1 Introduction

Does violence in the media trigger violent crime? This question is important for policy and scientific research alike. 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 risks. 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).

A key issue is the validity of the evidence used in these reports. This evidence, surveyed by Anderson and Buschman (2001) and Anderson et al. (2003) and summarized in Table 1, is largely based on two strands of psychological research. The experimental literature, starting with Lovaas (1961) and Bandura, Ross, and Ross (1963), expose subjects (typically kids) to short, violent video clips. These experiments find a sharp increase in aggressive behavior immediately after the media exposure, compared to a control group. 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 (including 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 sum, the research in psychology does not answer the question about media violence and crime.[1]

In this paper, we attempt to 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 impact of exposure to violence in the short-run. Unlike in the experiments, our outcome variable is violent crime, rather than aggressiveness in the laboratory. The laboratory and field setups also differ due to self-selection and differences in context.

We measure the violence content of movies using a 0-10 rating developed by *kids-in-mind.com*, a non-profit organization. Combining the rating with daily revenue, we generate a daily measure of 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 since the release, there is substantial variation in exposure to movie violence over time. The audience for strongly violent movies is as high as 10 million people on some weekends, and is close to zero on others (see Figures 1a-1b).

[1] 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).

Using this variation, we estimate the same-day impact of exposure to violent movies on violent crime, holding constant the total movie audience. We use crime data from the National Incident Based Reporting System (NIBRS) for the years 1995-2004. We measure violent crime on a given day using all reported assaults (simple or aggravated) and intimidation. Since our measure of movie violence does not vary across cities, we use the total number of assaults on a given day as our outcome measure.

Our initial findings offer little support for the theory that exposure to 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, though not significantly so. This negative correlation may be due to unobserved variables that contemporaneously increase movie attendance and decrease violence, such as rainy weather. To address this possibility, we use two strategies. First, we add a flexible set of weather controls. Second, and most importantly, 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 the weather controls and instrumenting does not alter the apparent puzzle: the correlation between movie violence and violent crime becomes more negative and statistically significant.

To better understand this result, which is contrary to what would be expected from the lab experiments, we separately estimate the effect on crime in four 6-hour blocks. As expected, exposure to violent movies has no impact on crime in the morning hours (6AM-12PM) or in the afternoon (12PM-6PM); indeed, movie attendance in these hours is minimal. In the evening hours (6PM-12AM), instead, we detect a significant negative effect on crime. For each million people watching a strongly violent movie, violent crimes decrease by 0.86 percent. We find a smaller, but still sizeable and significant, impact of exposure to mildly violent movies. There is no impact of exposure to non-violent movies. We interpret these results as 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 likely increasing in the violence of the movie because potential criminals sort into violent, rather than non-violent, movies.

We then present evidence for the nighttime hours following the movie showing (12AM-6AM), when most movie theaters are closed. This captures the short-run effect of movie exposure beyond incapacitation and is the field equivalent of the laboratory measurement of aggression following exposure. Over this time period, the effect of exposure to movie violence is also negative. For each million people watching a strongly violent movie, violent crimes decrease by 1.47 percent. The effect is slightly smaller for exposure to mildly violent movies. Non-violent movies have no significant impact. Unlike in the psychology experiments, therefore, media violence appears to decrease violent behavior in the immediate aftermath of exposure.

Before testing interpretations of this second finding, we examine its robustness. We present disaggregate effects by two-hour time blocks, and by individual violence levels ranging from 0 to 10. We also allow for non-linear specifications, including Poisson regressions. The results are all consistent with the baseline analysis. We find similar results (although less precisely estimated) using an alternative measure of movie violence based on the reasons provided for the MPAA's ratings. 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 over the years 1995-2004. These estimates are mostly consistent with our main estimates using the box office data, although the standard errors are large.

A key limitation of our research design (and the laboratory designs) is that we cannot answer the question of the long-run impact of media violence. However, we can estimate the effect of exposure to movie violence in the previous week, controlling for current exposure. We find no effect of lagged exposure, suggesting that the long-term effects, if any, appear only over longer time horizons.

We interpret our results in light of a simple model, which yields two key insights. First, our empirical estimates capture the impact for the self-selected population that chooses to attend violent movies, and not the population at large. Second, our estimates capture the net effect of watching a violent movie *and* not participating in the alternative activity. Holding violence level fixed, a higher-quality 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 and its associated level of violence.

We explore three interpretations for the negative impact of violent movies on crime in the nighttime hours (i.e., a net effect which is negative). (i) *Catharsis.* Movie violence provides a release of aggression and lowers the tendency to commit a crime, that is, the direct effect is negative. The next two explanations instead posit that exposure to movie violence may increase crime, but less so than the alternative, foregone activity. (ii) *Extended Incapacitation.* Exposure to movies lowers crime temporarily even after the end of the movie: when a potential criminal exits the movie theater, the situational opportunities to engage in violent crime are diminished relative to a comparable day with no movie attendance. (iii) *Sobriety.* In particular, theater attendance may reduce alcohol consumption, which in turn reduces the incidence of violent crime both during and after the movie.

A key difference between the Catharsis explanation and the other two explanations is whether the reduction in violent crime is due exclusively to the direct effect of exposure to movie violence. To test this, we look at non-violent movies which attract a demographic group more likely to commit crime: young males. We create this measure using the fraction of Internet Movie Database (IMDB) online movie ratings coming from 18 to 29 males. We find that, even after controlling for movie violence, exposure to movies that attract this group significantly lowers violent crime both in the evening hours and in the nighttime.

This suggests that differences in the alternative activity displaced by movie attendance are key to explain the effect, as suggested by the Extended Incapacitation or Sobriety interpretations. To provide additional evidence on sobriety, we separately examine crimes where alcohol was reported as a contributing factor. Consistent with this hypothesis, we find a larger displacement effect for assaults in which the criminal was under the influence of alcohol. We also find very large displacement for assaults taking place in bars and night clubs, although these estimates are imprecise given the relative rarity of such assaults. In general, our results imply that a night which involves movie theater attendance is less conducive to violent behavior than the foregone alternative activity.

Our results indicate the net effect of violent movies is to decrease assaults by roughly 175 occurrences per day, for an annual total of about 27,000 weekend assaults prevented. What accounts for this very different conclusion compared to the experimental literature in psychology, which finds large positive effects? The difference in findings between the field and the laboratory are likely due to three factors. (i) *Partial Equilibrium.* In the laboratory, subjects are not optimally choosing whether to watch a movie or participate in an alternative activity. Rather, all subjects are exposed to a movie. The violent-movie treatment does not displace an alternative activity (such as alcohol consumption), relative to the non-violent-movie treatment. The experiments hold constant the alternative activity. (ii) *Selection.* Subjects in the laboratory are a representative sample of the (student) population, while movie-goers in the field are a self-selected sample that prefers violent movies. (iii) *Type of Violence.* A third factor is differences in media 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.

Altogether, the laboratory setting is not representative of exposure to movie violence in most field settings, where consumers choose what type of film to watch and whether to do another activity besides watching a movie. However, some of the differences between laboratory and field can be altered by changes in design. For example, laboratory experiments can incorporate sorting into a violent movie (Lazear, Malmendier, and Weber, 2005) to replicate the selection in the field.

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 (2006) 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.

Disappointing outcomes, therefore, appear to induce frustration and impact family violence.

The 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, as in the case of school closings or incarceration.

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, calibrations, and comparisons to the psychology experiments. Section 7 concludes.

2 Model

Utility. In this section we model the choice to view a violent movie and the resulting impact on the level of aggregate violence. We begin by assuming individuals choose among a set of mutually exclusive activities, where for simplicity, we consider three options: watch a violent movie a_v, 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 all the alternative options. We assume the utility of a violent movie increases with the quality of the violent movie. 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 violent movies $P(a_v)$, demand for non-violent movies $P(a_n)$, and demand for the alternative activity $1 - P(a_v) - P(a_n)$. A higher-quality violent movie increases the probability $P(a_v)$. We do not make further assumptions about utility since the existence of probabilistic demand functions are sufficient for the derivations in this section.[2]

We allow for a simple form of heterogeneity in the taste for violent movies. For ease of exposition, we denote the group with high taste for violent movies as men m and the other group as women w. The fraction of the relevant population choosing activity j is denoted as $P(a_j^i)$ for $i = m, w$ and $j = v, n, s$. Since by assumption men like violent movies more than women, it follows that $P(a_v^m) > P(a_v^w)$. The aggregate demand functions for men and women

[2] 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 (as in Rosen, JPE 1974). 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 various choices as $U_j^* = \delta(I - p_j) + \theta q_j + e_j$ for $j = v, n, s$ where p_j, q_j, and e_j are the price, quality, and error term associated with the various 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, $Pr(a_j) = \frac{exp(\delta(I-p_j)+\theta q_j)}{\sum_{k=v,n,s} exp(\delta(I-p_k)+\theta q_k)}$ for $j = v, n, s$. We emphasize this is just an example, and that the multinomial logit setup is not imposed in our empirical work.

are simply these probabilities multiplied by group size N^i, that is, $N^i P(a_j^i)$.

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 the consumption of the alternative social activity. The level of aggregate log violence, 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 men and women:

$$\begin{aligned} \ln V \;=\;& \alpha_v^m N^m P(a_v^m) + \alpha_n^m N^m P(a_n^m) + \sigma^m N^m (1 - P(a_v^m) - P(a_n^m)) + \\ & \alpha_v^w N^w P(a_v^w) + \alpha_n^w N^w P(a_n^w) + \sigma^w N^w (1 - P(a_v^w) - P(a_n^w)). \end{aligned} \tag{1}$$

The key parameters in the production function are α_v^i, α_n^i, and σ^i. We illustrate the parameters for men ($i = m$); a similar interpretation holds for women. The parameter α_v^m indicates that increasing the male audience size of violent movie by 1, ceteris paribus, will result in roughly a α_v^m percent increase in violence (for small α_v^m). The parameter α_v^m thus will be positive if movie violence triggers violence, and negative if movie violence has a cathartic effect. A similar interpretation holds for α_n^m, as applied to non-violent movies. To the extent that non-violent movies do not impact violent crime, $\alpha_n^m = 0$. Finally, σ^m indicates that increasing the male audience for the alternative activity by 1 will result in a σ^m percent increase in violence. The parameter σ^m is likely to be positive if the alternative social activity, such as drinking at the bar, brings potential criminals together or triggers violence.

For expositional purposes, we assume men have a higher propensity to commit violence following exposure to movies compared to women, i.e., $\alpha_v^m > \alpha_v^w$ and $\alpha_n^m \geq \alpha_n^w$. We also assume that men are more prone to violence following social interactions (other than at movie theaters), and hence $\sigma^m > \sigma^w$.

How does the level of violence respond to increases in the quality of a violent movie (holding the other parameters constant)? Consider the case for men. The direct effect is that more men are watching a violent movie, i.e., $N^m P(a_v^m)$ increases. The indirect effect is that fewer men are watching the alternative nonviolent movie and fewer men are engaged in the alternative social activity, i.e., $N^m P(a_n^m)$ and $N^m(1 - P(a_v^m) - P(a_n^m))$ decrease. The effect of these changes depends on the signs and magnitudes of the coefficients α_v^m, α_n^m, and σ^m. A similar logic holds for women.

Unfortunately, individual-level consumption data for movie attendance for each movie is not readily available, so 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 men and women combined) and letting x_j^m denote the male audience share for movie j, log violence can be expressed as

$$\ln V = (\sigma^m N^m + \sigma^w N^w) + \sum_{j=v,n} \left[x_j^m (\alpha_j^m - \sigma^m) + (1 - x_j^m)(\alpha_j^w - \sigma^w) \right] A_j \tag{2}$$

where $A_j = N^m P(a_j^m) + N^w P(a_j^w)$ and $x_j = N^m P(a_j^m)/(N^m P(a_j^m) + N^w P(a_j^w))$. Equation (2) makes clear that the effect of total audience size on log violence is a weighted average of the effects for the male and female subgroups.

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

$$\ln V = \beta_0 + \beta_v A_v + \beta_n A_n + \varepsilon. \tag{3}$$

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, include control variables, and use total audience size together with the audience size for mildly and strongly violence movies.[3] Comparing the estimating equation (3) and equation (2), we can write the coefficients as

$$\beta_j = x_j^m(\alpha_j^m - \sigma^m) + (1 - x_j^m)(\alpha_j^w - \sigma^w) \text{ for } j = v, n. \tag{4}$$

Notice that the parameter β_j is constant only if the male audience share x_j^m 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 men and women roughly rises and falls proportionately with each other.[4]

To illustrate the interpretation of expression (4), consider a simplified example. Suppose women do not commit violent acts under any circumstance, so that $\alpha_v^w = \alpha_n^w = \sigma^w = 0$.[5] Then the estimated coefficient for violent movies $\hat{\beta}_v$ is an estimate of $x_v^m(\alpha_v^m - \sigma^m)$. The impact of a violent movie is the sum of two effects: a direct effect, captured by α_v^m, and an indirect effect, captured by σ^m. The direct effect is the impact of violent movies on violence for men. It can be positive, in the case of Arousal or Imitation, as suggested by the experiments, or negative, 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 that these activities trigger crime ($\sigma^m > 0$), this contributes to making β_v negative. A reduction in alcohol consumption and a different set of activities in the nighttime hours after a movie finishes could lead to

[3] This formulation is very similar to that of a Poisson count model. We have opted for the current formulation, treating violence (as well as movie attendance) 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.

[4] This is true for the example given in footnote 2, when utility is modified to account for gender differences. Adding gender-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 male to female demand for each movie type.

[5] Of course women may commit some violent crime, but that does not change the main insights in the following paragraphs. Moreover, this analysis could readily be extended to more than two groups of individuals or to more movie types.

extended incapacitation. This is the case, for example, if the alternative activity is drinking at a bar. Finally, the impact β_v of violent movies is increasing in the share x_v^m of the violent sub-group (the men) that watch the movie. Notice that, since men like violent movies more than women, they will be over-represented, and hence x_v^m will be larger than $N^m/(N^m+N^w)$. Hence, even in the general case captured in (4), male movie-goers will contribute most to the identification of β_v.

This discussion makes clear that while an estimate of β_v answers the important question of how violent crime responds to violent movies, it cannot by itself separate the direct effect through α_v^m from the indirect effect through σ^m. For example, if β_v is negative, it could be due to incapacitation ($\sigma^m > \alpha_v^m$) or catharsis ($\alpha_v^m < 0$).

