DOES MOVIE VIOLENCE INCREASE VIOLENT CRIME?*

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Laboratory experiments in psychology find that media violence increases aggression in the short run. We analyze whether media violence affects violent crime in the field. We exploit variation in the violence of blockbuster movies from 1995 to 2004, and study the effect on same-day assaults. We find that violent crime *decreases* on days with larger theater audiences for violent movies. The effect is partly due to voluntary incapacitation: between 6 P.M. and 12 A.M., a one million increase in the audience for violent movies reduces violent crime by 1.1% to 1.3%. After exposure to the movie, between 12 A.M. and 6 A.M., violent crime is reduced by an even larger percent. This finding is explained by the self-selection of violent individuals into violent movie attendance, leading to a substitution away from more volatile activities. In particular, movie attendance appears to reduce alcohol consumption. The results emphasize that media exposure affects behavior not only via content, but also because it changes time spent in alternative activities. The substitution away from more dangerous activities in the field can explain the differences with the laboratory findings. Our estimates suggest that in the short run, violent movies deter almost 1,000 assaults on an average weekend. Although our design does not allow us to estimate long-run effects, we find no evidence of medium-run effects up to three weeks after initial exposure.

I. INTRODUCTION

Does media violence trigger violent crime? This question is important for both policy and scientific research. In 2000, the Federal Trade Commission issued a report at the request of the president and the Congress, surveying the scientific evidence and warning of negative consequences. In the same year, the American Medical Association, together with five other public-health

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The Quarterly Journal of Economics, May 2009

organizations, issued a joint statement on the risks of exposure to media violence (American Academy of Pediatrics et al. 2000).

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

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

Using a violence rating system from kids-in-mind.com and daily revenue data, we generate a daily measure of national-level box-office audience for strongly violent (e.g., *Hannibal*), mildly violent (e.g., *Spider-Man*), and nonviolent movies (e.g., *Runaway Bride*). Because blockbuster movies differ significantly in violence rating, and movie sales are concentrated in the initial weekends after release, there is substantial variation in exposure to movie violence over time. The audience for strongly violent and mildly violent movies, respectively, is as high as 12 million and 25 million people on some weekends, and is close to 0 on others (see Figures Ia and Ib). We use crime data from the National Incident Based Reporting System (NIBRS) and measure violent crime on a given day as the sum of reported assaults (simple or aggravated) and intimidation.

