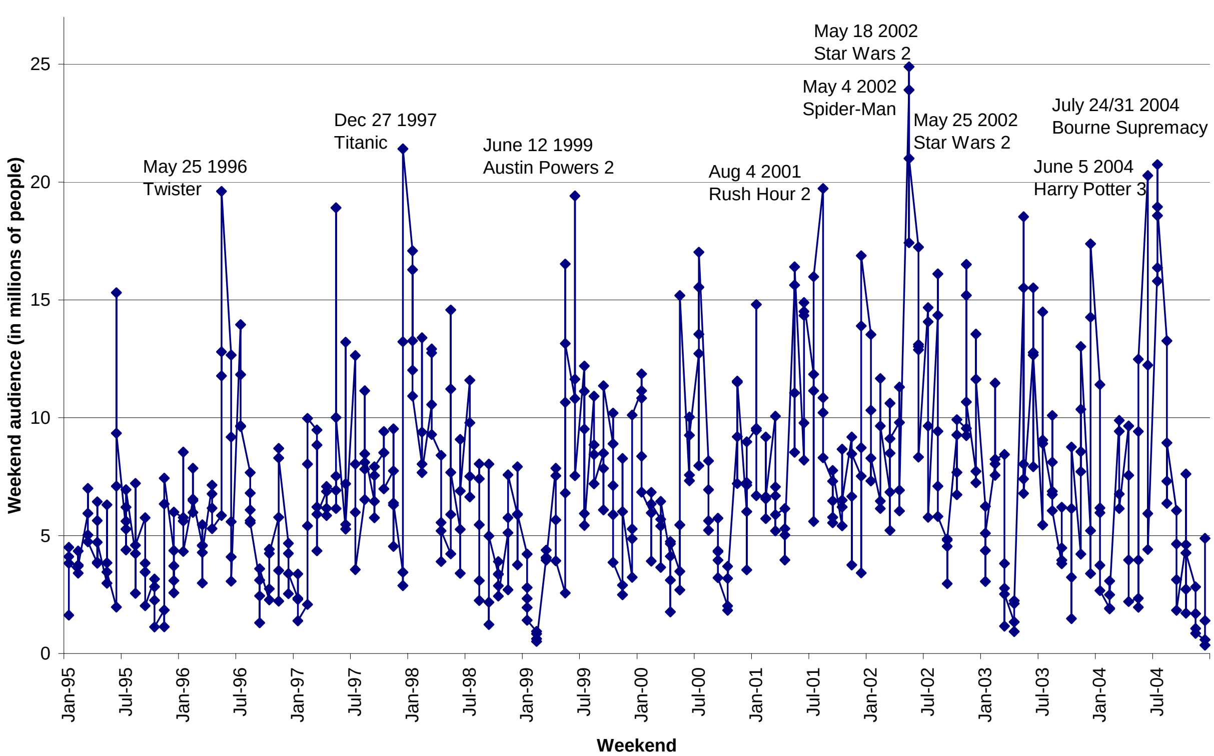


Figure 1b. Weekend Theater Audience of Mildly Violent Movies



Notes: Plot of weekend (Friday through Sunday) box-office audience in millions of people for movies rated as strongly violent (Figure 1a) and mildly violent (Figure 1b). The 10 weekends with the highest audience for strongly violent (respectively, mildly violent) movies are labeled in Figure 1a (Figure 1b). Movies are rated as strongly violent (respectively, mildly violent) if they have a *kids-in-mind.com* rating 8-10 (5-7). The audience data is from box-office sales (from *the-numbers.com*) deflated by the average price of a ticket.

Figure 1c. Log Weekend Assaults

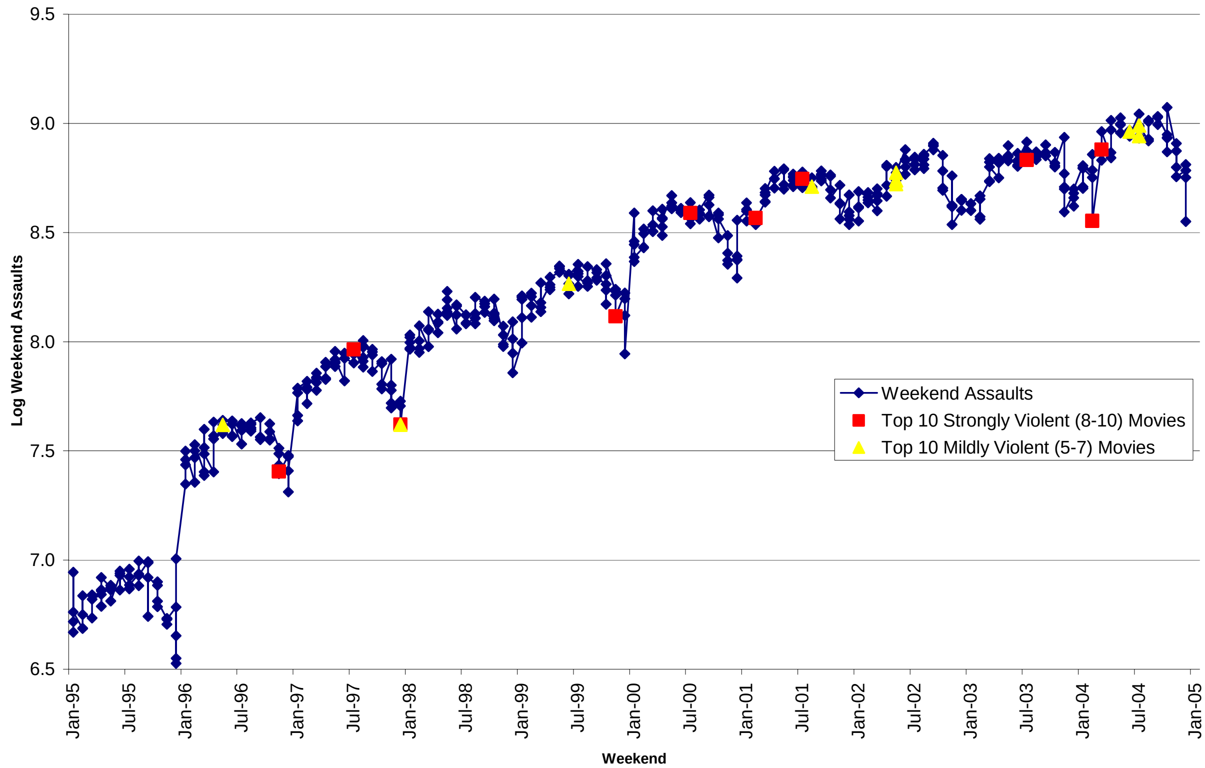
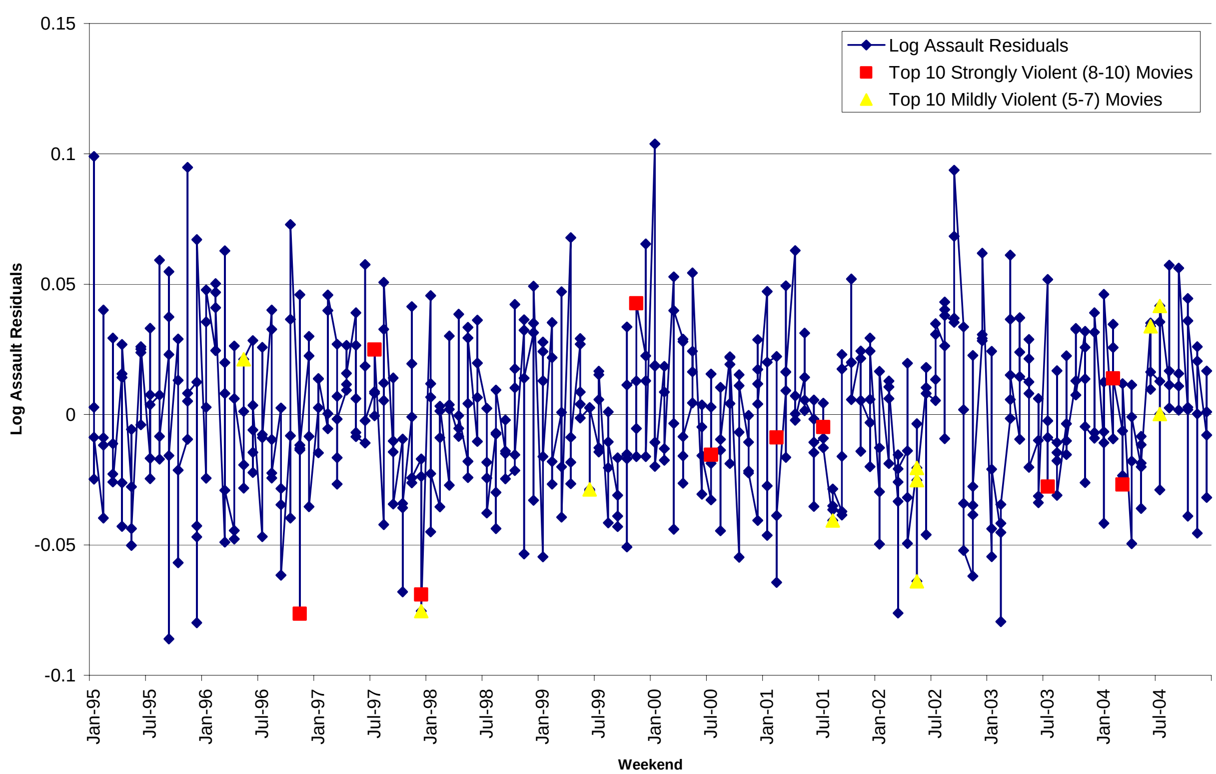


Figure 1d. Residuals of Regression of Log Assault on Seasonality Controls



Notes: Plot of weekend (Friday through Sunday) log assaults in Figure 1c and average (Friday through Sunday) residuals of weekend log assaults after controlling for seasonality, holidays, and weather controls (see text for list of all the controls) in Figure 1d. The assault data is from *NIBRS*. The figure highlights the 10 weekends with the largest strongly violent movie audience (see Figure 1a) and the 10 weekends with the largest mildly violent movie audience (see Figure 1b).