Continuing with this simple example, consider the coefficient for nonviolent movies, β_n. The direct effect of this type of movie should be zero, i.e., $\alpha_n^m = \alpha_n^w = 0$ (or in theory even negative if it is a "feel good" movie and has a cathartic effect). If this type of movie primarily attracts women, then there should also be little incapacitation effect. That is, $-\left(x_n^m\sigma^m + (1-x_n^m)\sigma^w\right)$ should be close to zero as the fraction of men viewing the movie x_n^m is small.

Now extend this simple example to include more that just two movie types. Suppose there is also a third movie type: nonviolent movies which appeal to men. For ease of exposition, we refer to these movies as comedies, and label them with the subscript c. The model above could easily be extended to include this third type of movie. What can these movies tell us about the effect of violent movies on violent crime?

In the discussion above, we did not separate out the direct effect of a violent movie from the incapacitation effect. Nonviolent movies which appeal to the same potentially violent crowd (i.e., comedies) can help to identify the direct effect of violent movies α_v^m. The reason is that both types of films should have the same weighted incapacitation effect, but different direct effects. In the current example, $\hat{\beta}_c$ is an estimate of $x_c(\alpha_c^m - \sigma^m)$. The alternative option effect is the same for both types of movies, as long as both movies are drawing the same potentially violent crowd (i.e., $x_c^m = x_v^m$ so that $-x_c^m\sigma^m = -x_v^m\sigma^m$). Under the assumption that comedic films do not play a cathartic role in reducing violence, the direct effect of such a movie should be 0 and it immediately follows that $\beta_v - \beta_c = \alpha_v^m$. If one is unwilling to assume comedic films do not play a cathartic role, a slightly different interpretation applies. In this case, it seems plausible to assume that comedic films (not containing violence) do not stimulate arousal or imitation of violence. In this case, $\alpha_c^m \leq 0$, so that $\beta_v - \beta_c$ provides an upper bound on the Arousal/Imitation effect. In other words, if $\beta_v - \beta_c$ is estimated to be negative, then the Arousal/Imitation hypothesis would be rejected. Of course, we recognize that this is a simplified example, and it may be difficult to identify violent and comedic films which have the same potentially violent crowd.

Before continuing, a brief comparison to the psychology experiments is in order. In the experiments, exposure to violent and non-violent movies a_v and a_n 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

$$\beta_v^{Lab} = \frac{N^m}{N^m + N^w}\alpha_v^m + \left(1 - \frac{N^m}{N^m + N^w}\right)\alpha_v^w.$$

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 operating through the alternative activity. By virtue of experimental control, the indirect effect is 'shut down.' Second, the weights on the male and female coefficients are very different (compare $N^m/(N^m + N^w)$ to x_v^m). 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 'men'). 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. We obtain the data on box-office revenue from *www.the-numbers.com*, which uses the studios and *Exhibitor Relations* as data sources. Data on weekend box-office sales is available for the top 50 movies consistently from January 1995 until the present; this data includes weekend sales from Friday to Sunday[6]. Daily data is available for the top 10 movies from October 1997 to the present. 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 Figure 2). To obtain an estimate of 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 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 (Figure 2). 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 *.9842 with an* R^2 *of .9190.*

[6] In more recent years, the data covers all movies. We keep only the data for the top 50 movies to ensure consistency with the older data.

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 volunteer-trained members 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. As Column 2 shows, ratings violence ratings between 3 and 6 account for most of the audience data. Within each violence category, we list the top-3 blockbuster movies, the weekend date, and the weekend audience. 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" vs. "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 a rating is not available; these movies almost always have very limited audiences.[7]

After harmonizing the title of the movie across the two datasets, we match the ratings data to the box office data. The match quality is very high for movies in the top-20 list. Overall, we can assign a violence rating to 96 percent of box office revenue.

Movie violence measures. We define the number of people (in millions) exposed to movies of violence level v on day t as $A_t^v = \sum_{j \in J} d_j^v a_{j,t}$, where $a_{j,t}$ is the audience of movie j on day t, d_j^v is an indicator for film j belonging to violence level v, and J is the set of all movies. The violence level varies between 0 and 10. The measure of overall exposure to movies on day t, A_t, is the audience for all movies on day t. To deal 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^v accordingly. The average share of missing ratings is 4.11% across days.

We define two measures of exposure to violent movies on day t. The measure of exposure to strong violence on day t is the audience for movies with violence levels between 8 and 10, $A_t^{[8,10]} = \sum_{v=8}^{10} A_t^v$. The measure of exposure to mild violence on day t is the audience for movies with a violence level between 5 and 7, $A_t^{[5,7]} = \sum_{v=5}^{7} A_t^v$.

Figure 1a plots the measure of strong movie violence, $A_t^{[8,10]}$, 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

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

the movie responsible for the spike. The series exhibits sharp fluctuations. Several weekends have close to zero violent movie audience. On other weekends, over 10 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, $A_t^{[5,7]}$. 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. Compared to a U.S. population of roughly 300 million, strongly violent and mildly violent blockbusters attract up to 3% and 8%, respectively, of the U.S. population over a weekend. Excluding babies and other groups unlikely to attend movies (and commit violent acts) from the calculation would make these fractions even larger. This extensive exposure provides the identifying variation in our setup.

Violent Crime data. The source of violence data is the National Incident Based Reporting System (NIBRS), which is a detailed reporting system for all crimes known to the police. 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 throughout the year, we limit our sample each year to agencies which contribute data for all 12 months, submit data (including a report of 0) for any type of crime for at least 300 days, and for which data is not missing for more than 7 consecutive days. If no crime is reported on a given day after this filter, we set that day's crime count to zero.

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 represented only 17% of the nation's reported crime, which reflects the fact that NIBRS data is more heavily weighted towards smaller cities and counties (where crime rates are lower).

The NIBRS data set is unique in two important dimensions. First, it reports all known incidents of crime reported to police, and second, it identifies the date and time an incident took place. Most alternative large-scale data sets, instead, only include data for arrests, and are aggregated at the monthly or yearly level. One advantage for the current study is that we can observe violent acts reported to police, such as verbal intimidation or fistfights, which do not necessarily result in an arrest. We define assaults, our measure of violent crime, as the sum of aggravated assault, simple assault, and intimidation.[8]

Our main violence measure is the total number of assaults across all agencies on day t, V_t. In most specifications, we separate assaults into 4 time blocks: assaults occurring between 6AM and 12PM, 12PM and 6PM, 6PM and 12AM, and 12AM and 6AM. We assign assaults occurring in the nighttime hours (12AM and 6AM) to the previous calendar day to match them to movies played on day t. In some specifications, we present separate series by age and gender of the offender, and by type of offense. These series are constructed in a similar way.

Figure 1c plots the average number of weekend assaults V_t over time. The series is highly seasonal, with troughs in assaults in the winter and peaks in the summer. The number of assaults is also increasing over time as a result of increased coverage in NIBRS. 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 from this figure.

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. To illustrate what variation is left after controlling for these variables, we generate the residual of a regression of log(violence) on the full set of controls (excluding the movie violence measure). 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. Relatively few weekends differ from the mean by more than 0.05 log points, and only three weekends differ 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 negative residuals for log(assaults). (One of the positive residuals for the strongly violent movies is for the movie "Passion of the Christ", an atypical violent movie, both for its target audience and its potential effect on crime.) In addition, out of 18 weekends with a residual more negative than -.05 log points, 2 are among the top 10 weekends for strongly violent movies, and 3 are among the top 10 weekends for mildly violent movies.

The graphical evidence in Figure 1d suggests a negative relationship between violent movies

[8]Aggrevated assault is defined as 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 defined as placing a person in reasonable fear of bodily harm, but without a weapon or actual physical attack.

and violent crime. We examine this relationship in detail in the next Section.

Summary statistics. After matching the panel of assaults with the time series of movie violence, the resulting data set includes 1,524 weekend (Friday through Sunday) observations, covering the time period from January 1995 to December 2004. Table 2 reports summary statistics. The average number of assaults on any given day in our sample is 1,310. The assaults occur mostly in the evening (6PM-12AM), but are also common in the afternoon (12PM-6PM) and in the night (12AM-6AM). Across weekdays, assaults are highest on Friday and Saturday (Figure 2). Across demographic characteristics, assaults are decreasing in the age of the offender (for ages above 18), and are three times larger for males than for females. In the sub-category of alcohol-related assaults, the share of assaults where the offender is suspected of using alcohol is 16.5 percent over the whole day, and the assaults taking place at a bar are 3.8 percent. The incidence of these assaults is two to three times larger in the night hours. The severity of the assaults also increases in the night hours: the percentage of assaults with major injury increases from 4.3 percent in the morning to 9.3 percent at night.

Table 2 also reports summary statistics for the daily weekend movie audience data. The average daily movie audience on a weekend day is 6.31 million people, while the audience for strongly and mildly violent movies is respectively 0.87 million and 2.46 million. The audience of strongly and mildly violent movies peaks on Saturday, with Friday and Sunday as the next highest days (Figure 2). The table also presents information on an alternative system of classification of violent movies and on rentals, which we discuss below in Section 4.

Patterns of movie attendance. We use data from the Consumer Expenditure Survey (CEX) to provide an external check on the validity of the movie attendance data. This data also provides evidence on the patterns of movie attendance at the individual level.

We take advantage of the fact that the CEX time diaries record all expenditures of surveyed households day-by-day for a period of one or two weeks. For each day, we compute the share of households that watch a movie at the theater on day t, to see how well it matches our measure of daily aggregate movie attendance V_t described above. In Table 3, we regress the share variable from CEX data on the corresponding share variable using our box office revenue data

$$share_t = \alpha + \beta(A_t/Population) + \Gamma X_t + \varepsilon_t. \tag{5}$$

In calculating the fraction of individuals attending a movie using box office data, we use a U.S. population of 300 million people. The regressions are weighted by the number of households reporting consumption expenditures for day t. In column (1) we report the estimate using the standard set of controls X_t used later in the paper (detailed below). Since both s_t^m and $A_t/Population$ are measures of the share of the population attending a movie on day t, we expect β to be close to 1. Indeed, the estimated coefficient $\hat{\beta}$ equals .866, and is statistically indistinguishable from 1 (but significantly different from zero). Our benchmark measure of movie audience A_t, therefore, is validated by the corresponding measure constructed using the CEX data. In Column (2) we obtain similar results after instrumenting for movie audience with the predicted audience next week (see Section 4 for details). In Column (3), we add measures of the audience shares of strongly violent and mildly violent movies. As expected, these additional terms are not significantly different from zero.

In columns (4) through (7) we take advantage of the individual-level demographic data in the CEX to estimate sorting by demographics into violent and non-violent movies. In particular, we estimate separate regressions for households where the head of household is between the ages of 15 and 29 (columns (4)-(5)) and for households where the head of household is age 45 or over (Columns (6)-(7)).[9] We find evidence of substantial sorting into violent movies. Younger households are much more likely to watch violent movies than to watch non-violent movies (column (5)); that is, $\beta^{[5,7]}$ and $\beta^{[8,10]}$ are positive (the latter significantly so). Conversely, older households are less likely to watch violent movies compared to non-violent movies; that is, $\beta^{[5,7]}$and $\beta^{[8,10]}$ are negative, though not significantly so. We examine the consequences of sorting by younger audiences into more violent movies below.

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,[10], 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

$$\log V_t = \beta^{[8,10]} A_t^{[8,10]} + \beta^{[5,7]} A_t^{[5,7]} + \beta A_t + \Gamma X_t + \varepsilon_t \qquad (6)$$

The number of assaults depends on the exposure to strongly violent movies $A_t^{[8,10]}$ and mildly violent movies $A_t^{[5,7]}$, controlling for total audience for all movies A_t. The coefficient $\beta^{[8,10]}$ can be interpreted as the percent increase in assaults for each million people watching movies with violence levels between 8 and 10 on day t, controlling for total movie audience. The interpretation of the coefficient $\beta^{[5,7]}$ is similar. Including total movie audience A_t as a

[9]Unfortunately, we cannot separate movie consumption by gender since purchases are aggregated at the household level. This makes it difficult to separate the consumption decisions of husbands and wives, for example.

[10]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.

control implies that we obtain a difference-in-difference estimate of the effect of violent movies. We compare the difference in crime V_t on days with high violent-movie audience and days with low violent-movie audience, to the difference in crime between high total-movie audience days and low total-movie audience days.

The variables X_t are a set of seasonal control variables: indicators for year, month, day-of-week, day-of-year, holidays, and weather. 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 4 we estimate equation (6) including only year controls. The year controls are necessary since the number of cities and counties in the sample varies year-by-year. In this simple time-series specification, exposure to media violence appears to increase crime, consistent with the evidence from the psychology experiments. For each additional one million people exposed to a violent movie, the probability of assault increases by 1.5-2.1 percent, depending on whether we consider the mild or strong violence measure. In addition, we obtain the (puzzling) result that exposure to any movie (as captured by A_t) increases crime significantly.

In Columns 2 and 3 we include additional controls: indicators for month-of-year and for day-of-week. These indicators are significant determinants of assault rates, since violent crime varies by weekday (Figure 2) and has important seasonal patterns (Figure 1c). While introducing these course seasonal variables increases the R^2 substantially, from .9192 to .9824, 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 (Columns 4) and holiday indicators (Column 5), raising the R^2 to .9893.[11] (The full set of holiday indicators is described in Appendix A.) As we add these control variables, the coefficients $\beta^{[5,7]}$ and $\beta^{[8,10]}$ on the violent movie measures flip sign and become *negative*, though not significantly so.

This negative correlation, however, may be due to an unobserved variable η_t that contemporaneously increases movie attendance A_t and decreases violence ε_t. For example, on rainy days assaults are lower, but movie attendance is higher. 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 (Column 6). (The weather controls are described in Appendix A.) Second, and more importantly, we instrument for movie audience on day t using information on the following weekend's audience for the same movie. (Details on how the instrument is constructed are found in Appendix B.) Our instrumental variable (IV) strategy exploits the predictability of the weekly decrease in attendance. At the same time, it get rids of contemporaneous information at time period t which could be contaminated, such as

[11]To guarantee that leap years are comparable to the other years, we drop February 29 from the sample.

unobserved one-time temporal variables which influence both movie attendance and assaults.