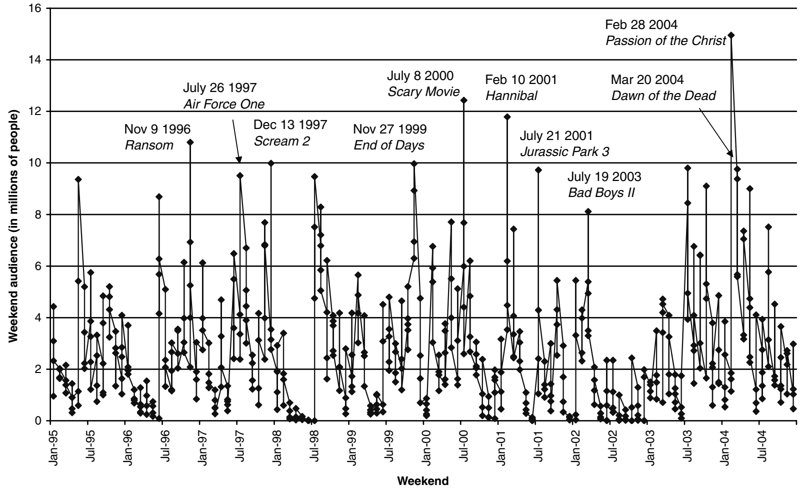

FIGURE Ia
Weekend Theater Audience of Strongly Violent Movies

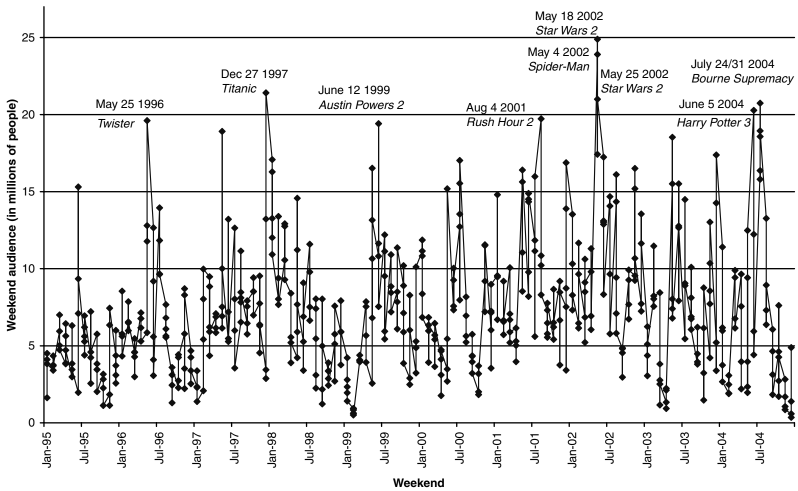

FIGURE Ib
Weekend Theater Audience of Mildly Violent Movies

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

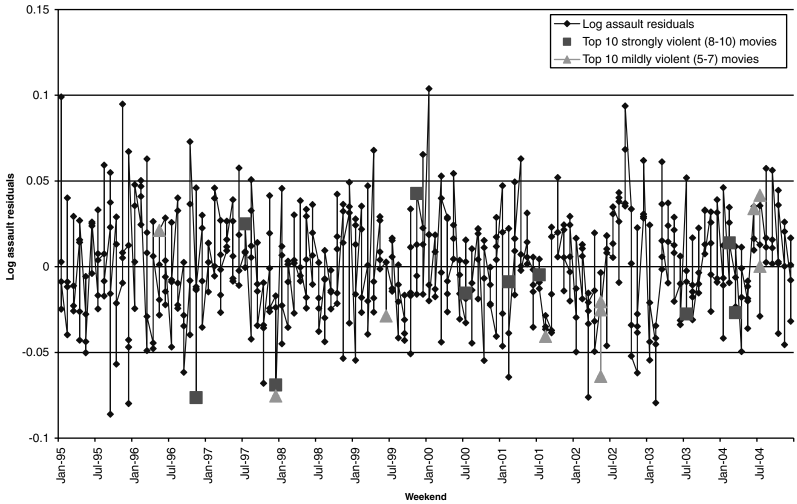

FIGURE Ic

Log Assaults and the Top Ten Violent Movies (Controlling for Seasonality)

Plot of average (Friday through Sunday) residuals of weekend log assaults after controlling for seasonality, holidays, and weather controls (see text for list of all the controls). The assault data are from NIBRS. The figures highlight the ten weekends with the largest strongly violent movie audience (see Figure I(a)) and the ten weekends with the largest mildly violent movie audience (see Figure I(b)).

We find that, on days with a high audience for violent movies, violent crime is lower, even after controlling flexibly for seasonality. To rule out unobserved factors that contemporaneously increase movie attendance and decrease violence, such as rainy weather, we use two strategies. First, we add controls for weather and days with high TV viewership. Second, we instrument for movie audience using the predicted movie audience based on the following weekend's audience. This instrumental variable strategy exploits the predictability of the weekly decrease in attendance. Adding in controls and instrumenting, the correlation between movie violence and violent crime becomes more negative and remains statistically significant.

The estimated effect of exposure to violent movies is small in the morning or afternoon hours (6 A.M.–6 P.M.), when movie attendance is minimal. In the evening hours (6 P.M.–12 A.M.), instead, we detect a significant negative effect on crime. For each million people watching a strongly or mildly violent movie, respectively, violent crimes decrease by 1.3% and 1.1%. The effect is smaller and statistically insignificant for nonviolent movies. In the nighttime hours following the movie showing (12 A.M.–6 A.M.), the delayed effect of exposure to movie violence is even more negative. For each million people watching a strongly or mildly violent movie, respectively, violent crime decreases by 1.9% and 2.1%. Nonviolent movies have no statistically significant impact. Unlike in the psychology experiments, therefore, media violence appears to decrease violent behavior in the immediate aftermath of exposure, with large aggregate effects. The total net effect of violent movies is to decrease assaults by roughly 1,000 occurrences per weekend, for an annual total of about 52,000 weekend assaults prevented. This translates into an estimated yearly social gain of approximately $695 million in avoided victimization losses (direct monetary costs plus intangible quality-of-life costs). The results are robust to a variety of alternative specifications, measures of movie violence, instrument sets, and placebo tests. Additional estimates using variation in violent DVD and VHS video rentals are consistent with our main findings.

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

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

We interpret the first empirical result, that exposure to violent movies lowers same-day violent crime in the evening (6 P.M. to 12 A.M.), as voluntary incapacitation. On evenings with high attendance at violent movies, potential criminals choose to be in the movie theater and hence are incapacitated from committing crimes. The incapacitation effect is larger for violent movies because potential criminals self-select into violent, rather than nonviolent, movies. Indeed, using data from the Consumer Expenditure Survey time diaries, we document substantial self-selection. Demographic groups with higher crime rates, such as young men, select disproportionately into watching violent movies.