Figure 2. Theoretical Effect of Movie Violence on Assaults

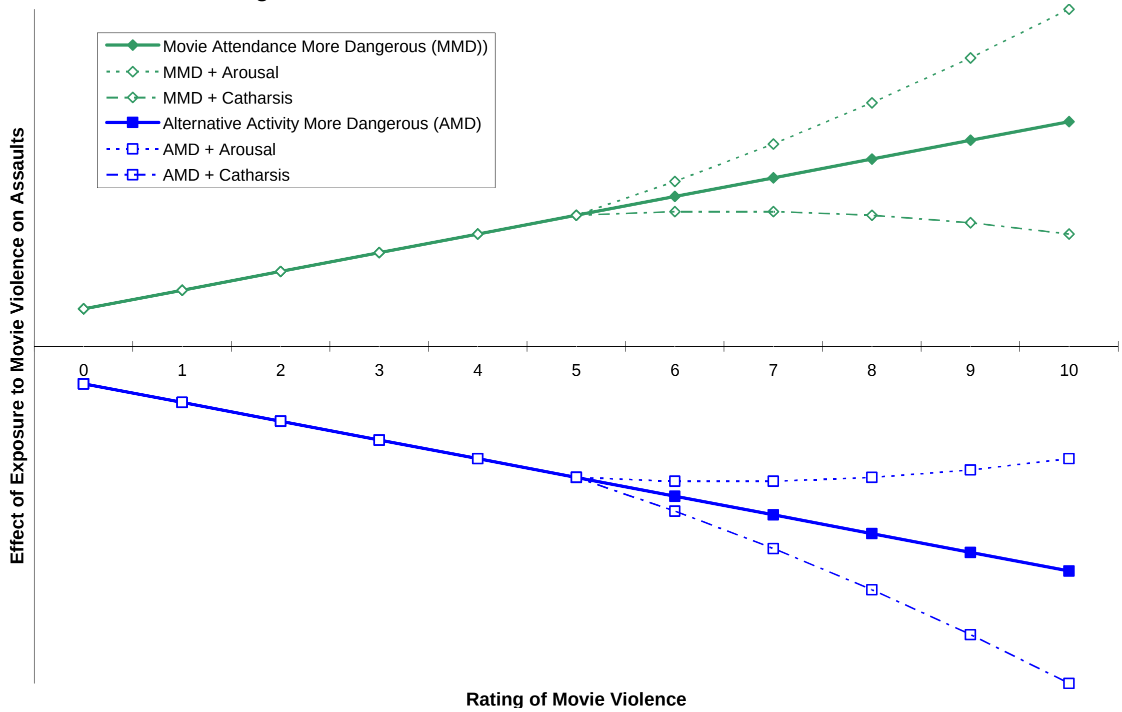
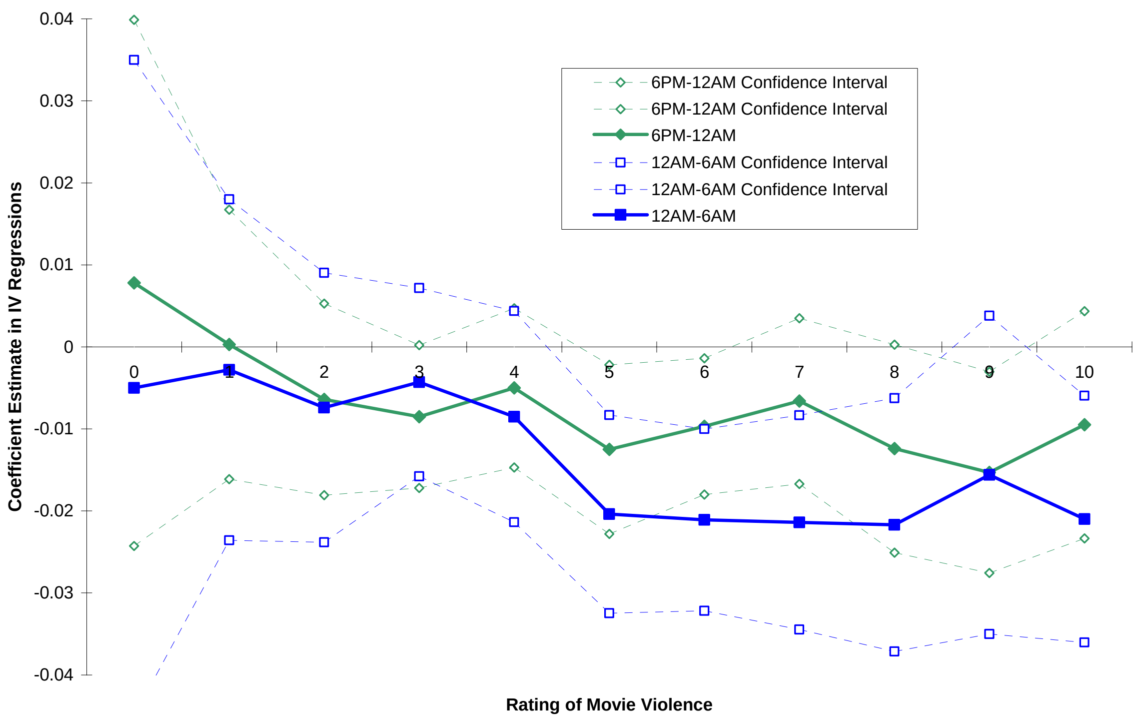
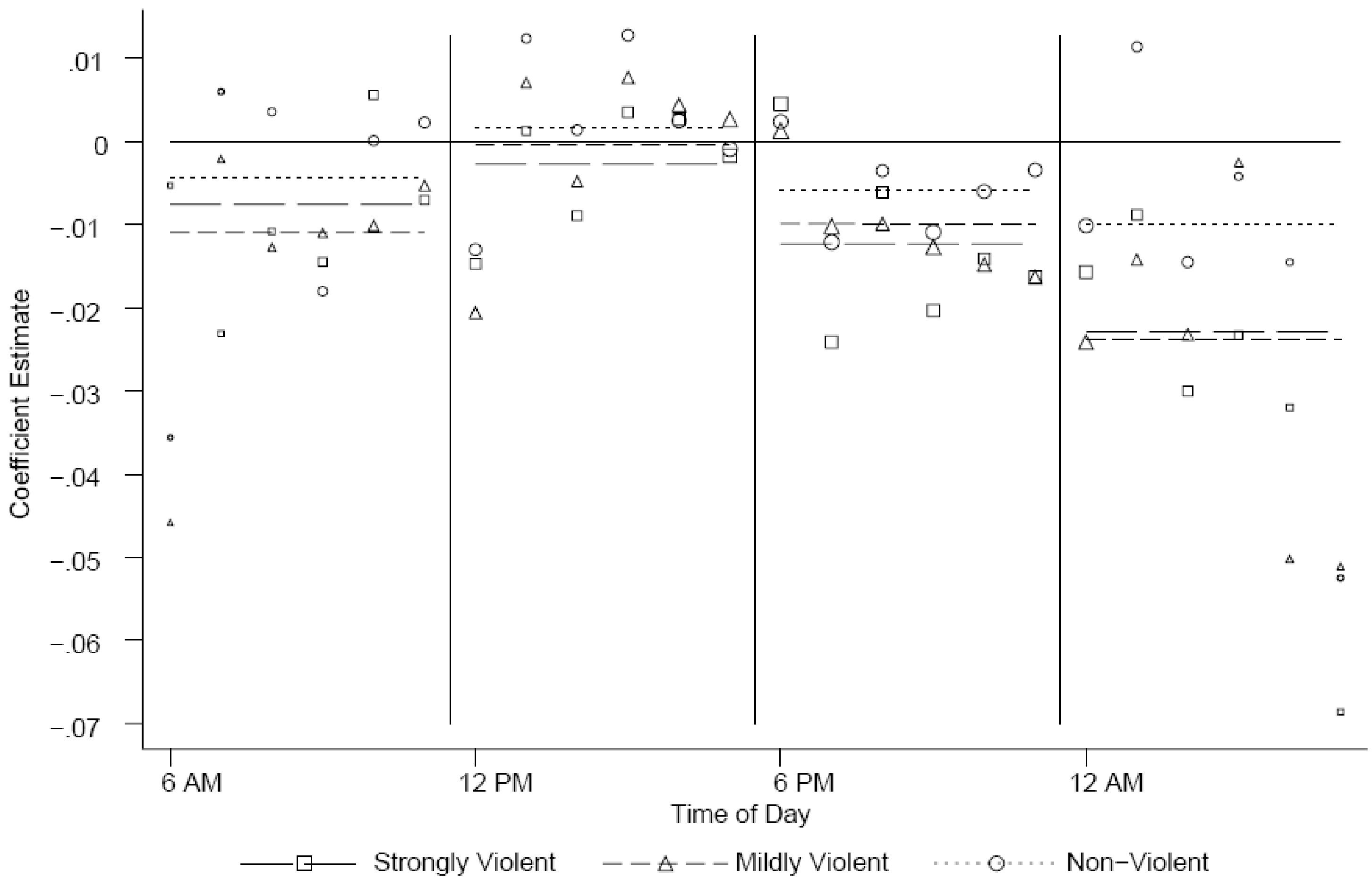