Column 7 presents the IV estimates, where we have instrumented for movie audiences $A_t^{[5,7]}$, $A_t^{[8,10]}$, and A_t with their predicted values. These instruments remove 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. Panel B in Table 5 shows that the first stages are all very strong. Consider column (1), which shows the first stage for the audience of strongly violent movies. The coefficient on the *predicted* audience size for strongly violent movies is highly significant and close to one (0.97), as predicted. The other two coefficients in this regression are close to zero, but also significant. A similar pattern is found in column (2) for mildly violent movies. In column (3), the first stage is also highly significant, but the coefficient on the predicted audience of all movies is further away from one (0.61).[12]

Returning to Table 4, adding the weather controls (Column 6) and instrumenting (Column 7) does not solve the puzzle: the correlation between movie violence and violent crime becomes more negative and statistically significant. An increase of one million in the audience for violent movies decreases violent crime by .42 percent (mildly violent movies) or .56 percent (strongly violent movies), substantial effects on violence. After instrumenting, total movie audience is no longer a significant predictor of assaults. Although not reported in the table, it is interesting to note that the IV estimates do not noticeably change if the weather controls are excluded. This suggests the instruments are working as they should, since they take care of temporary weather shocks.

Summary. 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, and particularly so for more violent movies. This result stands in contrast to the findings of the psychology experiments.

4.2 Theater Audience – Time of Day

To clarify this potentially puzzling result, we separately examine the effect of violent movies on violent crime by time of day. In these and all following specifications, we include the full set of controls X_t and instrument for the actual audiences $A_t^{[5,7]}$, $A_t^{[8,10]}$, and A_t using the predicted audiences.

6-Hour Time Blocks (Baseline Estimates). In Table 5, we present results for separate 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

[12]If we reparameterize the model to have three mutually exclusive and exhaustive violence categories, and regress the audience of nonviolent movies on the predicted audience of nonviolent movies, the coefficient is much closer to one.

to watch movies in the morning and in the afternoon, and especially so for violent movies, we expect to find no effect of exposure to violent movies in the first two time blocks. Indeed, exposure to violent movies has no differential impact on assaults in the morning (column 1), or in the afternoon (column 2). Since we consistently find similar effects for these two time periods, 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 0.56 percent. Exposure to strongly violent movies has an even larger effect. Exposure of one million additional people reduces assaults by 0.86 percent. We interpret this as evidence that exposure to violent movies incapacitates people who may otherwise be at risk for committing crimes. The larger effect for more violent movies plausibly reflects the fact that audiences for more violent movies are more likely to be selected among the potential criminals. Below, we argue that the magnitude of the coefficients $\beta^{[5,7]}$ and $\beta^{[8,10]}$ is consistent with incapacitation. Exposure to non-violent movies is negatively correlated with violent crime, but the point estimate for β 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 mildly violent movies for one million people decreases violent crimes by 1.29 percent. Exposure of one million people to strongly violent movies reduces assaults by 1.47 percent. These strong negative effects imply that we can confidently reject a positive short-run impact of violent movies on crime implied by the psychology evidence. In this specification as well, the impact of non-violent movies is also negative but substantially smaller and not significantly different from zero.

2-Hour Time Blocks. To provide additional evidence on the timing of the effect of violent movies, we re-run specification (6) separately by two-hour time blocks. We examine the time blocks from 6AM-8AM on the same day of exposure to the violent movies until 10AM-12PM on the next day. This captures the impact six hours beyond the last time block considered in Table 5. In Figure 3 we plot the coefficients, with confidence intervals, capturing the impact of mild and strong screen violence (the total audience variable is also included in the regressions). To interpret the coefficients, one should regard the time stamp as indicating either the time of the assault, or the time of the police report. As such, the crime is likely to have occurred in the indicated time block, or potentially in the previous two-hour block.

During the same-day morning hours and the afternoon, no coefficient is significantly different from zero, and no pattern is apparent, consistent with the results of columns 1 and 2 of Table 4. In the time block 8PM-10PM, exposure to strong violence has a negative and marginally significant effect, while for the time blocks 10PM-12AM and 12AM-2AM, both measures of violence have a significant and sizeable negative effect. The timing of this effect lines up with incapacitation from movie attendance if we assume that the time blocks are on average delayed by two hours: most showings for movies take place between 6PM and 12AM, and violent movies attract larger audiences later in the day.

Over the time blocks 2AM-4AM and 4AM-6AM of the next day the estimates are significantly negative and even larger for the series of strongly violent movies. However, the estimates are more imprecise since fewer assaults take place in these time periods. The pattern is more uneven the for series of mildly violent movies. In contrast, there is no evidence of an impact of exposure to violent movies from 6AM to 12PM of the next day. Overall, the negative impact of movie violence on assaults persists with large magnitudes into the early morning hours, to then disappears as the next day re-starts.

Summary. Unlike in the psychology experiments, therefore, 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.

4.3 Theater Audience – Robustness

Individual Movie Violence Level. To complement the findings in Table 5, we present more disaggregated evidence on the effect of movies using different violence categories. We estimate the regression

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

using the same sample, control variables, and IV approach as before. That is, we estimate separately the effect on assaults of exposure to movies of violence level v, with $v = 0, 1, ..., 10$.

In Figure 4, we plot the coefficients β^v for evening assaults and for nighttime assaults. Over the evening hours (6PM-12AM), the decrease in assaults is fairly monotonic in the violence level of the movie. Movies with low levels of violence do not affect the frequency of assaults. Violent movies lower the frequency of assaults, consistent with incapacitation, and more so the more violent is the movie. Over the night hours (12AM-6AM), the pattern is similar, with larger negative effects. Across both time periods, the most negative effects of movie exposure on assaults occurs for movies of violence level 9, the second-highest. Overall, the negative impact of movie violence on assaults is remarkably monotonic in the rated violence level of the movie. No single violence group appears to be driving the results.

Alternative Movie Violence Measure. In our next robustness exercise, we cross-validate our results using the MPAA ratings of each movie. In addition to the rating of a movie ("R", "PG", etc.), the MPAA summarizes in one sentence the reason for the rating including references to sex, violence, and profanity. 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 to violence is qualified by "Brief", "Mild", or "Some", we classify the movie as non-violent. (ii) 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 described in Section 3 for the benchmark measures.[13] The average MPAA-based mild violence measure averages 2.21 million in audience, compared to 2.46 million for the *kids-in-mind*-based mild violence measure (Table 2). The two measures have a correlation of .80 across the days in the sample when they are both non-missing. The MPAA-based measure of strong violence is substantially more restrictive than the *kids-in-mind*-based-measure, averaging an audience of 0.48 millions, compared to 0.87 million for the *kids-in-mind* measure. The correlation between these two measures is .63.

In columns (1) through (3) of Table 6 we replicate the results of Table 5 using the MPAA-based measure of movie violence. Over the morning and afternoon period (6AM-6PM), as expected, we find no significant effect of exposure to mildly violent or strongly violent movies. Over the evening period (6PM-12PM), the point estimates of the effect of exposure to movie violence are negative but not significant. The estimates are about 30 percent smaller than using the *kids-in-mind*-based measures of violence (column 3 of Table 5). Over the night following the exposure (12AM-6AM), we find a significant negative effect of exposure to both mild movie violence and strong movie violence. The point estimates are about 10 percent smaller than with the *kids-in-mind*-based measures (column 4 of Table 5). When we replicate these results using both the MPAA-based measures of violence and the *kids-in-mind*-based measures of violence (columns 4-6), we find that the effects on assaults depend mostly on the *kids-in-mind* measures.

Overall, the alternative MPAA measure of movie violence produces comparable, but somewhat smaller and less precise, results than the *kids-in-mind* measure. The *kids-in-mind* measure appears to be a more detailed measure of movie violence, which is not surprising given that the *kids-in-mind* raters refine the MPAA rating and transform it into a 0-10 scale. We therefore use the *kids-in-mind* ratings in the rest of the paper.

Placebo Dataset. Although we have included a very exhaustive set of seasonal control variables, there is still the possibility that some seasonality remains which could bias our estimates. We estimate a placebo treatment to test whether our findings are due to such unobserved seasonal factors. We generate a placebo data set by re-assigning the assault measure 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). It is important to match up both on day-of-year and day-of-week, since there is substantial variation in assaults and movie attendance along both dimensions.

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

[13]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 for that week.

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). The years are matched so that all regularly-scheduled events will occur on the same date and day of week in the two years to fully control for seasonality. Overall, 1,160 observations (out of 1,523) are in this data set.

To the extent that the negative correlation between movie violence and violent crime is due to unobserved seasonality, we would expect to find a negative correlation also in this placebo data set. If the effect is a causal effect due to violent movie attendance, we should not find an effect in the placebo treatment. Before estimating the placebo regression, in columns 1-3 of Table 7 we first replicate the benchmark results of Table 5 over the sub-sample of 1,160 observations in this data set. The results are similar, with somewhat less precise estimates due to the smaller sample. In columns 4-6 of Table 7, then, we implement the placebo regression as in equation (6), but using the assault data for the placebo-matched year.

We do not find any significant evidence that exposure to movie violence decreases assaults in the placebo specification. Out of 9 coefficients, the only significant coefficient (in column 6) implies that strongly violent movies may, if anything, increase assaults in this placebo specification. Overall, therefore, the negative correlation between movie violence and assaults does not appear to be due to unobserved seasonality.

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 of exposure to violent movies in the previous weekend, or an anticipated impact of exposure to violent movies in the next weekend (a placebo specification). In doing this, one needs to take into account that the audience in consecutive weeks is fairly correlated, given that the audience for a movie decays by only about thirty percent in one week.

In columns 1-4 of Table 8, we estimate a specification where we allow for an impact of the movie audience 7 days ago. Lagged movie attendance is instrumented using a similar methodology as for the other movie attendence variables. For space reasons, we present just the results for the evening hours and the morning after exposure. If we do not control for audience in day t (columns 1-2), lagged exposure to violent movies decreases violent crime, significantly so in the morning hours (column 2). When we control for the audience level in day t (column 3-4), however, this effect disappears and all lagged variables ($A_{t-7}^{[8,10]}$, $A_{t-7}^{[5,7]}$, and A_{t-7}) are insignificant predictors. This indicates that: (i) the impact of movie audience in date t truly captures contemporaneous exposure; (ii) there does not appear to be a medium-run effect of exposure to movie violence.

In columns 5-8 of Table 8, we estimate a similar specification, except that we use movie attendance on date $t + 7$. If we do not control for audience in day t (columns 5-6), these leads of exposure to violent movies decrease violent crime, similarly to the finding with lagged exposure. When we control for audience in day t (columns 7-8), the negative effect of violent movie audience on crime is stronger for the time t variables in the morning hours (column 8), and is imprecisely estimated for both the time t and the time $t+7$ variables in the evening hours (column 7).

Overall, the test of the timing of effect suggests that it is mostly the current level of movie violence that affects violent crime, as opposed to leads or lags.

Demographics. So far, we have presented the impact of movie violence on assaults irrespective of demographics. Separate effects by age group and gender can be found in Appendix Table 2. We do not report the results for the morning and afternoon hours in this appendix table, as we consistently find no impact.

4.4 DVD and VHS Rental Audience

While most of the paper focuses on the effect of releases in theaters, a similar design exploits the releases in VHS and DVD. These releases typically occurs a few months after the theatrical release, and have similar features to the release in theaters. The rental of newly released VHSs and DVDs peaks in the first week of release and decays quickly in the following weeks. Moreover, the top 1-2 movies capture a large share of the rental revenue.

We use data on weekly DVD and VHS rental revenue from *Video Store Magazine.* The data covers the top 25 movies over the period January 1995-December 2004[14]. To estimate the number of rentals, since the magazine does not publish a deflator series, we deflate the rental revenue by the average price estimated using the *Consumer Expenditure Survey.* In addition, to make this data compatible with the daily format of the box office audience data, 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 (Friday through Sunday).

Combining this data with the violence ratings from *kids-in-mind*, we compute a daily measure of audience for mildly violent and violent movies. The average number of daily rentals of any movie in the weekend is 3.98 millions (Table 2). The weekly rentals of strongly violent (mildly violent) movies are 0.65 (1.58) million. We note that multiple people may view a rental. The audience reached by DVD and VHS rentals, therefore, is roughly comparable to the audience reached at the theaters. The violent audience sizes for DVD and VHS rentals are only mildly correlated to the box office measure in the corresponding week. The correlation between the two measures of strong (mild) violence is -.01 (.35).

In columns 1-3 of Table 9, we estimate specification (6) using DVD and VHS rentals instead of box office audience. We include the full set of controls and instrument using a 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), we obtain point estimates comparable to those for box office data (Table 5), but the effects are not significant given that the standard errors are 2 to 3 times larger. In the morning hours

[14]The data is missing for *20* weeks in which the magazine did not publish the data.

(column 3), we also find non-significant effects, with mixed signs: the impact of mildly violent movies is negative, but the impact of strongly violent movies is positive. In addition, we find a (significant) negative effect of the rental audience of all movies, which may be capturing some unobserved time-series factor that is not eliminated by the instrumenting or the controls. The results are similar when we control also for box office movie audience (columns 4-6).

The results on DVD and VHS releases, while qualitatively consistent with an incapacitation effect over the evening hours, are too imprecisely estimated to provide precise evidence on the effect of movie violence on violent crime.

5 Interpretation and Additional Evidence

Interpretation. The main results so far are that exposure to violent movies (i) lowers same-day violent crime in the evening and (ii) lowers violent crime to an even larger extent the ensuing night. We now provide interpretations in light of the model in Section 2. While the first result in the paper is easy to interpret as an incapacitation effect, the interpretation of the second result is less clear, especially in light of the opposing experimental results. We provide three main interpretations: Catharsis, Extended Incapacitation, and Sobriety.

1. *Catharsis.* The consumption of movie violence has a cathartic effect, freeing tensions that would have been expressed otherwise in violent acts. This is an explanation in line with Aristotle's explanation in his *Poetics* of the nature of the Greek tragedy. Catharsis was a leading theory among psychologists in the 1950s and 1960s before the experiments on media violence and aggressiveness (leading to the opposite result) were run.

2. *Extended Incapacitation.* Exposure to movies lowers crime temporarily even after the end of the movie: when a potential criminal exits the movie theater, the situational opportunities to engage in violent crime are diminished relative to a comparable night with no movie attendance. For example, after watching a movie, individuals may go to sleep earlier than if they had instead chosen to go to a night club.