The second result is that violent movies lower violent crime in the night after exposure (12 A.M. to 6 A.M.). These estimates reflect the difference between the direct effect of movie violence and the violence level associated with an alternative activity. Hence, the reduction in crime associated with violent movies is best understood as movie attendance displacing more volatile alternative activities both during and after movie attendance. Because alcohol is a prominent factor that has been linked to violent crime (Carpenter and Dobkin 2009), and alcohol is not served in movie theaters, one potential mechanism is a reduction in alcohol consumption associated with movie attendance. Consistent with this mechanism, we find larger decreases for assaults involving alcohol or drugs and for assaults committed by offenders just over (versus just under) the legal drinking age.

A common theme to the findings above is the importance of self-selection of potential criminals into violent movies. We provide additional evidence on selection using ratings data from the Internet Movie Database (IMDb). We categorize movies based on how frequently they are rated by young males. We find that, even after controlling for the level of violence, movies that disproportionately attract young males significantly lower violent crime.

Our second result appears to contradict the evidence from laboratory experiments, which find that violent movies increase aggression through an arousal effect. However, the field and laboratory results are not necessarily contradictory. The laboratory experiments estimate the impact of violent movies in partial equilibrium, holding the alternative activities constant. Our natural experiment instead allows individuals to decide in equilibrium between a movie and an alternative activity. Exposure to movie violence can lower violent behavior relative to the foregone alternative activity (the field findings), even if it increases violent behavior relative to exposure to nonviolent movies (the laboratory findings). Under assumptions that allow us to estimate the amount of selection, our field estimates can be used to infer the effect of exposure, holding the alternative activities constant (as in the laboratory).

Using this methodology, we find evidence of an arousal effect consistent with the laboratory experiments; violent movies induce more violent crime relative to nonviolent movies. However, this estimated arousal effect is smaller than the time-use effect—on net, violent movies still induce substantially less violent behavior than the alternative activity. Hence, the field evidence provides a bound for the size of the arousal effect identified in the laboratory. This example also suggests that other apparent discrepancies between laboratory and field studies (see Levitt and List [2007]) might be reconciled if differences in treatment and setup are taken into account.

Our research is related to a growing literature in economics on the effect of the media. Among others, Besley and Burgess (2002), Stromberg (2004), Gentzkow (2006), and DellaVigna and Kaplan (2007) provide evidence that media exposure affects political outcomes. Card and Dahl (2009) show that emotional cues provided by local NFL football games (in the form of unexpected upset losses) cause a spike in family violence. Relative to this media literature that emphasizes the effect of content, our paper stresses the impact of time use. In our context, the substitution in activities induced by violent movies dominates the effect of content. This mechanism also operates in Gentzkow and Shapiro (2008), who show the introduction of television during preschool had positive effects on test scores for children of immigrants, who otherwise would have had less exposure to the English language.

Our paper also complements the evidence on incapacitation, from the effect of school attendance (Jacob and Lefgren 2003) to the effect of imprisonment (Levitt 1996). Our paper differs from this literature because the incapacitation is optimally chosen by the consumers, rather than being imposed. Not all leisure activities have an incapacitation effect, however. Rees and Schnepel (2009) document an increase in crimes by spectators of college football games in the host community. The prevalence of alcohol consumption at football games, but not in movie theaters, plausibly explains the difference.

Finally, this paper is related to the literature on the impact of emotions such as arousal (Loewenstein and Lerner 2003; Ariely and Loewenstein 2005) on economic decisions.

The remainder of the paper is structured as follows. Section II presents a simple model of movie attendance choice and its effect on violence. Section III describes the data, and Section IV presents the main empirical results. Section V provides interpretations and additional evidence. Section VI concludes.

II. Framework

II.A. Model

In this section we model the choice to view a violent movie and the resulting impact on the level of violence following exposure. Our setup is meant to illustrate (i) the importance of self-selection, (ii) the effect of time use versus content for violent movies, and (iii) how estimates in the laboratory and field differ.

Individuals choose the utility-maximizing activity among four mutually exclusive options: watching a strongly violent movie a^v, watching a mildly violent movie a^m, watching a nonviolent movie a^n, or participating in an alternative social activity a^s. Although we could assume a standard multinomial choice model, any choice model implies probabilistic demand functions for movies $P(a^v)$, $P(a^m)$, $P(a^n)$, and for the alternative activity $1 - P(a^v) - P(a^m) - P(a^n)$. For each type of movie, demand $P\left(a^j\right)$ varies based on the quality and overall appeal of the movie (which we do not observe).