Figure 3. Observed Effect of Movie Violence on Assaults



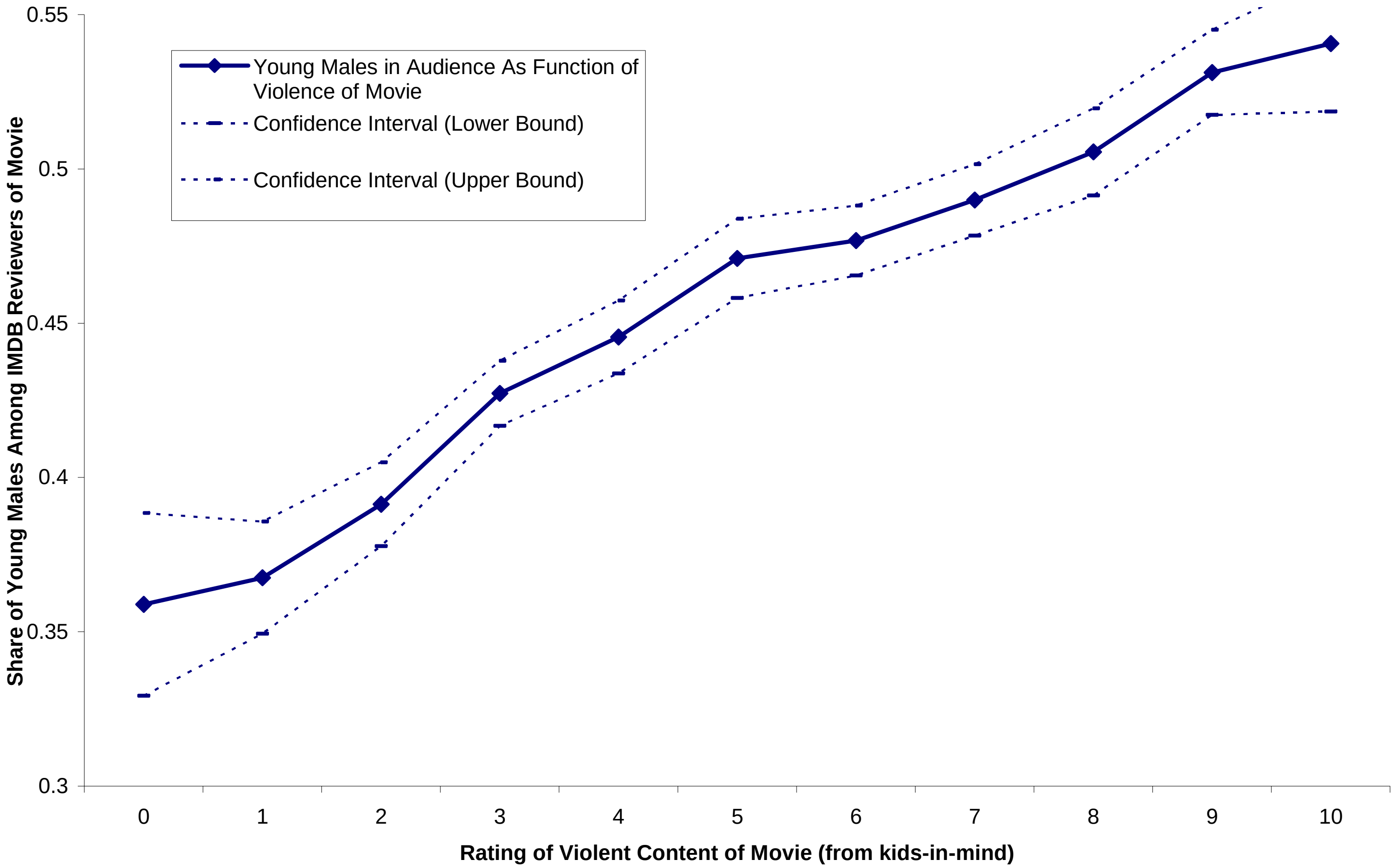
Notes: Theoretical scenarios (Figure 2) and empirical estimates (Figure 3) of the effect of exposure to movies of violence v=0,…,10 on assaults. The scenario "Movie Attendance More Dangerous" in Figure 2 indicates that, compared to the alternative activity, movie attendance induces more violent behavior in the aftermath of exposure. The scenario "Alternative Activity More Dangerous" refers to the opposite possibility. In both scenarios, the coefficients fan out with movie violence due to the increased self-selection of potential criminals. The "Arousal" scenario indicates that the direct effect of exposure to violent movies is to induce more crime than exposure to non-violent movies because of arousal. The "Catharsis" scenario indicates an opposite effect because of catharsis. Figure 3 plots the coefficients and 95% confidence intervals from IV regression of log (assaults) on 11 variables for the daily audience for movies rated with violence level *v=0,1,…,10*. Separate regressions are run for assaults in the 6PM-12AM and 12AM-6AM time periods. The coefficients can be interpreted as the percent change in assaults for an increase of one million in the audience for movies of violence *v*.

Figure 4. Effect of Movie Violence by One-Hour Time Blocks



Notes: Plot of coefficients from 24 separate IV regressions of log(assaults) on the audience size of strongly, mildly, and non-violent movies using the baseline specification. The size of each point is inversely proportional to the estimated variance of the coefficient estimate. The horizontal lines within each 6-hour time block are the weighted average of the estimated coefficients within a violence category, where the weights are the inverse of the estimated variances. The violence rating of movies is from *kids-in-mind.com*. The audience data is obtained from box office sales (from *the-numbers.com*) deflated by the average price of a ticket.

Figure 5. Share of Young Males in Audience As Function of Violence (Internet Movie Database Data)



Notes:.Plot of the share of *IMDB* reviewers who are young males for a movie versus violent content. Young males are defined as men between the ages of 18 and 29. The violence rating of movies is from *kids-in-mind.com*. The dotted lines are pointwise 95% confidence intervals.

Table 1. Summary Statistics

	Assaults (per day)			
	Entire Day	6AM to 6PM	6PM to 12AM	12AM to 6AM
Assault Data For All Days	(1)	(2)	(3)	(4)
Weekend (Friday - Sunday)	1454	569	531	354
Friday	1589	614	543	432
Saturday	1564	557	558	449
Sunday	1209	536	491	182
Weekday (Monday - Thursday)	1293	608	480	205
Assault Data For Weekends (Friday - Sunday)	Share of weekend assaults in category			
By gender of offender				
Share with Male Offender	0.779	0.755	0.784	0.811
By age of offender				
Share with offender of age 13 to 17	0.107	0.136	0.114	0.051
Share with offender of age 18 to 29	0.378	0.340	0.359	0.467
Share with offender of age 30 to 44	0.326	0.317	0.342	0.315
Share with offender of age 45-54	0.076	0.082	0.082	0.059
Share with offender of age 55+	0.027	0.034	0.026	0.016
Alcohol-related assaults				
Share with offender suspected of using alc. or drugs	0.170	0.082	0.185	0.290
Share at a bar involving alcohol or drugs	0.014	0.002	0.011	0.039
Number of Observations	N = 1,563 days, 2,272,999 assaults, 1,781 agencies			

	Movie Audience (in millions of tickets / rentals per day)	
	Theater Audience	VHS/DVD rentals
Movie Audience Data For All Days	(5)	(6)
Weekend (Friday - Sunday)	6.29	3.92
Friday	5.74	4.13
Saturday	7.90	4.82
Sunday	5.24	2.82
Weekday (Monday - Thursday)	2.00	2.09
Movie Audience Data For Weekends (Friday - Sunday)		
By Kids-in-Mind rating		
Strongly violent movies	0.87	0.64
Mildly violent movies	2.43	1.56
Non violent movies	2.99	1.72
Movies with strong sexual content	0.19	
Movies with mild sexual content	1.37	
Movies with no sexual content	4.72	
Movies with strong profanity	0.82	
Movies with mild profanity	2.35	
Movies with no profanity	3.12	
By alternative MPAA rating		
Strongly violent movies	0.48	
Mildly violent movies	2.19	
Non violent movies	3.65	

Notes: An observation is a day over the years 1995-2004. Assault data comes from the National Incident Based Reporting System (NIBRS), and the sample includes agencies that do not have missing data on any crime (not just assaults) for more than seven consecutive days for that year. The movie audience numbers are obtained from the-numbers.com and are daily box-office revenue divided by the average price per ticket. The ratings of violent movies are from www.kids-in-mind.com. The audience of mildly violent movies is the audience of all movies with a violence rating 5-7. The audience of strongly violent movies is the audience of all movies with a violence rating 8-10. These groupings are the same for sexual content and profanity as well, which are also obtained from kids-in-mind.com. The alternative MPAA rating is based on the presence of key words used to describe why a movie received a certain rating by the MPAA. VHS/DVD rental data comes from Video Store Magazine.