3. *Sobriety.* Theater attendance reduces the consumption of alcohol, which in turn reduces the incidence of violent crime both during and after the movie.

A key difference between the first interpretation and the last two interpretations is whether the effect is due exclusively to exposure to violent movies. The first interpretation holds that the decrease in violent crime is directly due to exposure to violent movies. The last two interpretations instead imply that any movie (or incapacitating event, for that matter) that attracts potential criminals will temporarily decrease violent crime.

Test of Catharsis. To differentiate the two groups of explanations, we evaluate whether nonviolent movies that attract potential criminals also decrease violent crime. A model of pure catharsis where the alternative activities do not matter predicts that the effect instead should not differ.

We employ a measure of the extent to which a movie attracts a demographic group that is more likely to commit crime: young males (see Table 2). While we do not have information on the demographic profile of the audience of each movie, we can use demographic information for a related variable, the number of ratings on an Internet website. In particular, the Internet Movie Database (*IMDB*) maintains a very popular website for movie-goers which invites its users to rate movies. *IMDB* then displays, for each movie, statistics on the rating by 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 attractiveness of a movie to potential criminals, we use the share of raters that are male and are aged 18 to 29. We then divide movies into thirds using this variable, and denote the middle third of movies as liked by young males, and the top third as highly liked by young males. This definition requires us to assume that there is a monotonic relationship between the share of young males watching a movies and the share of young males rating it online.

Appendix Table 1b reports information on the Top 6 blockbusters within the three categories, holding constant the *kids-in-mind* violence rating. Among the non-violent movies, "Harry Potter and The Chamber of Secrets" is the largest blockbuster 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 distinguished between movies in the middle group such as "Passion of the Christ" and movies highly liked by young males such as "Hannibal."

To estimate the impact on violence of movie attendance within each of the nine cells, we estimate the regression

$$\log V_t = \sum_{j=1}^{9} \beta^j A_t^j + \Gamma X_t + \varepsilon_t,$$

where $j = 1, ..., 9$ denotes the nine cells. We adopt the full set of controls and instrument set. Appendix Table 1b 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 associated with lower crime, even holding constant the liking by young males. For example, among the movies liked by young males, the estimated parameters $\hat{\beta}^j$ are -.0035 (non-violent), -.0099 (mild violence), and -.0091 (strong violence) for the evening hours, and -.0045 (non-violent), -.0169 (mild violence), and -.0200 (strong violence). More importantly for the test of Catharsis, moving along a row the coefficients also become more negative. For example, among the mildly violent movies, the estimated parameters $\hat{\beta}^j$ are .0080 (not liked by young males), -.0099 (liked), and -.0116 (strongly liked) for the evening hours, and -.0147 (not liked), -.0169 (liked), and -.0173 (strongly liked). Movies that attract more young males, therefore, appear to lower the incidence of violent crimes, even holding constant the violence of a movie. This supports the finding that the results are due to variation in the alternative activity (young males would have undertaken more dangerous activities had they not gone to the movie theater), rather than just catharsis.

As another test of the significance of this finding, we test whether the measures of movies by liking by young males are significant. We define the variables A_t^{Mid}, the audience of movies that are liked by young males in day t, and A_t^{High}, the audience of movies that are highly liked. In columns 1-3 of Table 10 we estimate

$$\log V_t = \beta^{High} A_t^{High} + \beta^{Mid} A_t^{Mid} + \beta A_t + \Gamma X_t + \varepsilon_t \tag{7}$$

where we use the usual set of controls and instruments. Exposure to movies liked by young males significantly (or marginally so in one specification) lowers violent crime both in the evening hours (6PM-12AM, column 2) and in the morning hours (12AM-6AM, column 3). The effect is larger for exposure to movies highly liked by young males. The point estimates of the impact are somewhat larger than the point estimates of the comparable measures of movie violence. In columns 4-6 of Table 10, we add to the regression the controls for movie violence, $A_t^{[8,10]}$ and $A_t^{[5,7]}$. We find that both exposure to violent movies and exposure to movies that attract young audiences contribute to reduce violent crime in the evening hours (6PM-12AM, column 5) and in the morning hours (12AM-6AM, column 6). It should be remembered that the point estimates of the coefficients β^{High} and β^{Mid} are effects above and beyond the sizeable effects estimated for the violent movie attendance variables.

Even after controlling for movie violence, movies that attract young audiences incapacitate criminals. Selection into movie theaters of potential criminals (here measured as young males) appears to play a key role. As the model in Section 2 suggests, movies that are more likely to attract potential criminals will be associated with a more negative estimate of the impact of movie violence, since movie attendance displaces more potentially violent activities. These results do not support the hypothesis that the results are due to a pure cathartic effect of violent movies (though we cannot reject a combination of a cathartic effect and selection).

Test of Sobriety. To test the Sobriety explanation, we examine whether the displacement of violent crimes is larger for crimes involving alcohol consumption. In columns 1 and 2 of Table 11 we estimate the impact of exposure to violent movies on assaults in which the offender consumed alcohol; column 1 reports the impact in the evening hours, while column 2 reports the impact in the morning hours. (We find no impact in the morning and afternoon hours.) Columns 3 and 4 of Table 11 report the comparable results for assaults with no consumption of alcohol. While the negative impact of movie violence on assaults is present in both samples, the estimates are on average 1.5 to 2 times as large for assaults involving alcohol.

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 very large displacement for assaults taking place in bars and night clubs, although these estimates are very imprecise given the relative rarity of these assaults.

Overall, the evidence suggests that decrease in alcohol consumption is likely to play a role in the negative correlation between audience of violent movies and assaults in the evening and morning hours.

6 Magnitudes and Psychology Experiments

Magnitudes. The first main finding is that, in the evening hours (6PM-12AM, column 3 of Table 4), one million additional audience for strongly violent movies reduces violent crime by 0.86 percent. Extrapolating out of sample, on a hypothetical day with 116 million people in the audience for strongly violent movies, violent crimes should be zero. This might at first seems like an implausibly large effect since the American population is approximately 300 million, but it is not. In the midpoint of our sample (1998), the US Population, excluding people below age 14 and above age 65 (who are very unlikely to be attending violent movies which are almost always rated "R"), was about 180 million people. Among this subpopulation, those at risk for commiting assaults are likely to be highly over-represented in the audience for violent movies, which would explain the size of our finding. In Table 3, in fact, we document a substantial selection of young people (that are more at risk of committing crime) into violent movies (Table 3). In a laboratory setting, Bushman (1995) offers subjects 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.

The second main finding is that, in the night hours following the movie exposure (12AM-6AM), one million additional audience for strongly violent movies significantly reduces violent crime by 1.47 percent. The size of this effect is at first puzzling. The highest decrease in crime should occur when potential criminals are in the movie theater, when committing crimes is nearly impossible. However, when comparing the effects for the evening hours to the nighttime hours, it is important to remember that assaults are 50% higher on average in the evening hours. So the percent effects are estimated off of different levels of violence.

We also note a large difference in the composition of evening and nighttime crimes. As Table 2 shows, the share of assaults involving alcohol consumption, as well as assaults with the most severe injuries, are more common in the morning hours. These are precisely the assaults that respond the most to exposure to violent movies (see Table 11 and Appendix Table 3).

Predicted Impact on Assaults. We now use our baseline estimates to calibrate the impact of movie violence on the average number of assaults in the US. More precisely, we calculate the change in assaults that would occur if all violent movies were substituted by non-violent movies with the same audience numbers. These predictions rely on three restrictive assumptions: (i) no impact of media violence on assaults beyond the night of the media exposure, (ii) replacement by non-violent movies with the same audience, and (iii) effects for the whole population being the same as for the set of cities in the NIBRS sample. Details of the calculation are found in the notes to Table 12.

The results are as follows. On average, strongly violent movies in the evening hours (6PM-12AM) prevent about 24 assaults daily across the US, out of 6,010 assaults. Mildly violent movies (that are more common) are predicted to prevent 55 assaults. The estimates for the short-run impact on violence in the night hours (12AM-6AM) have a similar size (the point estimates are more negative, but the baseline assault rate is lower). Strongly violent movies are predicted to decrease the number of night assaults by 24, and mildly violent movies by 72. The point estimate of the total number of assaults prevented due to exposure to violent movies is 175 assaults per day, adding up to about 64,000 assaults yearly. In addition to the point estimates, we compute 95 percent confidence intervals taking into account the uncertainty in the estimates of the effect of violent movies[15] The upper bound of the estimate is a decrease of 58 assaults per day, still a very significant impact of exposure to movie violence.

These predictions should be taken with caution, since they rely on a number of restrictive assumptions. This being said, they indicate that media violence has a sizeable impact on violent crime in the short-run. In particular, Table 12 suggests a substantial reduction in crime due to a substitution away from alternative activities (with higher levels of violence). This effect has largely been overlooked by the previous literature, yet it is substantial. Put somewhat differently, our estimates imply that a strongly violent blockbuster movie like Hannibal reduced assaults by 1,052 on its opening weekend.

Psychology Literature. We now compare our findings to the evidence from the psychology literature. The top part of Table 1 summarizes the results of representative experiments. Columns (1) and (2) present the features of the treatment and of the control group. The first experiments (Lovaas, 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; Leyens et al., 1975) are run with larger samples and on more varied populations. Across the different experiments, the treatment usually consists in exposure to a 5 to 15 minute video of violent scenes from a violent movie. The scenes are often explicitly chosen to induce violence, depicting violence in a positive light. The control group usually watches a video of comparable length with non-violent scenes. Finally, 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

[15]The confidence intervals in column 6 of Table 9 do not take into account uncertainty in either the average number of assaults, or average movie audience.

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 1, exposure to the violent movie doubles the incidence of violence. The large size of this effect, though, 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.)

Leyens et al. (1975) stands out from the other experiments 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 of 1.5 minutes. 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. These results suggest that the effects of media violence, when present, are likely to be short-lived. The large difference compared to our framework relates to the foregone alternative. Here subjects were offered a violent or non-violent movie, but not the alternative social activities avaiable in the field (i.e., to those outside of detention facilities).

A second set of evidence in Psychology comes from cross-section or longitudinal surveys. In these studies, self-reported measures of media exposure are correlated with measures of aggressiveness and violence. An example is Johnson et al. (2002), who find 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.

Overall, these studies suggest a large impact of media violence on violent behavior in the time period immediately following the exposure to the media violence. While it is hard to quantify this effect, most papers in Table 1 find that violent behavior doubles. In our findings, instead, we find a negative effect of media violence on violent crime, and reject positive effects.

Lab Experiments and Field Evidence. Reconciling the differences 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, 2006).

The difference in findings between the field and the laboratory are likely due to three factors, two of which are suggested by the model in Section 2. (i) *Partial Equilibrium.* In the laboratory, the subjects are not optimally choosing whether to watch a movie or do an alternative activity; rather, they are forcedly exposed to a movie. The violent-movie treatment does not displace an alternative activity (such as alcohol consumption), relative to the non-violent-movie treatment. The experiments hold constant the alternative activity. (ii) *Selection.* Subjects in the laboratory are a representative sample of the (student) population, while moviegoers in the field are a self-selected sample that prefers violent movies. (iii) *Type of Violence.* A third factor is differences in media 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 that follow a logic.

Given these differences, field evidence and laboratory experiments help to evaluate different treatments. The laboratory experiments evaluate the treatment for people that are unexpectedly exposed to an elevated level of violence, as in the case of a violent advertisement or a trailer placed within family programming. The field evidence in this paper evaluates the treatment to elevated violence of people that choose to expose themselves, and have seen violence before. This amounts to the effect of a marginal increase in violence over an habituation level.

Interestingly, 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 attempted to provide 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 two effects on violent crimes: (i) It reduces significantly violent crime in the evening of the day of exposure. (ii) By an even larger percent, it reduces violent crime during the night hours following exposure. Based on our estimates, we estimate that a blockbuster violent movie like "Hannibal" (with 10 million viewers on opening weekend) deters over 1,000 assaults.

We interpret the first finding as incapacitation: potential criminals that choose to attend a violent movie at the theater forego more volative activities with higher violent crime rates. As simple as this finding is, it had been neglected in the literature, despite its quantitative importance. We interpret the second finding as extended incapacitation and sobriety. Blockbuster violent movies attract individuals that would otherwise have engaged in activities, such as drinking at a bar, that would have led to more violent crime later in the night.

We attribute the difference in results from the psychology experiments to differences in the details of exposure to media violence in the lab versus the field and to sorting in the field. Perhaps most importantly, in the field violent movie attendance seems to crowd out other activities associated with high levels of crime, while the foregone activity is not present in the lab experiments.

This paper cannot address the important question about the long-run effect of exposure to movie violence. As such, it should not be used to inform policy on the long-term effects of limiting the level of violence allowed in the media. Instead, it provides evidence on the effect of making an additional violent movie available to consumers, some of whom will choose to watch the violent movie instead of participating in another activity. Our paper suggests an additional opportunity for exposure to media violence will reduce violent crime in the short run. We hypothesize that other activities with a similarly controlled, alcohol-free environment that attract young men will likewise reduce crime in the short run. This insight should be taken into account in the policy debate.

A Appendix A - Data

Imputation of daily box-office audience. The daily box-office movies data 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 impute the daily data, whenever missing, using the weekend box-office data for the same movie in the same week. Fortunately, the weekend data is available throughout the whole sample for the 50 highest-selling movies. For the imputation, we exploit the regularity in the within-week pattern of sales (Figure 2). Ticket sales peak on Saturday, Friday, and Sunday (in decreasing order) and are lowest on Tuesday (Figure 2).

For the imputation, 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, $s(Y)$: $a_{j,t} = s(X)\, a^w_{j,w(t)}$. 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: different weekdays capture a different share of the overall revenue (Figure 2). We allow the weekday share to differ by month (in the summer the Monday-Thursday audience is larger), rating type (G/PG/PG-13/R/NC-17/Unrated/Missing Rating) and in the first week of release. This set of controls X (month indicators, rating indicators, and indicator for first week) therefore, 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 data is defined as the actual box-office data $a_{j,t}$ whenever available, and the predicted value otherwise.

The accuracy of the imputation is high. Over the sample on which both the daily and the weekend data are available, a regression of predicted daily revenue $\hat{a}_{j,t}$ on actual daily revenue $a_{j,t}$ yields a slope coefficient of .9842 with an R^2 of .9190.