We allow for heterogeneity in the taste for movies. We label the group with high demand for violent movies as young y and the other group as old o. Within each group, the fraction choosing activity j is denoted as $P(a_i^j)$ for $i = y, o$ and $j = v, m, n, s$. The aggregate demand functions for the young and old are simply these probabilities multiplied by group size N_i.

Violence, which does not enter individuals' utility functions, depends on the type of movies viewed, as well as on participation in the alternative social activity. We model the production function for aggregate log violence as linear in the demand for movies and the alternative social activity, aggregated over young and old:

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

The parameters α_i^v, α_i^m, α_i^n, and σ_i, all (weakly) positive, capture the effects on violence from the four alternative activities. Given the log specification (motivated by the similarity to a Poisson model), increasing the young audience size of violent movies by 1, *ceteris paribus*, results in roughly a α_y^v percent increase in violence.

Because individual-level data on movie attendance are not available, we rewrite (1) in terms of aggregate movie attendance for the young and old combined. (In Section IV, we discuss ways to identify consumer types using auxiliary data.) The effect of total audience size $A_j = N_y P(a_y^j) + N_o P(a_o^j)$ on log violence is a weighted average of the effects for the young and old subgroups:

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

where $x^j = N_y P(a_y^j)/(N_y P(a_y^j) + N_o P(a_o^j))$ denotes the young audience share for movie j.

The estimating equation we use in Section IV follows directly from (2):

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

where ε is an additively separable error term. Comparing (3) and (2), we can write the coefficients as

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

Notice the parameter β^j is constant only if the young audience share x^j is constant in response to changes in movie quality. In what follows, we assume that this is approximately the case, that is, that when movie quality changes, demand by the young and old roughly rises and falls proportionately with each other (as would be true for a multinomial logit model).

II.B. Interpretation

Expression (4) illustrates several points. First, the impact of a violent movie β^v on violence is the sum of two effects: a direct effect, captured by α_i^v, and an indirect effect, captured by σ_i. The direct effect is the impact of violent movies, holding everything else constant. There are two broad theories about the direct impact of violent movies immediately after exposure. The first theory is that exposure to media violence triggers additional aggression, whether through arousal or the imitation of violent acts (Anderson et al. 2003). The second, opposite theory is that exposure to movie violence leads to a decrease in aggression because of a cathartic effect of viewing violence on screen. This theory, which parallels Aristotle's theory about the effect of the Greek tragedy, was a leading theory among psychologists until 1960. Since the 1960s, a series of laboratory experiments, from Bandura, Ross, and Ross (1963) to Buschman (1995), have found substantial support for arousal and imitation and little support for catharsis. In our model, α_y^v is large if movie violence triggers violence through arousal or imitation, and small if movie violence has a cathartic effect.

In addition to the direct effect, there is an indirect effect due to the displacement of alternative social activities that occurs when an individual chooses to watch a violent movie. A first possibility is that these displaced activities trigger crime at a lower rate than movie attendance. This can be the case, for example, if movies provide a meeting point for potential criminals who would otherwise stay home. In this case, movie attendance, on net, increases crime (positive β_v) after exposure. A second possibility is that the aftermath of movie attendance is more dangerous that the alternative activity. This can occur, for example, if movie attendance leads to earlier bedtimes and lower alcohol consumption, compared to, say, bar attendance. In this case, movie attendance, on net, decreases crime (negative β_v).

We note that the effect of movies during exposure (the contemporaneous effect) differs from the effect after exposure (the delayed effect). During the movie showing, the direct effect of movie exposure α^j approximately equals 0 for all types of movies because very few crimes are committed while physically in the movie theater. In this sense, movie attendance can be viewed as a form of voluntary incapacitation: movies take individuals "off the streets" and place them into relatively safe environments.

A second insight from (4) is that heavy moviegoers contribute most to the identification of β^v. This parameter is a weighted average of the net effects for old and young people. To the extent the young like violent movies more than the old, they will be overrepresented in the audience for violent movies, and hence the weight representing their audience share will be larger than their share in the population. Because the young and old have very different crime patterns, this type of sorting can have a large impact on the aggregate estimate.

To illustrate the importance of selection, suppose that the direct effect of movie exposure is the same for all movie types ($\alpha_i^n = \alpha_i^m = \alpha_i^v = \alpha$ for $i = y, o$), but that the violent subpopulation engages in more dangerous alternative activities ($\sigma_y > \sigma_o$). In this case $\beta^j = \alpha - \sigma_o - x^j(\sigma_y - \sigma_o)$. Even in the absence of a differential direct effect for violent movies, the level of violence in a movie can affect crime. If violent movies are more likely to attract the violent subpopulation (i.e., $x^v > x^m > x^n$), as we document empirically below, then the effect of exposure becomes more negative with the violence level of the movie: $\beta^v < \beta^m < \beta^n$. Exposure to violent movies can lower crime relative to nonviolent movies simply because violent movies induce more substitution away from dangerous activities for the violent subgroup.