Table 2. The Effect of Movie Violence on Same-Day Assaults

Specification:	OLS Regressions						IV Regressions
Dep. Var.:	Log (Number of Assaults in Day t)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Audience Of Strongly Violent Movies	0.0324	0.0005	-0.0061	-0.0051	-0.0072	-0.0091	-0.0106
(in millions of people in Day t)	(0.0053)***	(0.0053)	(0.0033)*	(0.0033)	(0.0033)**	(0.0026)***	(0.0031)***
Audience Of Mildly Violent Movies	0.0246	0.0017	-0.0084	-0.0042	-0.0056	-0.0079	-0.0102
(in millions of people in Day t)	(0.0030)***	(0.0029)	(0.0020)***	(0.0026)	(0.0027)**	(0.0022)***	(0.0028)***
Audience Of Non-Violent Movies	0.0082	-0.0164	-0.0062	-0.0023	-0.0029	-0.0035	-0.0050
(in millions of people in Day t)	(0.0029)***	(0.0030)***	(0.0021)***	(0.0024)	(0.0026)	(0.0024)	(0.0029)*
Control Variables:							
Year Indicators	X	X	X	X	X	X	X
Day-of-Week Indicators		X	X	X	X	X	X
Month Indicators			X	X	X	X	X
Day-of-Year Indicators				X	X	X	X
Holiday Indicators					X	X	X
Weather and TV Audience Controls						X	X
F-Test on Additional Controls	F=1934.02	F=1334.31	F=88.56	F=13.37	F=15.05	F=18.58	
Audience Instrumented With Predicted Audience Using Next Weekend's Audience							X
R^2	0.9344	0.9711	0.9846	0.9904	0.9912	0.9931	.
N	N = 1563	N = 1563	N = 1563	N = 1563	N = 1563	N = 1563	N = 1563

Notes: An observation is a Friday, Saturday, or Sunday over the years 1995-2004. Assault data comes from the National Incident Based Reporting System (NIBRS), where the sample includes agencies that do not have missing data on any crime (not just assaults) for more than seven consecutive days. The movie audience numbers are obtained from the-numbers.com and are daily box-office revenue divided by the average price per ticket. The ratings of violent movies are from www.kids-in-mind.com. The audience of strongly violent movies is the audience of all movies with a violence rating 8-10. The audience of mildly violent movies is the audience of all movies with a violence rating 5-7. The specifications in Columns (1) through (6) are OLS regressions with the log(number of assault occurring in day t) as the dependent variable. The specification in Column (7) instruments the audience numbers with the predicted audience numbers based on next weekend's audience. Details on the construction of the predicted audience numbers are in the text. Robust standard errors clustered by week in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3. The Effect of Movie Violence on Same-Day Assaults by Time of Day.

Panel A. Benchmark Results

Specification:	Instrumental Variable Regressions			
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)			
	(1)	(2)	(3)	(4)
Audience Of Strongly Violent Movies	-0.0050	-0.0030	-0.0130	-0.0192
(in millions of people in Day t)	(0.0066)	(0.0050)	(0.0049)***	(0.0060)***
Audience Of Mildly Violent Movies	-0.0106	-0.0001	-0.0109	-0.0205
(in millions of people in Day t)	(0.0060)*	(0.0045)	(0.0040)***	(0.0052)***
Audience Of Non-Violent Movies	-0.0033	0.0016	-0.0063	-0.0060
(in millions of people in Day t)	(0.0060)	(0.0046)	(0.0043)	(0.0054)
Time of Day	6AM-12PM	12PM-6PM	6PM-12AM	12AM-6AM next day
Control Variables:				
Full Set of Controls	X	X	X	X
Predicted Audience Using Next Week's Audience	X	X	X	X
N	N = 1563	N = 1563	N = 1563	N = 1562

Panel B. First Stage

Specification:	IV Regression, First Stage		
Dep. Var.:	Audience of Strongly Violent Movies	Audience of Mildly Violent Movies	Audience of Non Violent Movies
	(1)	(2)	(3)
Pred. Audience Of Strongly Violent Movies	0.9145	-0.1431	-0.1694
(in millions of people in Day t)	(0.0196)***	(0.0210)***	(0.0281)***
Pred. Audience Of Mildly Violent Movies	-0.0399	0.8532	-0.1817
(in millions of people in Day t)	(0.0101)***	(0.0255)***	(0.0296)***
Pred. Audience Of Non-Violent Movies	-0.0480	-0.1363	0.8138
(in millions of people in Day t)	(0.0097)***	(0.0195)***	(0.0309)***
Control Variables:			
Full Set of Controls	X	X	X
F-Test on Instruments	F = 1050.89	F = 889.02	F = 730.85
N	N = 1563	N = 1563	N = 1563

Notes: See notes to Table 2.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4. Medium-Run Effect of Movie Violence

Specification:	OLS Regressions							
Timing:	Next Monday and Tuesday		Next Week		Two Weeks Later		Three Weeks Later	
Dep. Var.:	Log (Number of Assaults On Monday and Tuesday in Time Window)		Log (Number of Assaults in Day t in Time Window)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience Of Strongly Violent Movies			-0.0127	-0.0081	-0.0142	-0.0209	-0.0136	-0.0199
(in millions of people in day t)			(0.0045)***	(0.0060)	(0.0051)***	(0.0067)***	(0.0051)***	(0.0063)***
Audience Of Mildly Violent Movies			-0.0061	-0.0087	-0.0096	-0.0194	-0.0114	-0.0199
(in millions of people in day t)			(0.0031)**	(0.0043)**	(0.0042)**	(0.0056)***	(0.0041)***	(0.0052)***
Audience Of Non-Violent Movies			-0.0027	0.0030	-0.0050	-0.0079	-0.0070	-0.0076
(in millions of people in day t)			(0.0033)	(0.0050)	(0.0046)	(0.0061)	(0.0044)	(0.0056)
Lagged Audience Of Strongly Violent Movies	0.0019	-0.0004	0.0046	-0.0017	-0.0028	0.0020	0.0017	-0.0065
(in millions of people in day t)	(0.0058)	(0.0087)	(0.0042)	(0.0054)	(0.0047)	(0.0062)	(0.0044)	(0.0056)
Lagged Audience Of Mildly Violent Movies	-0.007	-0.0146	-0.0018	0.0001	-0.0061	-0.0056	0.0002	-0.0105
(in millions of people in day t)	(0.0050)	(0.0076)*	(0.0026)	(0.0037)	(0.0037)	(0.0049)	(0.0031)	(0.0045)**
Lagged Audience Of Non-Violent Movies	0.0012	-0.0065	-0.0007	0.0031	-0.0060	0.0012	0.0011	-0.0049
(in millions of people in day t)	(0.0054)	(0.0074)	(0.0028)	(0.0041)	(0.0042)	(0.0055)	(0.0036)	(0.0048)
Lag Specification	Lag: Weekend Before		Lag: 7 Days Before		Lag: 14 Days Before		Lag: 21 Days Before	
Time of Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day
Control Variables:								
Full Set of Controls	X	X	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Following Week's Audience	X	X	No	No	X	X	X	X
N	N = 1041	N = 1041	N = 1559	N = 1558	N = 1556	N = 1555	N = 1553	N = 1552

Notes: See notes to Table 2. The specifications are IV regressions with the log(number of assault occurring in day t) as the dependent variable. The specifications in Columns 3 and 4 are not instrumented, since the predictors for the audience of the previous week are highly collinear with the contemporaneous audience.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Placebo Tests