Holiday controls. We define a fairly exhaustive 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 the day before 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 Day, Memorial Day, Labor Day, and Columbus Day, and separate indicators for the Sunday preceding each of these holidays. We also include an indicator for Independence 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 observed on a Monday or a Friday if they fall on a weekend (Independence Day, Christmas, New Year, Veteran's Day), and an indicator for Sunday before these holidays, if they are observed on Monday. Finally, we include an indicator for St. Patrick Day, Valentine Day, Halloween, Cinco de Mayo, Mother's Day, and Superbowl.

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 data 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 state and year due to 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 in Fahrenheit; wind speed measured in knots, and using the Beaufort scale measures indicating a fresh breeze (smaller trees sway) and a strong breeze or higher (large branches in motion, umbrella use becomes difficult); rainfall; and snow.

Before averaging, the temperature variables are constructed as dummy variables for the maximum daily temperature falling in one of three categories (> 80 *and* $\leq 90, > 90$ *and* $\leq 100, > 100$), the minimum daily temperature falling in one of three categories ($\leq 10, > 10$ *and* $\leq 20, > 20$ *and* ≤ 32), the heat index falling in one of three categories (> 100 *and* $\leq 115, > 115$ *and* $\leq 130, > 130$), the windspeed falling in one of two categories (> 17 *and* $\leq 21, > 21$), any rain, and any snow.

B Appendix B - Instrument

Our set of instruments uses information on the following weekend's audience for the same movie to predict current movie attendance. To motivate the instrumental variable specification, consider 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 audience of movie j on the weekend corresponding to date t. We assume the daily audience is a share s of the weekend audience, 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: $a^w_{j,w(t)+1} = d(Y_j)\, a^w_{j,w(t)}$.

We can combine the two expressions to obtain $a_{j,t} = [s(Y_j)/d(Y_j)]\, a^w_{j,w(t)+1}$. After taking logs, the model can be written as $\ln(a_{j,t}) - \ln(a^w_{j,w(t)+1}) = \ln(s(Y_j)) - \ln(d(Y_j))$. 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 weekdays capture a different share of the overall revenue (Figure 2). We allow the weekday share to differ by month (in the summer the Monday-Thursday audience is larger), rating type (G/PG/PG-13/R/NC-17/Unrated/Missing Rating) and by week of release. This set of controls Y_j (month indicators, rating indicators, and indicator for weeks of release) therefore, is interacted with the day-of-week dummies, as well as present in levels. Finally, we add the holiday controls H_t.

We estimate

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

(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 $\hat{A}_t^{[5,7]}$, $\hat{A}_t^{[8,10]}$, and $\hat{A}_t$, we simply aggregate across the movies in the relevant violence category. For example, $\hat{A}_t^{[8,10]} = \sum_{v=8}^{10} \sum_{j \in J} d_j^v \hat{a}_{j,t}$, where d_j^v is an indicator for film j belonging to violence level v.

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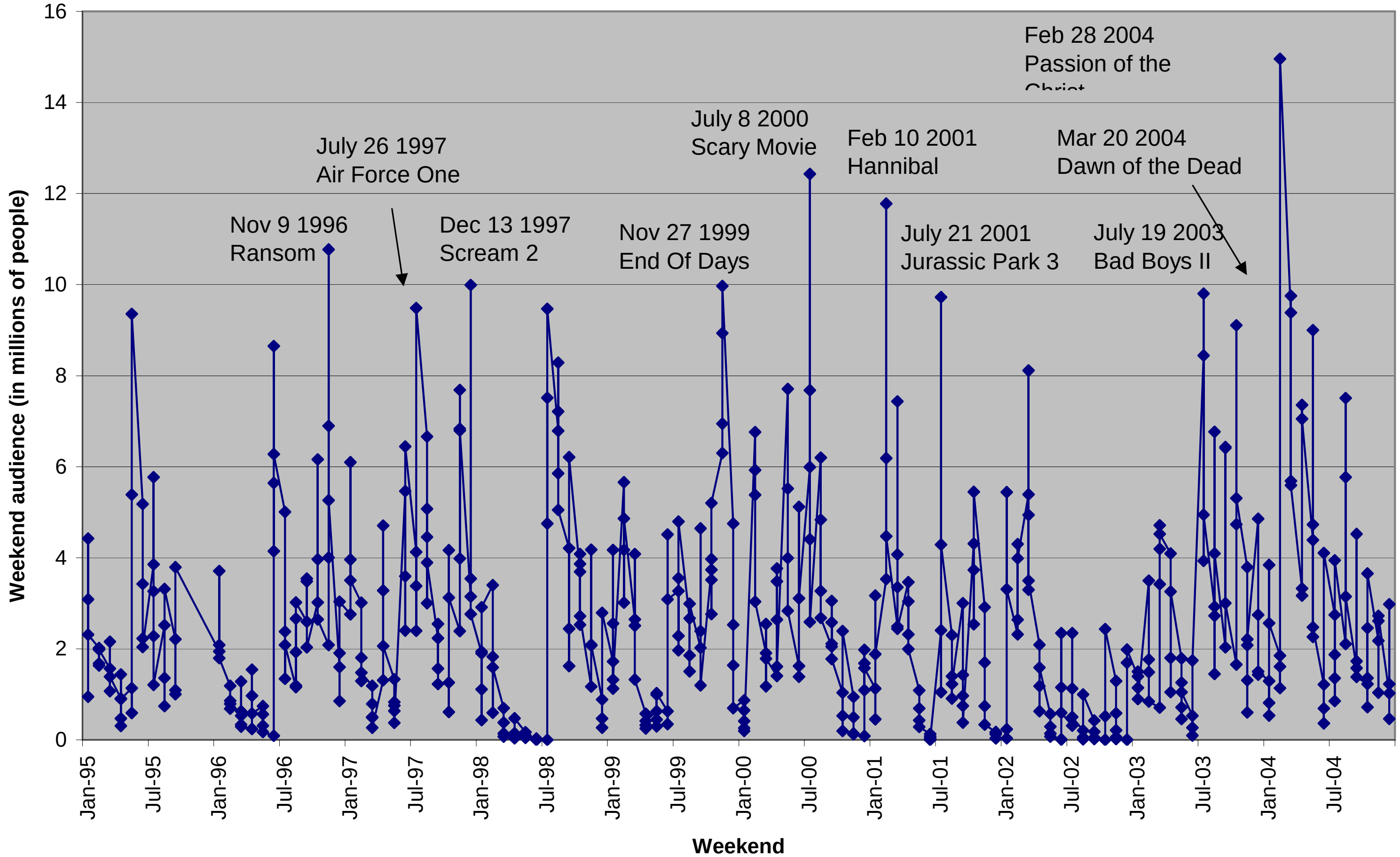
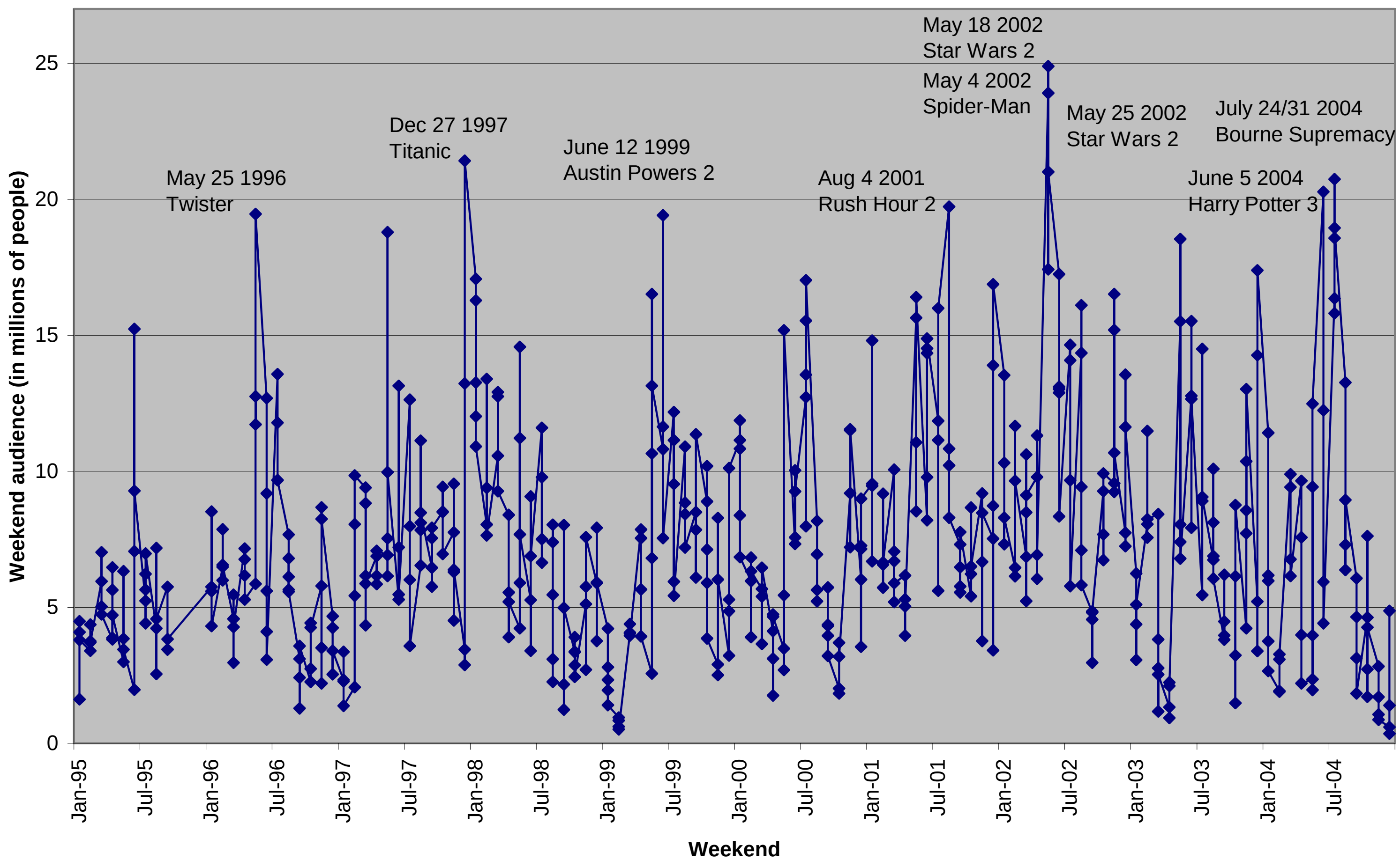
Figure 1a. Weekend Theater Audience of Strongly Violent Movies

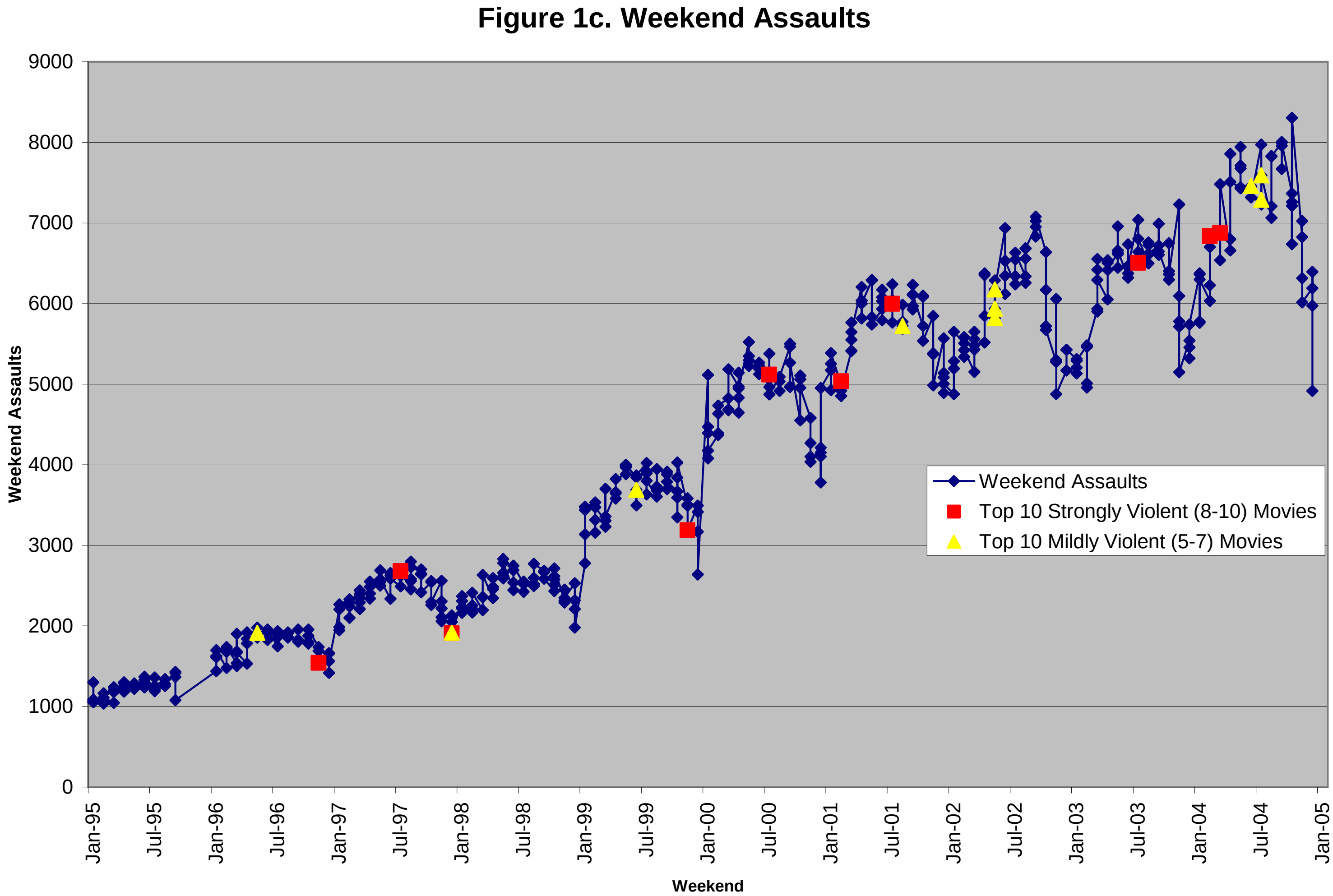


Notes: Plot of weekend (Friday through Sunday) box-office audience (in millions of people) for movies rated as strongly violent. The 10 weekends with the highest audience for strongly violent movies are labeled in the Figure. Movies are rated as strongly violent if they have a kids-in-mind.com rating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