Specification:	Placebo IV Regressions								
Dep. Var.:	Log (Number of Assaults in Day t)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Audience Of Strongly Violent Movies	-0.0018	-0.0143	-0.0207	-0.0007	-0.0108	-0.0169	-0.0027	-0.0133	-0.0203
(in millions per day in day t)	(0.0063)	(0.0072)**	(0.0091)**	(0.0049)	(0.0054)**	(0.0068)**	(0.0046)	(0.0049)***	(0.0062)***
Audience Of Mildly Violent Movies	-0.0004	-0.0148	-0.0288	-0.0026	-0.0103	-0.0188	-0.0033	-0.0102	-0.0194
(in millions per day in day t)	(0.0056)	(0.0059)**	(0.0073)***	(0.0045)	(0.0045)**	(0.0057)***	(0.0042)	(0.0041)**	(0.0052)***
Audience Of Non-Violent Movies	0.0038	-0.0115	-0.0089	0.0024	-0.0055	-0.0077	0.0007	-0.0069	-0.0087
(in millions per day in day t)	(0.0060)	(0.0061)*	(0.0078)	(0.0046)	(0.0049)	(0.0062)	(0.0043)	(0.0044)	(0.0056)
Placebo Audience Of Strongly Violent Movies	0.0076	0.0015	0.007	-0.0083	-0.0062	-0.007	-0.0049	0.0025	0.0051
(in millions per day in day t)	(0.0063)	(0.0070)	(0.0099)	(0.0047)*	(0.0050)	(0.0064)	(0.0041)	(0.0043)	(0.0059)
Placebo Audience Of Mildly Violent Movies	0.0083	0.0016	-0.0031	-0.0061	-0.0046	-0.0068	-0.0027	0.0022	0.0024
(in millions per day in day t)	(0.0054)	(0.0055)	(0.0079)	(0.0039)	(0.0038)	(0.0057)	(0.0034)	(0.0035)	(0.0046)
Placebo Audience Of Non-Violent Movies	0.0081	0.0003	0.0034	-0.0092	-0.0042	0.0001	-0.0035	0.0068	0.0125
(in millions per day in day t)	(0.0056)	(0.0060)	(0.0084)	(0.0038)**	(0.0040)	(0.0061)	(0.0034)	(0.0035)*	(0.0052)**
Placebo Audience	Audience on Same Day and Day-Of-Week in Another Year			Audience 14 Days Later			Audience 21 Days Later		
Time of Day	6AM-6PM	6PM-12AM	12AM-6AM next day	6AM-6PM	6PM-12AM	12AM-6AM next day	6AM-6PM	6PM-12AM	12AM-6AM next day
Control Variables:									
Full Set of Controls	X	X	X	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Following Week's Audience	X	X	X	X	X	X	X	X	X
N	N = 1200	N = 1200	N = 1199	N = 1556	N = 1556	N = 1555	N = 1553	N = 1553	N = 1552

Notes: We generate the placebo audiences for columns 1-3 by re-assigning the audience measures to the other date in the sample that falls on both the same day-of-year and the same day-of-week (if such date exists). This correspondence is complicated by the presence of February 29 in leap years. For example, all dates between January 1 and February 28 of 1996 are matched to the corresponding date in 2001 (and viceversa). All dates between March 1 and December 31 in 1996, instead, are matched to the corresponding date in 2002 (and viceversa). The specifications in columns 4-9 generate placebo audiences using the audiences 14 and 21 days in the future. The IV regressions include both the real audience sizes as well as the placebo audience sizes. See also notes to Table 2.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. The Effect of DVD/VHS Movie Violence on Same-Day Assaults

Specification:	Instrumental Variable Regressions					
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)					
	(1)	(2)	(3)	(4)	(5)	(6)
DVD/VHS Rentals Of Strongly Violent Movies	-0.0042	-0.0078	-0.0148	-0.0051	-0.0044	-0.0107
(in millions of people in day t)	(0.0058)	(0.0063)	(0.0078)*	(0.0101)	(0.0104)	(0.0120)
DVD/VHS Rentals Of Mildly Violent Movies	-0.0041	-0.0148	-0.0311	-0.0034	-0.0227	-0.0193
(in millions of people in day t)	(0.0059)	(0.0052)***	(0.0071)***	(0.0103)	(0.0092)**	(0.0102)*
DVD/VHS Rentals Of Non-Violent Movies	-0.0029	-0.0043	-0.0225	-0.0054	-0.0041	-0.0199
(in millions of people in day t)	(0.0066)	(0.0060)	(0.0076)***	(0.0115)	(0.0106)	(0.0114)*
Theater Audience Of Strongly Violent Movies				0.0017	-0.0098	-0.0192
(in millions of people in day t)				(0.0082)	(0.0077)	(0.0089)**
Theater Audience Of Mildly Violent Movies				0.0034	-0.0119	-0.0202
(in millions of people in day t)				(0.0076)	(0.0070)*	(0.0080)**
Theater Audience Of Non-Violent Movies				0.0042	-0.0049	-0.0071
(in millions of people in day t)				(0.0078)	(0.0070)	(0.0079)
Time of Day	6AM-6PM	6PM-12AM	12AM-6AM next day	6AM-6PM	6PM-12AM	12AM-6AM next day
Control Variables:						
Full Set of Controls	X	X	X	X	X	X
Rental and Theater Audiences Instrumented With Predicted Audiences Using Next Week's Audiences	X	X	X	X	X	X
N	N = 1475	N = 1475	N = 1475	N = 1475	N = 1475	N = 1475

Notes: The daily audience numbers are computed from weekly data on DVD and VHS rental revenue from Video Store Magazine. The weekly revenue is divided by the average price of a rental and proportionately attributed to the Friday, Saturday, and Sunday using the average within-week distribution of rentals in the CEX diaries. The specifications are IV regressions with the log(number of assault occurring in day t) as the dependent variable. See also notes to Table 2.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Patterns of Movie Attendance By Demographics (CEX Data)

Specification:	OLS Regressions				
Dep. Var.:	Share of Households Interviewed Watching a Movie At the Theater in Day t				
	(1)	(2)	(3)	(4)	(5)
Share of Audience Of Strongly Violent Movies	0.9469	2.094	1.146	0.4323	2.7751
(in share of US population in Day t)	(0.1883)***	(0.5602)***	(0.3328)***	(0.2580)*	(1.4550)*
Share of Audience Of Mildly Violent Movies	0.7736	1.4642	1.4499	0.1259	2.7825
(in share of US population in Day t)	(0.1419)***	(0.4407)***	(0.2623)***	(0.1711)	(1.3110)**
Share of Audience Of Non-Violent Movies	0.7614	1.0786	1.1555	0.392	0.4031
(in share of US population in Day t)	(0.1440)***	(0.4652)**	(0.2491)***	(0.1741)**	(1.2926)
Demographic Groups (By Head of Household)	All	Age 18-29	Age 30-44	Age 45+	Single Males Age 18-29
Full Set of Controls	X	X	X	X	X
Regressions Weighted by Number of Households Interviewed in Day t	X	X	X	X	X
Average Number of Households in Demographic Group Interviewed on Day t	157.88	22.61	53.94	81.29	3.96
N	N = 1563	N = 1558	N = 1560	N = 1563	N = 1474

Notes: An observation is a Friday, Saturday, or Sunday over the years 1995-2004. The dependent variable is the share of the households in the diary CEX sample that reported attending a movie on day t. The audience numbers are obtained from daily box-office revenue divided by the average price per ticket. See also notes to Table 2.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Test of Sobriety: Effect of Alcohol Consumption

Specification:	Instrumental Variable Regressions							Reg. (CEX Data)
Dep. Var.:	Log (Number of Assaults of a Type in Day t in Time Window)						Log (Arrests for Drunkenness in Day t)	Share Consuming Alcohol Away From Home
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience Of Strongly Violent Movies	-0.012	-0.0287	-0.0137	-0.0164	-0.0157	-0.0471	-0.0178	-0.3303
(millions of people in day t) (shares in Col. (7))	(0.0080)	(0.0109)***	(0.0056)**	(0.0070)**	(0.0320)	(0.0275)*	(0.0096)*	(0.2696)
Audience Of Mildly Violent Movies	-0.0183	-0.025	-0.0088	-0.0197	-0.0042	-0.0313	-0.0029	-0.1921
(millions of people in day t) (shares in Col. (7))	(0.0071)**	(0.0107)**	(0.0046)*	(0.0059)***	(0.0292)	(0.0252)	(0.0092)	(0.2077)
Audience Of Non-Violent Movies	-0.0068	-0.0102	-0.0057	-0.0039	0.0077	-0.0229	-0.002	-0.0271
(millions of people in day t) (shares in Col. (7))	(0.0076)	(0.0114)	(0.0048)	(0.0060)	(0.0297)	(0.0250)	(0.0092)	(0.1993)
Type of Crime	Assaults Involving Alcohol or Drugs		Assaults Not Involving Alcohol or Drugs		Assaults At A Bar Involving Alc. or Drugs		Arrests for Drunkenness	Alcohol Consumption Away From Home
Time of Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	All day	Same Day
Control Variables:								
Full Set of Controls	X	X	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X	X	
N	N = 1563	N = 1560	N = 1563	N = 1562	N = 1477	N = 1479	N = 1563	N = 1563

Notes: The specifications in are IV regressions for specific types of assaults using NIBRS data in columns 1-6. The arrest data in column 7 is not available by time of day, and also comes from NIBRS. Column 8 uses the CEX data used in Table 7, where the dependent variable is the share of the households in the diary CEX sample that reported consuming alcohol away from home. See also notes to Table 2.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Demographic Decomposition Of The Effect of Movie Violence