Figure 1b. Weekend Theater Audience of Mildly Violent Movies

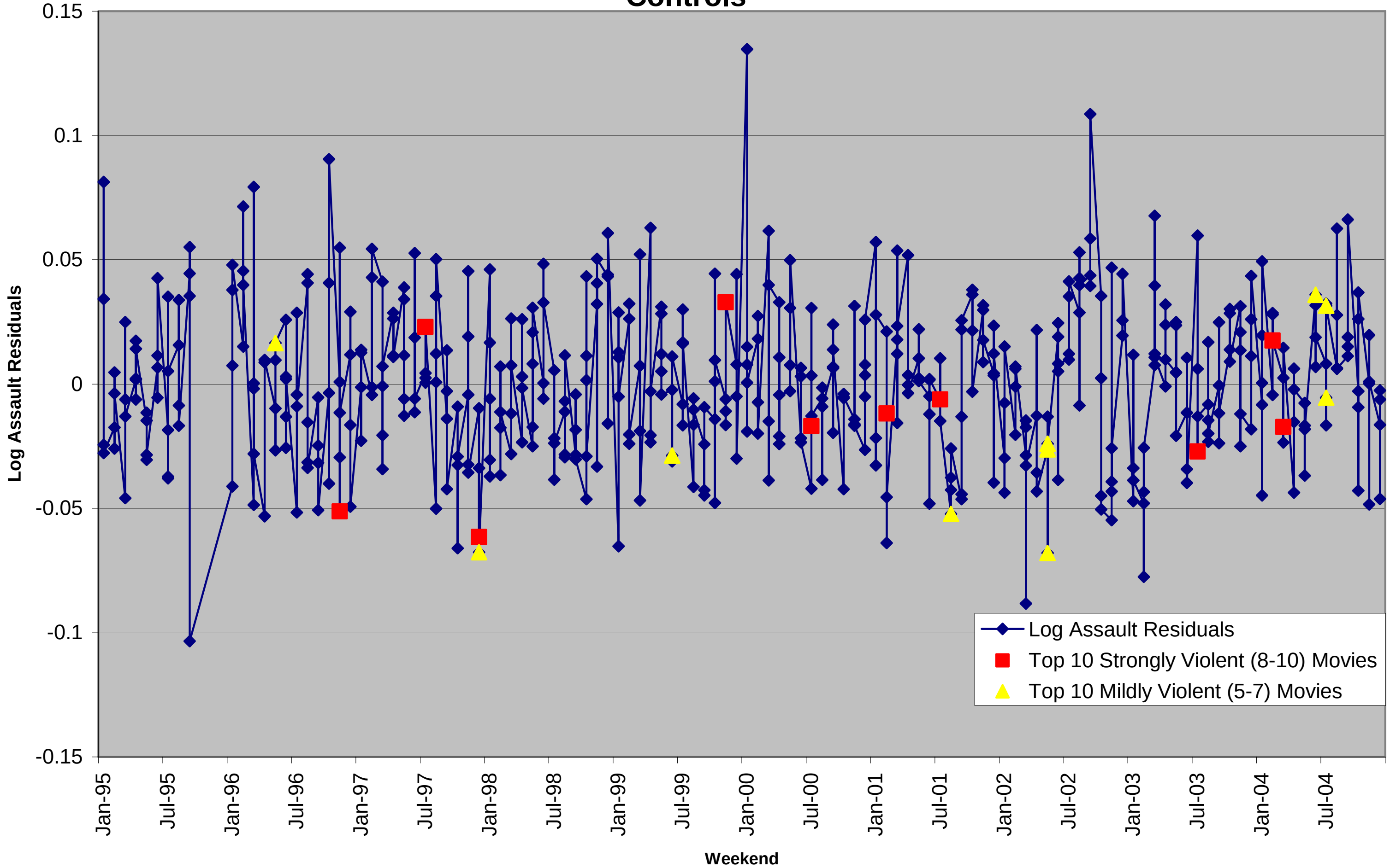


Notes: Plot of weekend (Friday through Sunday) box-office audience (in millions of people) for movies rated as mildly violent. The 10 weekends with the highest audience for mildly violent movies are labeled in the Figure. Movies are rated as mildly violent if they have a kids-in-mind.com rating 5-7.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



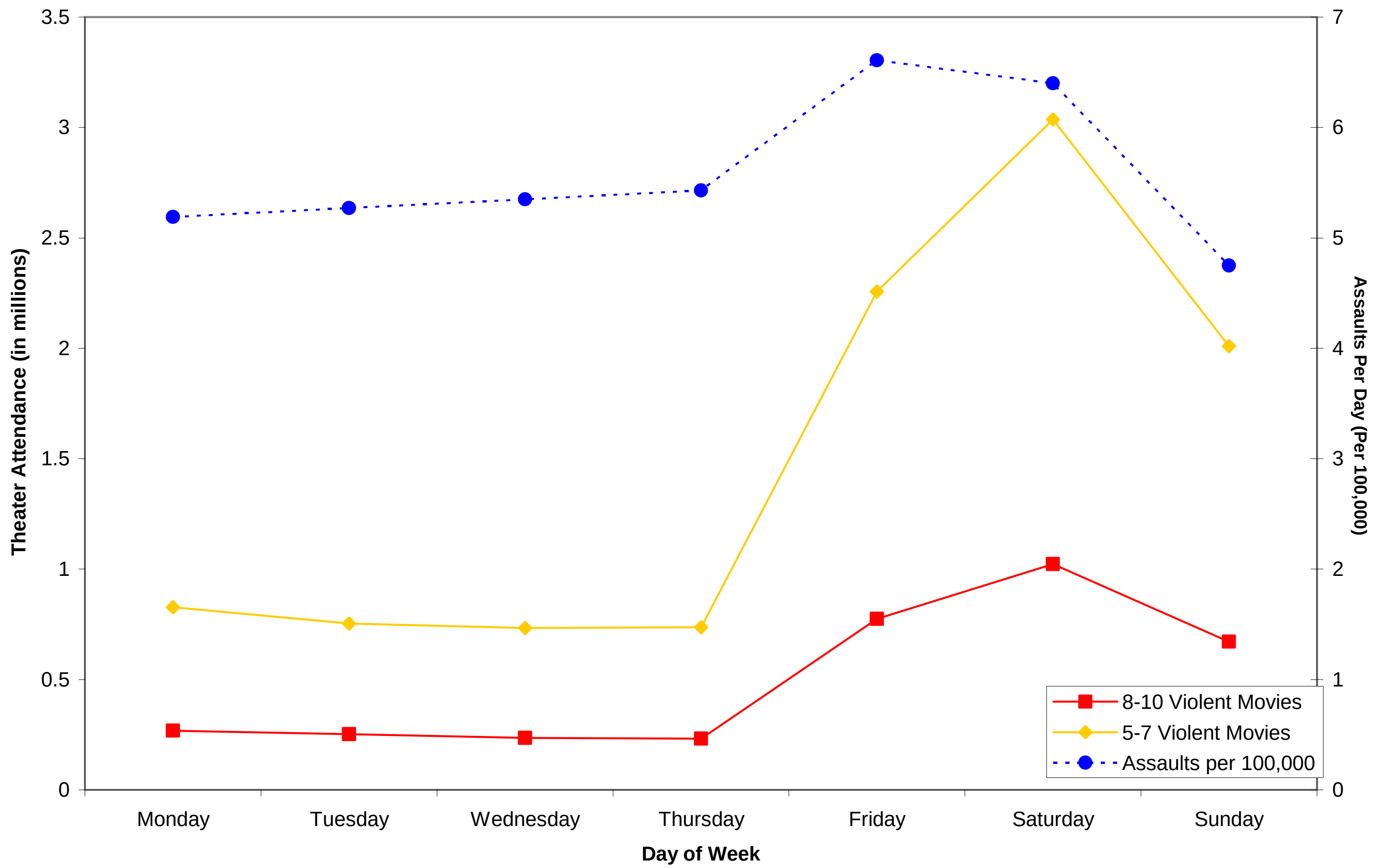
Notes: Plot of weekend (Friday through Sunday) assaults. The assault data is from NIBRS. The 10 weekends with the highest assault rates are listed in the Figure, together with the 10 weekends with the highest strong movie violence audience (Figure 1a) and the 10 weekends with the highest mild movie violence audience (Figure 1b).

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



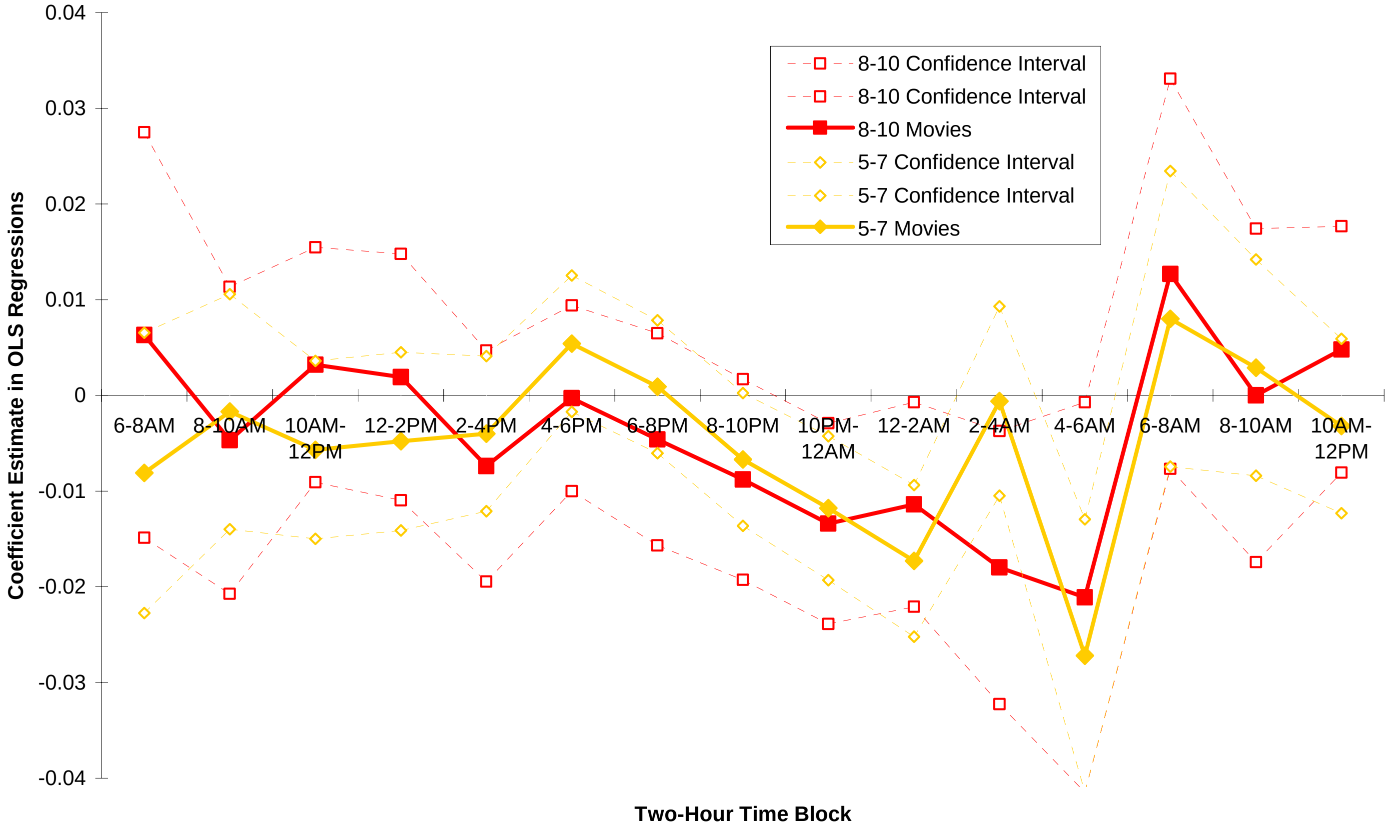
Notes: Plot of residuals of log weekend (Friday through Sunday) assaults after controlling for seasonality, holidays, and weather controls. The assault data is from NIBRS. The 10 weekends with the highest assault rates are listed in the Figure, together with the 10 weekends with the highest strong movie violence audience (Figure 1a) and the 10 weekends with the highest mild movie violence audience (Figure 1b).

Figure 2. Violent Movie Attendance and Assault Rate by Day of Week



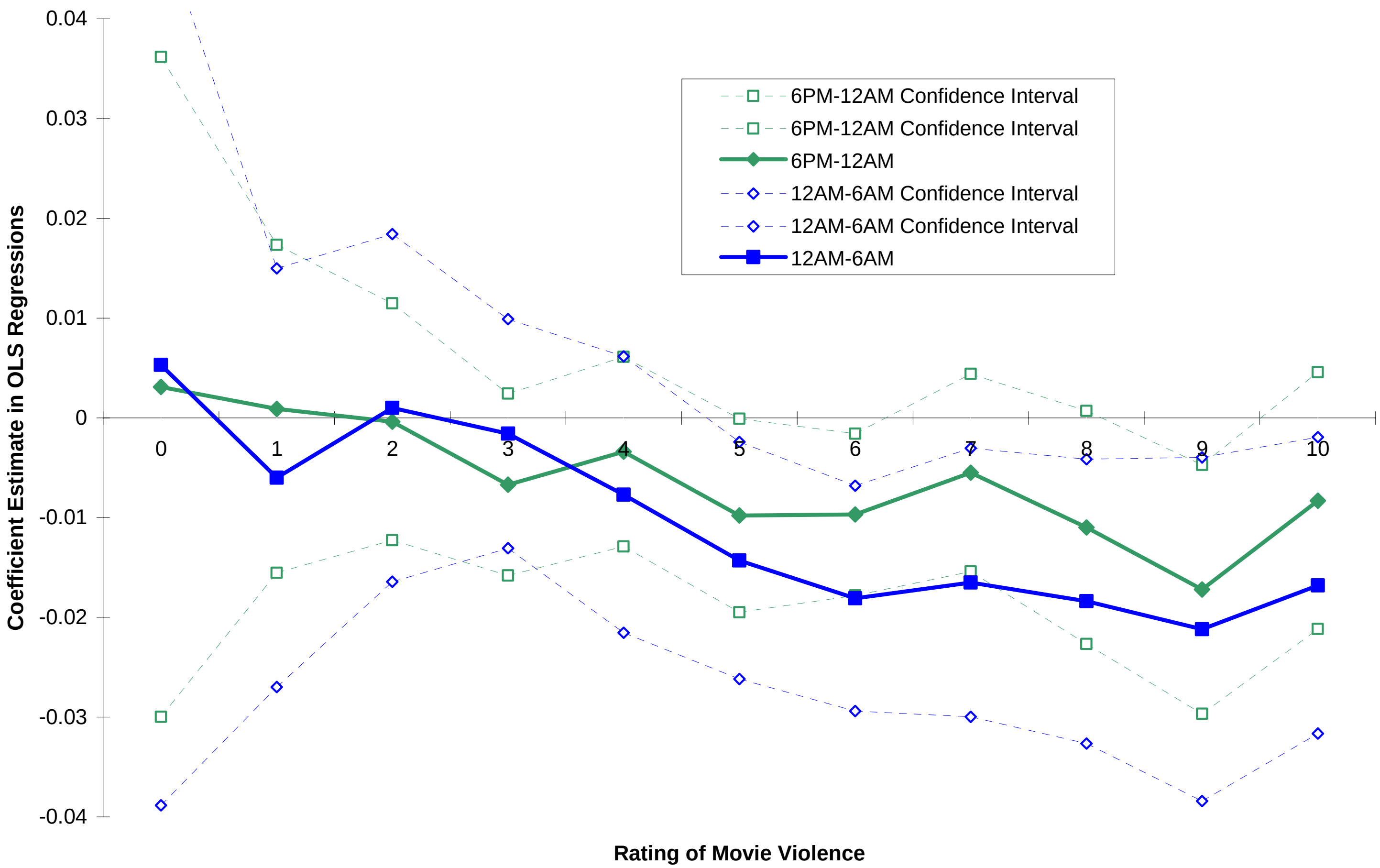
Notes: Plot of average daily box-office audience (in millions of people) for movies rated as strongly violent or mildly violent, and for assaults (per 100,000) by day of week. Movies are rated as strongly violent (mildly violent) if they have a kids-in-mind.com rating 8-10 (5-7). The audience data is obtained from box-office sales (from the-numbers.com) deflated by the average price of a ticket.