Specification:	Instrumental Variable Regressions							
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Effects by Gender of Offender								
Audience Of Strongly Violent Movies	-0.0153	-0.0339	-0.0165	-0.0142				
(in millions of people in day t)	(0.0074)**	(0.0106)***	(0.0085)*	(0.0103)				
Audience Of Mildly Violent Movies	-0.0133	-0.0372	-0.0086	-0.0193				
(in millions of people in day t)	(0.0059)**	(0.0100)***	(0.0070)	(0.0089)**				
Audience Of Non-Violent Movies	-0.0069	-0.0149	-0.0063	-0.0046				
(in millions of people in day t)	(0.0062)	(0.0109)	(0.0073)	(0.0094)				
Gender of Offender	Male	Male	Female	Female				
N	N = 1563	N = 1562	N = 1563	N = 1562				
Panel B. Effects by Age of Offender								
Audience Of Strongly Violent Movies	-0.017	-0.0204	-0.0067	-0.0163	-0.0211	-0.0588	-0.0026	-0.0077
(in millions of people in day t)	(0.0069)**	(0.0077)***	(0.0065)	(0.0090)*	(0.0106)**	(0.0179)***	(0.0206)	(0.0267)
Audience Of Mildly Violent Movies	-0.0123	-0.0207	-0.0032	-0.0165	-0.0115	-0.0416	-0.0182	-0.0086
(in millions of people in day t)	(0.0058)**	(0.0070)***	(0.0057)	(0.0071)**	(0.0096)	(0.0189)**	(0.0186)	(0.0260)
Audience Of Non-Violent Movies	-0.0057	-0.0092	-0.0022	-0.0029	-0.0122	-0.0220	-0.0142	-0.0269
(in millions of people in day t)	(0.0061)	(0.0076)	(0.0058)	(0.0073)	(0.0102)	(0.0181)	(0.0170)	(0.0254)
Age Group of Offender	18-29	18-29	30-44	30-44	45-54	45-54	55+	55+
Time of Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day
Control Variables:								
Full Set of Controls	X	X	X	X	X	X	X	X
Predicted Audience Using Next Week's Audience	X	X	X	X	X	X	X	X
N	N = 1563	N = 1562	N = 1563	N = 1562	N = 1563	N = 1546	N = 1546	N = 1434

Notes: See notes to Table 2. The specifications are separate IV regressions each of the specified age and gender groups.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10. Movie Blockbusters by IMDB Rating and Violence

Violence Rating (1)		Blockbuster Movies Not Liked by Young Males (Date, Audience) (2)	Blockbuster Movies Liked by Young Males (Date, Audience) (3)	Blockbuster Movies Highly Liked by Young Males (Date, Audience) (4)
0-4 Non-Violent Movies	Top 1	Harry Potter And The Chamber Of Secrets (11/16/02, 15.2m)	Shrek 2 (5/22/04, 17.4m)	Austin Powers In Goldmember (7/27/02, 12.6m)
	Top 2	Harry Potter And The Chamber Of Secrets (11/23/02, 7.3m)	Harry Potter And The Sorcerer's Stone (11/17/01, 15.9m)	Incredibles (11/6/04, 11.3m)
	Top 3	Runaway Bride (7/31/99, 6.8m)	Shrek 2 (5/29/04, 11.8m)	Bruce Almighty (5/24/03, 11.2m)
	Top 4-6	Sweet Home Alabama, America's Sweethearts, Erin Brockovich	Finding Nemo, Toy Story 2, Monsters Inc.	Ace Ventura: When Nature Calls, Waterboy, Big Daddy
	Effect on Crime	-0.0041 (0.0062) (6PM-12AM) 0.0049 (0.0071) (12AM-6AM)	-0.0035 (0.0042) (6PM-12AM) -0.0057 (0.0055) (12AM-6AM)	-0.0090* (0.0053) (6PM-12AM) -0.0079 (0.0063) (12AM-6AM)
5-7 Mildly Violent Movies	Top 1	Double Jeopardy (9/25/99, 4.6m)	Harry Potter and The Prisoner Of Azkaban (6/5/04, 15.1m)	Spider-Man (5/4/02, 19.8m)
	Top 2	Save The Last Dance (1/13/01, 4.1m)	Mummy Returns (5/5/01, 12.4m)	Matrix Reloaded (5/17/03, 15.2m)
	Top 3	Double Jeopardy (10/2/99, 3.3m)	Planet Of The Apes (7/28/01, 12.3m)	Lost World: Jurassic Park (5/24/97, 14.3m)
	Top 4-6	Absolute Power, Random Hearts, Unfaithful	Day After Tomorrow, Independence Day, Pearl Harbor	Spider-Man 2, X2: X-Men, Star Wars 2
	Effect on Crime	0.0049 (0.0111) (6PM-12AM) -0.0268 (0.0141)* (12AM-6AM)	-0.0099** (0.0047) (6PM-12AM) -0.0177*** (0.0057) (12AM-6AM)	-0.0111*** (0.0039) (6PM-12AM) -0.0179*** (0.0052) (12AM-6AM)
8-10 Strongly Violent Movies	Top 1	Missing (11/29/03, 1.8m)	Passion Of The Christ (2/28/04, 13.5m)	Hannibal (2/10/01, 10.1m)
	Top 2	Nurse Betty (9/9/00, 1.3m)	Passion Of The Christ (3/6/04, 8.5m)	Jurassic Park 3 (7/21/01, 9.1m)
	Top 3	Copycat (11/4/95, 1.2m)	Air Force One (7/26/97, 7.9m)	Scary Movie (7/8/00, 8.2m)
	Top 4-6	Jade, In Dreams, A Rich Man's Wife	Ransom, Sleepy Hollow, General's Daughter	Bad Boys 2, Troy, Terminator 3
	Effect on Crime	0.0625 (0.0384) (6PM-12AM) 0.0526 (0.0549) (12AM-6AM)	-0.0084 (0.0082) (6PM-12AM) -0.0252*** (0.0087) (12AM-6AM)	-0.0140*** (0.0047) (6PM-12AM) -0.0150** (0.0061) (12AM-6AM)

Notes: We divide movies into thirds using the fraction of IMDB raters of a movie that are male and of age 18-29. Movies not liked by young males are defined by movies in the bottom third of this distribution, movies liked by young males are in the middle third, and movies strongly liked by young males are in the top third. The ratings of movie violence are from www.kids-in-mind.com. The table divides movies into 9 categories defined by the interaction of how liked the movie is by young males and the violence level. The top 3 movies with the highest weekend audience are reported for each category, along with the next 3 three largest distinct blockbuster movies. The "Effect on Crime" rows report the coefficients on the audience sizes for each of the 9 categories from two separate regressions for the evening (6PM-12AM) and nighttime hours (12AM-6AM), where the dependent variable is log(number of assault occurring in day t in the specified time block) and the independent variables are the audiences in millions of people for movies in each of the 9 categories. See also notes to Table 2.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11. Test of Selection: Effect of Sexual Content and Profanity

Specification:	OLS Regressions (CEX Data)			Instrumental Variable Regressions					
Dep. Var.:	Share of 18-29 Year-Old at Movie Theater			Log (Number of Assaults in Day t in Time Window)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Audience Of Movies With Strong Sexual Content	2.5784		1.2893	-0.0148	-0.0291			-0.0043	-0.0122
(share of pop. in day t) (milllions for Col. (4)-(9))	(1.1528)**		(1.1201)	(0.0071)**	(0.0097)***			(0.0065)	(0.0091)
Audience Of Movies With Mild Sexual Content	1.997		0.6965	-0.0125	-0.0183			-0.0015	0.0012
(share of pop. in day t) (milllions for Col. (4)-(9))	(0.5275)***		(0.4431)	(0.0048)***	(0.0066)***			(0.0034)	(0.0045)
Audience Of Movies With No Sexual Content	1.2924			-0.0095	-0.0152				
(share of pop. in day t) (milllions for Col. (4)-(9))	(0.4202)***			(0.0039)**	(0.0049)***				
Audience Of Movies With Strong Profanity		1.9073	-0.0479			-0.0153	-0.0169	-0.0039	-0.0008
(share of pop. in day t) (milllions for Col. (4)-(9))		(0.6475)***	(0.6048)			(0.0058)***	(0.0077)**	(0.0048)	(0.0067)
Audience Of Movies With Mild Profanity		1.484	-0.1814			-0.0115	-0.0196	-0.001	-0.0046
(share of pop. in day t) (milllions for Col. (4)-(9))		(0.4913)***	(0.3916)			(0.0042)***	(0.0052)***	(0.0027)	(0.0035)
Audience Of Movies With No Profanity		1.3417				-0.0092	-0.0131		
(share of pop. in day t) (milllions for Col. (4)-(9))		(0.4315)***				(0.0039)**	(0.0052)**		
Audience Of Strongly Violent Movies			2.0275					-0.0116	-0.0168
(share of pop. in day t) (milllions for Col. (4)-(9))			(0.5900)***					(0.0051)**	(0.0065)**
Audience Of Mildly Violent Movies			1.3937					-0.0103	-0.0182
(share of pop. in day t) (milllions for Col. (4)-(9))			(0.4554)***					(0.0041)**	(0.0053)***
Theater Audience Of Non-Violent Movies			1.0526					-0.0059	-0.0041
(share of pop. in day t) (milllions for Col. (4)-(9))			(0.4852)**					(0.0043)	(0.0055)
Time of Day	All Day	All Day	All Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day
Control Variables:									
Full Set of Controls	X	X	X	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	.	.	.	X	X	X	X	X	X
N	N = 1558	N = 1558	N = 1558	N = 1563	N = 1562	N = 1563	N = 1562	N = 1563	N = 1562

Notes: The ratings of violent, sexual, and profanity content of movies are from www.kids-in-mind.com. The audience of strong, mild, and no sexual (profanity) content use the same breakpoints as for violence: categorizations (8-10, 5-7, and 0-4 ratings from kids-in-mind.com). In Columns 1-3 the dependent variable is the share of households with head aged 18-29 in the diary CEX sample that reported spending on atteding a movie at the movie theater on day t. Attendance by young males is a proxy for attendance by violent sub-groups of the population. See also notes to Tables 2 and 7.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12. Examples of Studies of Media Effects on Violence in Psychology

Paper	Exposure to violence (Type of movie) (1)	Control Group (2)	Subjects (3)	Location (4)	Sample Size (5)	Measure of Violence t (6)	Treatment Group t_T (7)	Control Group t_C (8)
Laboratory Experiments								
Lovaas (1961)	5-min. Extract from "Rassling Match" -- cartoon violence	5-min. Non-Violent Clip from "Bear Facts"	Children of Nursery School	Playroom	10 + 10	Time Spent Playing with Aggressive Doll (hits other doll)	98.2	58.6
Bandura, Ross, and Ross (1963)	10-min. Scenes of Aggression of Doll	No Movie	Children of Nursery School	Playroom	24 + 24	Aggression toward Doll	91.5	54.3
Geen and O'Neal (1969)	7-min. Prizefight Scene from "Champion" + 2 min. White Noise	7-min. Scenes on Non-violent Sport + 2 min. White Noise	College Students	Laboratory	12 + 12	Intensity Electric Shock Inflicted on Other Subject	22.2	10.3
	7-min. Prizefight Scene from "Champion"	7-min. Scenes on Non-violent Sport					12.7	14.7
Bushman (1995)	15-min. Violent Scenes from "Karate Kid III"	15-min. non-violent scenes from "Gorillas in The Mist"	College Students	Laboratory	738	Level of Noise Inflicted On Other Subject For Slow Answer	4.6	3.9
Josephson (1987)	14-min. Scenes of Killing of Police Officer and SWAT team in Action	14-min. Scenes of Motorcross Bike-Racing Team	Grades 2-3, Boys	School	396	Aggression in 9 Min. of Floor Hockey Game	6.6	3.6
Leyens et al. (1975)	Showing of 5 Violent Movies On 5 Consecutive Days	Showing of 5 Non-Violent Movies On 5 Consecutive Days	Juveniles in Belgium	Detention Facility	85	% Committing Phys. Aggression In Evening After Movie	4.0%	.2%
						% Committing Phys. Aggression At Noon Day After Movie	2.1%	1.5%
Surveys								
Johnson et al. (2002)	High (Self-reported) Television Viewing at Age 14 (>=3 hrs./day)	Low (Self-reported) Television Viewing at Age 14 (<1 hrs./day)	Random Sample	NY State	707	% Committing Assaults Causing Injury, at Age 16-22	25.3%	5.7%

Notes: Calculations of effects on violence are by the authors based on data from the papers cited. Columns (7) and (8) report the level of violence in the Treatment and Control group. The difference is always significant at the 5% level, except for the second comparison in the Geen and O"Neal (1969) paper and the second comparison in Leyens et al. (1975).

Appendix Table 1. Movie Blockbusters by Violence Level (Kids-in-mind Measure)

Violence Rating	Title of Blockbuster	Weekend Date	Weekend Theater Audience	Sexual Content Rating	Profanity Rating	MPAA Violence Rating	Liking By Young Males
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0	Birdcage	3/9/1996	4,026,083	4	6	Low	Low
	You've Got Mail	12/19/1998	3,925,587	2	3	Low	Low
	You've Got Mail	12/26/1998	3,855,011	2	3	Low	Low
1	Runaway Bride	7/31/1999	6,771,654	2	2	Low	Low
	Erin Brockovich	3/18/2000	5,178,850	3	8	Low	Low
	Notting Hill	5/29/1999	4,355,314	4	5	Low	Low
2	Liar Liar	3/22/1997	6,709,569	3	4	Low	High
	Toy Story	11/25/1995	6,599,610	0	0	Low	Medium
	Sweet Home Alabama	9/28/2002	6,135,755	2	3	Low	Low
3	Shrek 2	5/22/2004	17,397,404	3	2	Low	Medium
	Shrek 2	5/29/2004	11,838,217	3	2	Low	Medium
	Finding Nemo	5/31/2003	11,650,366	0	0	Low	Medium
4	Harry Potter And The Sorcerer's Stone	11/17/2001	15,953,113	0	2	Low	Medium
	Harry Potter And The Chamber Of Secrets	11/16/2002	15,207,829	1	3	Medium	Low
	Austin Powers In Goldmember	7/27/2002	12,576,592	6	6	Low	High
5	Harry Potter And The Prisoner Of Azkaban	6/5/2004	15,086,532	1	2	Medium	Medium
	X2: X-Men United	5/3/2003	14,188,845	4	3	Medium	High
	Star Wars 2: Attack Of The Clones	5/18/2002	13,774,151	2	1	Medium	High
6	Spider-Man	5/4/2002	19,766,628	3	3	Medium	High
	Spider-Man 2	7/3/2004	14,195,850	3	3	Medium	High
	Planet Of the Apes	7/28/2001	12,297,262	3	3	Medium	Medium
7	Matrix Reloaded	5/17/2003	15,219,637	6	5	Medium	High
	Lost World: Jurassic Park	5/24/1997	14,255,579	0	3	Medium	High
	Mummy Returns	5/5/2001	12,467,726	4	3	Medium	Medium
8	Jurassic Park 3	7/21/2001	9,104,505	1	2	Medium	High
	Scary Movie	7/8/2000	8,240,157	10	7	Medium	High
	Scream 2	12/13/1997	8,188,454	2	8	High	High
9	Bad Boys 2	7/19/2003	7,715,185	6	10	High	High
	Saving Private Ryan	7/25/1998	6,500,639	1	7	Medium	High
	Sleepy Hollow	11/20/1999	5,751,378	3	1	High	Medium
10	Passion Of The Christ	2/28/2004	13,484,402	1	1	High	Medium
	Hannibal	2/10/2001	10,114,135	4	5	High	High
	Passion Of The Christ	3/6/2004	8,531,673	1	1	High	Medium
Missing	A Perfect Murder	6/6/1998	3,545,842	Missing	Missing	Medium	Missing
	A Perfect Murder	6/13/1998	2,404,994	Missing	Missing	Medium	Missing
	A Cinderella Story	7/17/2004	2,207,419	Missing	Missing	Low	Low

Notes: The audience numbers are obtained from daily boxoffice revenue divided by the average price per ticket. The ratings of movie violence in column 1 are from www.kids-in-mind.com. The next three columns report the title (column 2), the weekend (column 3), and the weekend audience size (column 4) for the 3 movies with highest weekend sales in a given violence category. Columns 5-8 report the sexual and profanity content ratings (columns 5 and 6) obtained from kids-in-mind.com, an alternative violence rating using MPAA descriptions (column 7), and a measure of how liked the movie is by young males using IMDB movie ratings (column 8). These last two measures used in columns 7 and 8 are described in detail in the text.