Figure 3. Effect of Movie Violence By Two-Hour Time Blocks



Notes: Plot of coefficient from separate regressions of log (assaults) in two-hour time block (X axis) on daily audience for strongly violent movies (red line) and daily audience for mildly violent movies (orange line), controlling for daily total movie audience (coefficients not shown). The data spans until 12PM the day after the movie exposure. The plot also shows 95% confidence intervals. The coefficients can be interpreted as the percent change in assaults for an increase of one million in the audience for violent movies, holding constant the total movie audience. Movies are rated as strongly violent (mildly violent) if they have a kids-in-mind.com rating 8-10 (5-7). The audience data is obtained from box office sales (from the-numbers.com) deflated by the average price of a ticket.

Figure 4. Effect of Movie Violence by 0-10 Violence Rating



Notes: Plot of coefficients from OLS regression of log (assaults) on 11 variables for the daily audience for movies rated of violence level *v* (*v=0,1,…,10* on the right axis) The regressions are run separately for assaults in the 6PM-12AM and 12AM-6AM time period. The plot also shows 95% confidence intervals. 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*. 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.

Table 1. 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	Juvenile Detention	Cottage in Belgium	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).

Table 2. Summary Statistics

Assault Data For All Days	Assaults (per day) Entire Day (1)	6AM to 6PM (2)	6PM to 12AM (3)	12AM to 6AM (4)
Overall	1310	569	482	259
By day of week				
Weekday (Monday - Thursday)	1244	584	461	198
Weekend (Friday - Sunday)	1398	548	509	341
Friday	1526	591	520	416
Saturday	1503	536	534	432
Sunday	1165	518	472	175
Assault Data For Weekends (Friday - Sunday)				
By gender				
Male	1047	399	382	266
Female	351	150	127	75
By age				
13 to 17	144	71	56	17
18 to 29	510	180	176	154
30 to 44	437	168	166	103
Other ages	307	129	111	68
Alcohol-related assaults				
Offender suspected of using alcohol	214	38	85	91
Assaults taking place at a bar	49	3	13	33
By severity of assault				
No apparent physical injury	522	213	195	115
Minor injury	572	204	209	159
Majory injury	74	19	27	28
Number of Observations	N = 1,524 days			

Movie Audience Data For All Days	Movie Audience (in millions of tickets / rentals) Theater Audience (5)	VHS/DVD rentals (6)
Overall	3.9	2.9
By day of week		
Weekday (Monday - Thursday)	2.01	2.12
Weekend (Friday - Sunday)	6.31	3.98
Friday	5.75	4.18
Saturday	7.91	4.88
Sunday	5.27	2.86
Movie Audience Data For Weekends (Friday - Sunday)		
By Kids-in-Mind rating		
Strongly violent	0.87	0.65
Mildly violent	2.46	1.58
By alternative MPAA rating		
Strongly violent	0.48	0.38
Mildly violent	2.21	1.44

Notes: An observation is a day over the years 1995-2004. The sample includes agencies that report a crime in at least 12 months of a year and for at least 300 days in that year. The movie 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 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. 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.

Table 3. Patterns of Movie Attendance Using CEX Data

Specification:	OLS or IV Regressions						
Dep. Var.:	Share of Households Interviewed in CEX Watching a Movie in Day t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Theater Audience Of All Movies	0.8667	0.7923	0.7657	0.8094	0.5508	0.648	0.7781
(in 300 millions of people in day t)	(0.1108)***	(0.1757)***	(0.1886)***	(0.5827)	(0.6099)	(0.2270)***	(0.2431)***
Audience Of Mildly Violent Movies			0.1646		0.1449		-0.2432
(in 300 millions of people in day t)			(0.1907)		(0.3643)		(0.1595)
Audience Of Strongly Violent Movies			-0.0023		1.1812		-0.114
(in 300 millions of people in day t)			(0.1183)		(0.5548)**		(0.2459)
Control Variables:							
Full Set of Controls	X	X	X	X	X	X	X
Age Groups	All Ages	All Ages	All Ages	15-29	15-29	45+	45+
Audience Instrumented With Predicted Audience Using Next Week's Audience		X	X	X	X	X	X
Regressions Weighted by Number of Households Interviewed in Day t	X	X	X	X	X	X	X
N	N = 1575	N = 1575	N = 1575	N = 1575	N = 1575	N = 1575	N = 1575

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. 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 (2)-(7) are IV regressions where the theater audience is instrumented using the using the predicted audience numbers based on next weekend's audience. Details on the construction of the predicted audience numbers are in the text. The regression is weighted by the number of households interviewed in day t. Robust standard errors clustered by week in parenthesis.

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

Table 4. 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	0.0213	0.0081	0.001	-0.0033	-0.0042	-0.0053	-0.0056
(in millions of people in Day t)	(0.0063)***	(0.0042)*	(0.0033)	(0.0032)	(0.0032)	(0.0024)**	(0.0025)**
Audience Of Mildly Violent Movies	0.0154	-0.0019	-0.0016	-0.0017	-0.0023	-0.0032	-0.0042
(in millions of people in Day t)	(0.0041)***	(0.0031)	(0.0022)	(0.0023)	(0.0023)	(0.0019)*	(0.0021)**
Audience Of All Movies	0.0088	0.0248	-0.0078	-0.0067	-0.0051	-0.0058	-0.0048
(in millions of people in Day t)	(0.0030)***	(0.0024)***	(0.0020)***	(0.0025)***	(0.0027)*	(0.0023)**	(0.0031)
Control Variables:							
Year Indicators	X	X	X	X	X	X	X
Month Indicators		X	X	X	X	X	X
Day-of-Week Indicators			X	X	X	X	X
Day-of-Year Indicators				X	X	X	X
Holiday Indicators					X	X	X
Weather Controls						X	X
Audience Instrumented With Predicted Audience Using Next Weekend's							X
R^2	0.9192	0.9379	0.9824	0.9889	0.9893	0.9916	.
N	N = 1524	N = 1524	N = 1524	N = 1523	N = 1523	N = 1523	N = 1523

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 in Columns (1) through (6) are OLS regressions with the log(number of assault occurring in day t) as dependent variable. The specification in Column (7) the audience numbers are instrumented using 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 parenthesis.

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

Table 5. 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	0.0006	-0.002	-0.0086	-0.0147
(in millions of people in Day t)	(0.0045)	(0.0036)	(0.0035)**	(0.0045)***
Audience Of Mildly Violent Movies	-0.0049	-0.0004	-0.0056	-0.0129
(in millions of people in Day t)	(0.0036)	(0.0026)	(0.0024)**	(0.0033)***
Audience Of All Movies	0.0003	-0.0038	-0.004	-0.0034
(in millions of people in Day t)	(0.0061)	(0.0045)	(0.0043)	(0.0056)
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 = 1523	N = 1523	N = 1523	N = 1522

Panel B. First Stage

Specification:	IV Regression, First Stage		
Dep. Var.:	Audience of Strongly Violent Movies	Audience of Mildly Violent Movies	Audience of All Movies
	(1)	(2)	(3)
Pred. Audience Of Strongly Violent Movies	0.9652	-0.0243	-0.0367
(in millions of people in Day t)	(0.0091)***	(0.0172)***	(0.0300)
Pred. Audience Of Mildly Violent Movies	0.0131	0.9746	0.0114
(in millions of people in Day t)	(0.0064)**	(0.0122)***	(0.0213)
Pred. Audience Of All Movies	-0.0488	-0.1304	0.6165
(in millions of people in Day t)	(0.0073)***	(0.0138)***	(0.0242)***
Control Variables:			
Full Set of Controls	X	X	X
F-Test on Instruments	F = 1121.65	F = 677.77	F = 99.52
N	N = 1523	N = 1523	N = 1523

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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Alternative Movie Violence Measure Based on MPAA Rating

Specification:	Instrumental Variable Regressions					
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)					
	(1)	(2)	(3)	(4)	(5)	(6)
Audience Of Strongly Violent Movies - MPAA Meas.	-0.0043	-0.0065	-0.013	-0.0052	0.0019	-0.0044
(in millions of people in day t)	(0.0046)	(0.0046)	(0.0057)**	(0.0062)	(0.0060)	(0.0079)
Audience Of Mildly Violent Movies - MPAA Meas.	-0.0002	-0.0041	-0.0116	0.0001	-0.0013	-0.0074
(in millions of people in day t)	(0.0022)	(0.0022)*	(0.0032)***	(0.0027)	(0.0027)	(0.0038)*
Audience Of Strongly Violent Movies - Stand. Meas.				0.0008	-0.0098	-0.0107
(in millions of people in day t)				(0.0044)	(0.0045)**	(0.0061)*
Audience Of Mildly Violent Movies - Stand. Meas.				-0.0009	-0.0048	-0.0081
(in millions of people in day t)				(0.0028)	(0.0028)*	(0.0040)**
Theater Audience Of All Movies	-0.004	-0.0063	-0.0064	-0.0038	-0.004	-0.0031
(in millions of people in day t)	(0.0041)	(0.0042)	(0.0055)	(0.0041)	(0.0044)	(0.0057)
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
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X
N	N = 1499	N = 1499	N = 1499	N = 1499	N = 1499	N = 1499

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 MPAA ratings are obtained using the one-line MPAA summary of the movie. We characterize as mildly violent movies for which the MPAA Rating contains the word "Violence" of "Violent", with two exceptions: (i) If the reference to 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. 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.

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

Table 7. Placebo Specifications

Specification:	Benchmark IV Regressions			Placebo IV Regressions		
Dep. Var.:	Log (Number of Assaults in Day t)			Log (Number of Assaults in Day t in Placebo Matched Year)		
	(1)	(2)	(3)	(4)	(5)	(6)
Audience Of Strongly Violent Movies	-0.0018	-0.0078	-0.0155	-0.0004	0.0053	0.0138
(in millions per day in day t)	(0.0036)	(0.0043)*	(0.0053)***	(0.0039)	(0.0049)	(0.0061)**
Audience Of Mildly Violent Movies	-0.0013	-0.0049	-0.0156	0.0013	0.0004	0.0013
(in millions per day in day t)	(0.0028)	(0.0029)*	(0.0040)***	(0.0031)	(0.0027)	(0.0039)
Audience Of All Movies	-0.0037	-0.0085	-0.0092	0.0073	0.0066	0.0035
(in millions per day in day t)	(0.0044)	(0.0048)*	(0.0058)	(0.0044)*	(0.0045)	(0.0061)
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
Sub-Sample of Placebo Specification	X	X	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X
N	N = 1160	N = 1160	N = 1159	N = 1160	N = 1160	N = 1159

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. We generate a placebo data set by re-assigning the assault measure 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 4-6 are Placebo IV regressions with the log(number of assault occurring in day t in Placebo-matched year) as dependent variable. The audience numbers are instrumented using the predicted audience numbers based on next weekend's audience. Details on the construction of the predicted audience numbers are in the text. The specifications in Columns 1-3 are standard IV regressions on the subsample over which the placebo regressions are run. Robust standard errors clustered by week in parenthesis.

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

Table 8. Timing of Effect of Movie Violence -- Lags and Leads

Specification:	Instrumental Variable Regressions							
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience Of Strongly Violent Movies 7 Days Ago	-0.0032	-0.0097	0.0036	-0.0007				
(in millions of people in day t)	(0.0035)	(0.0043)**	(0.0044)	(0.0054)				
Audience Of Mildly Violent Movies 7 Days Ago	-0.0026	-0.0084	0.0008	-0.0018				
(in millions of people in day t)	(0.0026)	(0.0033)**	(0.0030)	(0.0042)				
Audience Of All Movies 7 Days Ago	-0.0009	0.003	-0.0005	0.0033				
(in millions of people in day t)	(0.0038)	(0.0048)	(0.0048)	(0.0066)				
Audience Of Strongly Violent Movies			-0.0103	-0.0137			-0.0037	-0.0142
(in millions of people in day t)			(0.0044)**	(0.0058)**			(0.0045)	(0.0061)**
Audience Of Mildly Violent Movies			-0.0059	-0.0118			-0.0038	-0.0082
(in millions of people in day t)			(0.0028)**	(0.0043)***			(0.0033)	(0.0046)*
Audience Of All Movies			-0.0044	-0.0049			-0.0047	-0.0075
(in millions of people in day t)			(0.0053)	(0.0076)			(0.0061)	(0.0079)
Audience Of Strongly Violent Movies 7 Days Later					-0.0089	-0.0078	-0.0072	-0.0009
(in millions of people in day t)					(0.0032)***	(0.0049)	(0.0042)*	(0.0064)
Audience Of Mildly Violent Movies 7 Days Later					-0.0053	-0.0122	-0.0032	-0.0072
(in millions of people in day t)					(0.0024)**	(0.0033)***	(0.0030)	(0.0041)*
Audience Of All Movies 7 Days Later					-0.001	0.0054	0.0003	0.007
(in millions of people in day t)					(0.0036)	(0.0052)	(0.0049)	(0.0070)
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 Next Week's Audience	X	X	X	X	X	X	X	X
N	N = 1523	N = 1522	N = 1523	N = 1522	N = 1523	N = 1522	N = 1523	N = 1522

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 standard 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.