Appendix Table 2. Robustness

Specification:	Instrumental Variables Regressions						OLS Reg.	Poisson Reg.
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)							No. of Assaults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Effects in Morning and Afternoon (6AM-6PM)								
Audience Of Strongly Violent Movies	-0.0037	-0.003	-0.0046	-0.0048	0.0005	-0.0044	-0.0096	-0.0081
(in millions of people in day t)	(0.0046)	(0.0048)	(0.0045)	(0.0043)	(0.0039)	(0.0043)	(0.0035)***	(0.0029)***
Audience Of Mildly Violent Movies	-0.003	-0.0022	-0.0046	-0.003	-0.0006	-0.0063	-0.0088	-0.0102
(in millions of people in day t)	(0.0041)	(0.0043)	(0.0042)	(0.0030)	(0.0033)	(0.0037)*	(0.0027)***	(0.0023)***
Audience Of Non-Violent Movies	0.0003	-0.0004	-0.0012	0.0008	-0.0012	-0.0029	-0.0079	-0.0098
(in millions of people in day t)	(0.0041)	(0.0044)	(0.0042)	(0.0036)	(0.0035)	(0.0037)	(0.0028)***	(0.0023)***
Panel B. Effects in The Evening (6PM-12AM)								
Audience Of Strongly Violent Movies	-0.013	-0.0131	-0.0158	-0.0141	-0.0144	-0.0115	-0.0099	-0.0081
(in millions of people in day t)	(0.0049)***	(0.0054)**	(0.0048)***	(0.0050)***	(0.0046)***	(0.0046)**	(0.0037)***	(0.0030)***
Audience Of Mildly Violent Movies	-0.0109	-0.009	-0.0107	-0.0074	-0.0165	-0.0121	-0.0065	-0.0075
(in millions of people in day t)	(0.0040)***	(0.0047)*	(0.0042)**	(0.0035)**	(0.0035)***	(0.0037)***	(0.0029)**	(0.0023)***
Audience Of Non-Violent Movies	-0.0063	-0.0049	-0.0062	-0.0041	-0.0098	-0.0076	-0.0026	-0.003
(in millions of people in day t)	(0.0043)	(0.0050)	(0.0044)	(0.0036)	(0.0040)**	(0.0039)**	(0.0030)	(0.0024)
Panel C. Effects in The Night (12AM-6AM)								
Audience Of Strongly Violent Movies	-0.0192	-0.0239	-0.0202	-0.0124	-0.0206	-0.0155	-0.0098	-0.0133
(in millions of people in day t)	(0.0060)***	(0.0066)***	(0.0059)***	(0.0064)*	(0.0054)***	(0.0055)***	(0.0052)*	(0.0035)***
Audience Of Mildly Violent Movies	-0.0205	-0.0207	-0.0202	-0.0123	-0.0245	-0.0167	-0.0089	-0.0106
(in millions of people in day t)	(0.0052)***	(0.0060)***	(0.0054)***	(0.0043)***	(0.0040)***	(0.0046)***	(0.0041)**	(0.0029)***
Audience Of Non-Violent Movies	-0.006	-0.0076	-0.0047	-0.0039	-0.0103	-0.0047	0.0045	0.0005
(in millions of people in day t)	(0.0054)	(0.0067)	(0.0056)	(0.0050)	(0.0042)**	(0.0049)	(0.0043)	(0.0029)
Robustness Specification	Benchmark IV Specification	IV: Instrument Next Week's Audience	IV: Instruments Budget and No. Theaters	Benchmark + Revenue From First Week of Release Only	Benchmark + Include Mo-Th	Benchmark + Control For Week-Of-Year (No Day-Of-Year)	OLS Regress. (No Instruments)	Poisson Regression (No Instruments)
Control Variables:								
Full Set of Controls	X	X	X	X	X		X	X
Audience Instrumented With Predicted Audience Using Following Week's	X			X	X	X		
N	N = 1563	N = 1563	N = 1563	N = 1563	N = 3645	N = 1563	N = 1563	N = 1563

Notes: This Table presents a series of robustness checks to the results in Table 3, reproduced in Column 1. Column 2 reports the estimates using, as an instrument for audience in week w(t), the weekend audience in week w(t)+1 for the same movies. Column 3 uses instruments constructed as in the benchmark instruments, but using the number of theaters showing the movie in week w(t) and the production budget (when available) as predictors. This specification also includes the instrument for overall movie audience constructed with the bechmark instruments. (See text for additional details) Column 4 uses only the audience from movies in the first week of release. Column 5 uses data also from Monday-Thursday, in addition to Friday-Sunday. Column 6 does not use the 365 day-of-year indicators and uses instead 52 week-of-year indicators. Column 7 presents an OLS specification, and Column 8 presents a Poisson regression (also not instrumented). to See also notes to Table 2.
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 3. Alternative MPAA-Based Measure of Movie Violence

Specification:	Instrumental Variable Regressions				OLS Reg. (CEX Data)	
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)				Share 18-29 Year Old at Movie Theater	
	(1)	(2)	(3)	(4)	(5)	(6)
Audience Of Strongly Violent Movies - MPAA Meas.	-0.0139	-0.0252	0.0005	-0.0091	3.5074	-0.6748
(millions of people in day t) (shares for Col. (5)-(6))	(0.0063)**	(0.0068)***	(0.0064)	(0.0084)	(1.0986)***	(0.9869)
Audience Of Mildly Violent Movies - MPAA Meas.	-0.0109	-0.0187	-0.0003	-0.0026	1.3357	-0.2593
(millions of people in day t) (shares for Col. (5)-(6))	(0.0039)***	(0.0050)***	(0.0027)	(0.0037)	(0.4308)***	(0.4235)
Audience Of Non-Violent Movies - MPAA Meas.	-0.008	-0.0104			1.1594	
(millions of people in day t) (shares for Col. (5)-(6))	(0.0042)*	(0.0053)*			(0.4544)**	
Audience Of Strongly Violent Movies - Stand. Meas.			-0.0138	-0.0149		2.5821
(millions of people in day t) (shares for Col. (5)-(6))			(0.0058)**	(0.0078)*		(0.8728)***
Audience Of Mildly Violent Movies - Stand. Meas.			-0.0109	-0.0187		1.6948
(millions of people in day t) (shares for Col. (5)-(6))			(0.0046)**	(0.0061)***		(0.5604)***
Theater Audience Of Non-Violent Movies - Stand. Meas.			-0.0062	-0.0067		1.1249
(millions of people in day t) (shares for Col. (5)-(6))			(0.0044)	(0.0055)		(0.4809)**
Time of Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	All day	All day
Control Variables:						
Full Set of Controls	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X		
N	N = 1539	N = 1538	N = 1539	N = 1538	N = 1534	N = 1534

Notes: The MPAA ratings are obtained using the one-line MPAA summary of the movie . We characterize as mildly violent movies those for which the MPAA rating contains the word "Violence" or "Violent", with two exceptions: (i) If the reference is qualified by "Brief", "Mild", or "Some", we classify the movie as non-violent; (ii) If the word violence is qualified by either "Bloody", "Brutal", "Disturbing", "Graphic", "Grisly", "Gruesome", or "Strong", we classify the movie as strongly violent. The standard ratings of violent movies are from www.kids-in-mind.com. In Columns 5-6 the dependent variable is the share of households with head aged 18-29 in the diary CEX sample that reported spending on atteding a movie at the movie theater on day t. Attendance by young males is a proxy for attendance by violent sub-groups of the population. See also Tables 2 and 7.

* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix Table 4. Effect of Movie Violence on Different Types of Crimes

Specification:	Instrumental Variable Regressions									
Dep. Var.:	Log (Number of Assaults of a Type in Day t in Time Window)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Audience Of Strongly Violent Movies	-0.0125	-0.0186	-0.0104	-0.0184	-0.0153	-0.0339	-0.0228	-0.0117	-0.0074	-0.0096
(millions of people in day t)	(0.0053)**	(0.0068)***	(0.0074)	(0.0085)**	(0.0074)**	(0.0106)***	(0.0129)*	(0.0142)	(0.0038)*	(0.0069)
Audience Of Mildly Violent Movies	-0.0084	-0.0213	-0.0132	-0.0189	-0.0133	-0.0372	-0.0099	-0.0112	-0.0025	-0.0042
(millions of people in day t)	(0.0045)*	(0.0060)***	(0.0065)**	(0.0074)**	(0.0059)**	(0.0100)***	(0.0116)	(0.0132)	(0.0030)	(0.0046)
Audience Of Non-Violent Movies	-0.0055	-0.006	-0.0046	-0.0055	-0.0069	-0.0149	-0.0011	0.0087	-0.0027	-0.0024
(millions of people in day t)	(0.0047)	(0.0062)	(0.0066)	(0.0077)	(0.0062)	(0.0109)	(0.0105)	(0.0128)	(0.0033)	(0.0049)
Type of Crime	Assaults At Home		Assaults Away From Home		Assaults of Known Person		Assaults of Stranger		Theft and Burglary	
Time of Day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day	6PM-12AM	12AM-6AM next day
Control Variables:										
Full Set of Controls	X	X	X	X	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X	X	X	X	X
N	N = 1563	N = 1562	N = 1563	N = 1562	N = 1563	N = 1562	N = 1563	N = 1560	N = 1563	N = 1562

Notes: An observation is a Friday, Saturday, or Sunday over the years 1995-2004. The total number of assaults is computed using all agencies with population of at least 25,000 and reporting crimes in at least 300 days in the year. The audience numbers are obtained from daily box-office revenue divided by the average price per ticket. The ratings of violent movies are from www.kids-in-mind.com. The audience of strongly violent movies is the audience of all movies with a violence rating 8-10. The audience of mildly violent movies is the audience of all movies with a violence rating 5-7. The specifications are IV regressions with the log(number of crimes of a given type occurring in day t) as dependent variable. The audience numbers are instrumented using the predicted audience numbers based on next weekend's audience. Robust standard errors clustered by week in parenthesis.

* significant at 10%; ** significant at 5%; *** significant at 1%