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

Table 9. 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	0.0004	-0.0059	0.0085	0.0007	-0.0048	0.0108
(in millions of people in day t)	(0.0073)	(0.0073)	(0.0086)	(0.0073)	(0.0073)	(0.0087)
DVD/VHS Rentals Of Mildly Violent Movies	-0.0023	-0.0113	-0.0107	-0.0018	-0.0089	-0.0061
(in millions of people in day t)	(0.0058)	(0.0059)*	(0.0074)	(0.0058)	(0.0059)	(0.0073)
DVD/VHS Rentals Of All Movies	-0.0049	-0.0039	-0.0177	-0.0048	-0.0037	-0.0179
(in millions of people in day t)	(0.0057)	(0.0058)	(0.0073)**	(0.0057)	(0.0058)	(0.0073)**
Theater Audience Of Strongly Violent Movies				-0.0019	-0.0083	-0.0116
(in millions of people in day t)				(0.0034)	(0.0036)**	(0.0048)**
Theater Audience Of Mildly Violent Movies				-0.001	-0.0051	-0.0113
(in millions of people in day t)				(0.0025)	(0.0026)**	(0.0035)***
Theater Audience Of All Movies				-0.0007	-0.0022	-0.0037
(in millions of people in day t)				(0.0042)	(0.0045)	(0.0060)
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
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X
N	N = 1441	N = 1441	N = 1441	N = 1441	N = 1441	N = 1441

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 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 standard 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.

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

Table 10. Test of Catharsis Using IMDB Data on Movie Ratings by Young Males

Specification:	Instrumental Variable Regressions					
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)					
	(1)	(2)	(3)	(4)	(5)	(6)
Audience Of Movies Highly Liked by Young Males (IMDB)	0.0006	-0.0117	-0.0199	0.0011	-0.0097	-0.0161
(in millions of people in day t)	(0.0044)	(0.0046)**	(0.0057)***	(0.0045)	(0.0046)**	(0.0058)***
Audience Of Movies Liked by Young Males (IMDB)	0.0043	-0.0079	-0.0166	0.0047	-0.0067	-0.014
(in millions of people in day t)	(0.0040)	(0.0041)*	(0.0051)***	(0.0040)	(0.0042)	(0.0051)***
Audience Of Strongly Violent Movies				-0.0013	-0.0067	-0.0119
(in millions of people in day t)				(0.0032)	(0.0035)*	(0.0047)**
Audience Of Mildly Violent Movies				-0.0021	-0.0046	-0.0109
(in millions of people in day t)				(0.0024)	(0.0024)*	(0.0034)***
Theater Audience Of All Movies	-0.0067	0.0009	0.0055	-0.0058	0.0032	0.0106
(in millions of people in day t)	(0.0058)	(0.0060)	(0.0072)	(0.0058)	(0.0061)	(0.0073)
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
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X	X	X
N	N = 1523	N = 1523	N = 1522	N = 1523	N = 1523	N = 1522

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. We divide movies into thirds using the fraction of raters of a movie on IMDB that are male and of age 18-29. Movies liked by Young Males are defined as movies in the mid third of this distribution. Movies strongly liked by Young Males are defined as movies in the top third of this distribution. The standard 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.

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

Table 11. Test of Sobriety -- Effect of Alcohol Consumption

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)
Audience Of Strongly Violent Movies	-0.0115	-0.0235	-0.0087	-0.0123	-0.0348	-0.0235
(in millions of people in day t)	(0.0064)*	(0.0094)**	(0.0039)**	(0.0051)**	(0.0171)**	(0.0149)
Audience Of Mildly Violent Movies	-0.0117	-0.0163	-0.0046	-0.0137	-0.0198	-0.0118
(in millions of people in day t)	(0.0048)**	(0.0068)**	(0.0025)*	(0.0039)***	(0.0137)	(0.0109)
Audience Of All Movies	-0.005	0.0005	-0.0027	-0.0026	0.0001	-0.0027
(in millions of people in day t)	(0.0076)	(0.0131)	(0.0049)	(0.0062)	(0.0213)	(0.0189)
Type of Crime	Assaults Involving Alcohol		Assaults Not Involving Alcohol		Assaults At A Bar	
Time of 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
Predicted Audience Using Next Week's Audience	X	X	X	X	X	X
N	N = 1523	N = 1522	N = 1523	N = 1522	N = 1518	N = 1515

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 standard 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.

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

Table 12. Calibration on the Short-Run Impact of Movie Violence on Assaults

Variable:	Estimated Effect on Assaults, with Conf. Interval (Table 4)	Assault Rate in Time Interval per 1m (Table 2)	US Population (in 2006)	Total Assaults in Time Interval	Average Audience of Violent Movie in 1m (Table 2)	Predicted Effect on Number of Assaults with Conf. Intervals
	(1)	(2)	(3)	(4)	(5)	(6)
6PM-12AM						
Strongly Violent movies	-0.0086	20.1	299,000,000	6,010	0.47	-24
	(-.0155,-.0016)					(-44,-5)
Midly Violent Movies	-0.0056	20.1	299,000,000	6,010	1.62	-55
	(-.0103,-.0008)					(-101,-8)
12AM-6AM						
Strongly Violent movies	-0.0147	11.6	299,000,000	3,468	0.47	-24
	(-.0236,-.0058)					(-38,-9)
Midly Violent Movies	-0.0129	11.6	299,000,000	3,468	1.62	-72
	(-.0194,-.0063)					(-109,-36)
TOTAL						-175

Notes: This Table presents the results of a calibration on the aggregate impact of violent movies on US daily assaults, based on the estimates in this paper. The final estimate is reported in Column (6), including confidence intervals. Columns (1) through (5) detail the procedure. Column (1) presents the estimated impact of movie violence on assaults in the indicated time period (from Table 5). Columns (2) through (4) present information on the assault rate, the US population, and the total number of US daily assaults in the time interval. Column (5) presents the average daily audience of violent movies. The predicted impact on assaults in Column (6) is computed as the product of the numbers in Columns (1), (4), and (5). 95 percent confidence intervals are computed taking into account the uncertainty in the estimates in Column (1). 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 mildly violent movies is the audience of all movies with a violence rating 5-7. The audience of violent movies is the audience of all movies with a violence rating 8-10.

Appendix Table 1a. Movie Blockbusters by Violence Level

Violence Rating (1)	Fraction Audience (2)	Title of Blockbuster (3)	Weekend Date (4)	Weekend Theater Audience (5)
0	0.013	Birdcage	3/8/1996	4,134,803
		You'Ve Got Mail	12/18/1998	3,928,944
		You'Ve Got Mail	12/25/1998	3,859,694
1	0.038	Runaway Bride	7/30/1999	6,900,700
		Erin Brockovich	3/17/2000	5,220,494
		Contact	7/11/1997	4,484,729
2	0.115	Liar Liar	3/21/1997	6,845,975
		Toy Story	11/24/1995	6,698,992
		Space Jam	11/15/1996	6,228,174
3	0.161	Shrek 2	5/21/2004	17,397,404
		Finding Nemo	5/30/2003	11,650,367
		Shrek 2	5/28/2004	11,621,637
4	0.134	Harry Potter And The Sorcerer's Stone	11/16/2001	15,953,113
		Harry Potter And The Chamber Of Secrets	11/15/2002	15,207,829
		Austin Powers In Goldmember	7/26/2002	12,576,797
5	0.132	Harry Potter And The Prisoner Of Azkaban	6/4/2004	15,086,533
		X2: X-Men United	5/2/2003	14,188,844
		Star Wars: Episode 2 - Attack Of The Clones	5/17/2002	13,774,150
6	0.160	Spider-Man	5/3/2002	19,766,629
		Spider-Man 2	7/2/2004	14,195,850
		Spider-Man	5/10/2002	12,292,173
7	0.112	Lost World: Jurassic Park	5/23/1997	15,715,204
		Matrix Reloaded	5/16/2003	15,219,637
		Lord Of The Rings: Return Of The King	12/19/2003	12,044,729
8	0.068	Jurassic Park 3	7/20/2001	8,970,255
		Air Force One	7/25/1997	8,089,870
		Scary Movie	7/7/2000	7,856,525
9	0.048	Bad Boys 2	7/18/2003	7,715,184
		Saving Private Ryan	7/24/1998	6,519,425
		Sleepy Hollow	11/19/1999	5,917,415
10	0.020	Passion Of The Christ	2/27/2004	13,502,107
		Hannibal	2/9/2001	10,247,901
		Passion Of The Christ	3/5/2004	8,574,364
Missing		A Perfect Murder	6/5/1998	3,542,794
		A Perfect Murder	6/12/1998	2,404,636
		Demon Knight	1/13/1995	2,303,346

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. Column (2) reports the average share of audience captured by movies with violence rating *j* . Columns (3) through (5) report the title (Column (3)), the weekend (Column (4)), and the weekend audience (Column (5)) for the 3 movies with highest weekend sales in violence category j. The last category includes movies for which the violence rating is not available.

Appendix Table 1b. 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 (11/15/02, 15.2m)	Shrek 2 (11/16/01, 17.4m)	Austin Powers In Goldmember (7/26/02, 12.6m)
	Top 2	Harry Potter And The Chamber Of Secrets (11/22/02, 7.2m)	Harry Potter And The Sorcerer's Stone (11/16/01, 15.9m)	Incredibles (11/5/04, 11.3m)
	Top 3	Runaway Bride (7/30/99, 6.9m)	Finding Nemo (5/30/03, 11.6)	Bruce Almighty (5/23/03, 11.3m)
	Top 4-6	Sweet Home Alabama, America's Sweethearts, Erin Brockovich	Toy Story 2, Monsters, Inc., How The Grinch Stole Christmas	Ace Ventura: When Nature Calls, Waterboy, Big Daddy
	Effect on Crime	-0.0018 (0.0062) (6PM-12AM) 0.0097 (0.0076) (12AM-6AM)	-0.0035 (0.0046) (6PM-12AM) -0.0045 (0.0063) (12AM-6AM)	-0.0070 (0.0051) (6PM-12AM) -0.0101 (0.0066) (12AM-6AM)
5-7 Mildly Violent Movies	Top 1	Save The Last Dance (1/12/01, 4.9m)	Harry Potter and The Prisoner Of Azkaban (6/4/04, 15.1m)	Spider-Man (5/3/02, 19.8m)
	Top 2	Double Jeopardy (9/24/99, 4.6m)	Planet Of The Apes (7/27/01, 12.1m)	Lost World: Jurassic Park (5/23/97, 15.7)
	Top 3	Absolute Power (2/14/97, 3.7m)	Mummy Returns (5/4/01, 12.0m)	Matrix Reloaded (5/16/03, 15.2m)
	Top 4-6	Random Hearts, Unfaithful, Enough	Independence Day, Men In Black, Day After Tomorrow	Spider-Man 2, X2: X-Men, Star Wars: Episode 2
	Effect on Crime	0.0080 (0.0100) (6PM-12AM) -0.0147 (0.0133) (12AM-6AM)	-0.0099** (0.0044) (6PM-12AM) -0.0169*** (0.0056) (12AM-6AM)	-0.0116*** (0.0042) (6PM-12AM) -0.0173*** (0.0056) (12AM-6AM)
8-10 Strongly Violent Movies	Top 1	Missing (11/28/03, 1.7m)	Passion Of The Christ (2.27/04, 13.5m)	Hannibal (2/9/01, 10.2m)
	Top 2	Nurse Betty (9/8/00, 1.3m)	Passion Of The Christ (3/5/04, 8.5m)	Jurassic Park 3 (7/20/01, 9.0m)
	Top 3	Copycat (11/3/95, 1.3m)	Air Force One (7/25/97, 8.1m)	Scary Movie (7/7/00, 7.9m)
	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	0.0035 (0.0256) (6PM-12AM) -0.0638** (0.0283) (12AM-6AM)	-0.0091 (0.0070) (6PM-12AM) -0.0200** (0.0078) (12AM-6AM)	-0.0127*** (0.0048) (6PM-12AM) -0.0163*** (0.0063) (12AM-6AM)

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.

Appendix Table 2. The Effect of Movie Violence on Same-Day Assaults, By Age Group and Gender

Specification:	Instrumental Variable Regressions							
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience Of Strongly Violent Movies	-0.0104	-0.0104	-0.0067	-0.0195	-0.0072	-0.0153	-0.0141	-0.012
(in millions of people in day t)	(0.0050)**	(0.0060)*	(0.0046)	(0.0068)***	(0.0035)**	(0.0045)***	(0.0059)**	(0.0075)
Audience Of Mildly Violent Movies	-0.0064	-0.0099	-0.004	-0.0119	-0.0058	-0.013	-0.0058	-0.0127
(in millions of people in day t)	(0.0036)*	(0.0045)**	(0.0038)	(0.0046)**	(0.0027)**	(0.0033)***	(0.0038)	(0.0057)**
Audience Of All Movies	-0.0035	-0.0069	0.0016	-0.0076	-0.0043	-0.0062	-0.0025	0.0062
(in millions of people in day t)	(0.0062)	(0.0080)	(0.0065)	(0.0074)	(0.0044)	(0.0055)	(0.0074)	(0.0101)
Age Group of Criminal	18-29	18-29	30-44	30-44	All	All	All	All
Gender of Criminal	All	All	All	All	Male	Male	Female	Female
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 = 1523	N = 1522	N = 1523	N = 1522	N = 1523	N = 1522	N = 1523	N = 1522

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 standard 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 assault occurring in day t) as dependent variable. The audience numbers are instrumented using 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 parenthesis.
* significant at 10%; ** significant at 5%; *** significant at 1%