In addition to this selection effect, there can be a direct effect of movie violence, as suggested by the arousal and catharsis theories. To capture this possibility, modify the example in the preceding paragraph so that strongly violent movies have a direct effect α^v (with nonviolent and mildly violent movies still having impact α). Then the impact of exposure to a violent movie is $\beta^v = (\alpha^v - \alpha) + (\alpha - \sigma_o) - x^v(\sigma_y - \sigma_o)$. If we could observe the selection of criminals x^j into the different types of movies, we could estimate the differential direct effect of violent movies (the parameter captured in the laboratory experiments) as

$$\alpha^v - \alpha = \beta^v - \left[\beta^n + \frac{x^v - x^n}{x^m - x^n}(\beta_m - \beta_n)\right]. \tag{5}$$

The solution for $\alpha^v - \alpha$ is the difference between the actual impact of strongly violent movies (β^v) and the predicted impact based on selection (the term in square brackets). If strongly violent movies trigger additional aggression due to arousal or imitation ($\alpha^v - \alpha > 0$), the impact of strongly violent movies β^v can be less negative than mildly violent movies β^m. In Section IV.A, we provide an estimate of $\alpha^v - \alpha$ under the assumptions outlined above.

Finally, although we have emphasized the impact of movies on potential criminals, we note that exposure to movies can also have a parallel effect on potential victims. During the duration of the movie, potential victims are likely to be protected from crime. After the movie, they may be more or less susceptible to assaults depending on whether their alternative activity would have placed them in a more or less volatile situation (accounting for any arousal or catharsis effects). Therefore, although we cannot distinguish between effects on the supply side and on the demand side of criminal activity, the interpretations of the results and the policy implications remain essentially unchanged. In fact, it is likely that any effect of movie attendance, such as a reduction of alcohol consumption, would operate symmetrically on both offenders and victims.

II.C. Comparison of Lab to Field

Before continuing, a brief comparison to the psychology experiments is in order. There are three factors that differ between the laboratory and the field. The first and most important is the comparison group. In the experiments, exposure to violent and nonviolent movies is manipulated as part of the treatment, whereas in the field, subjects optimally choose relative to a comparison activity a^s. Hence, in the laboratory, the treatment effects are estimated as the difference between the effect of violent versus nonviolent movies. In contrast, the effect of exposure in the field is measured as the difference between the effect of movie violence and the effect of the foregone alternative activity. The second factor is selection. Subjects in the laboratory are a representative sample of the (student) population, while moviegoers in the field are a self-selected sample. The sorting of violent individuals into violent movies, which could result in large displacement effects in the field, is not present in the lab. Finally, the third factor is the type of violence. The clips used in the experiments typically consist of five to ten minutes of selected sequences of extreme violence. In the field, instead, media violence also includes meaningful acts of reconciliation, apprehension of criminals, and nonviolent sequences. The exposure to random acts of violence may induce different effects from the exposure to acts of violence viewed in a broader context.

Within our empirical specification, an estimate of β^v in the laboratory experiment yields

$$\beta^v_{\text{lab}} = \frac{N_y}{N_y + N_o}\alpha^v_y + \left(1 - \frac{N_y}{N_y + N_o}\right)\alpha^v_o.$$

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

Recognizing these differences is important not only to better understand the effect of media on violence, but also more generally to understand the relationship between experimental and field evidence (Levitt and List 2007). In our setting, the field findings are important to evaluate policies that would restrict access to violent movies, as such policies would lead to substitution toward alternative activities in the short run. The results of the laboratory experiments, however, are useful to evaluate different policies, such as the short-run impact of unexpected exposure to media violence. In addition, some of 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 2006) to replicate the selection in the field, or can change the exposure to a full-length movie.

One important limitation of both the laboratory and field designs is that neither provides evidence on the long-term effects of repeated exposure to violent media. These cumulative effects could be substantial, yet they are difficult to estimate causally.

III. Data

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

III.A. Movie Data

Data on box-office revenue are from the-numbers.com, which uses the studios and *Exhibitor Relations* as data sources. Information on total weekend box-office sales is available for the top fifty movies consistently from January 1995 on. Daily revenue is available for the top ten movies beginning mid-August 1997. We focus on daily data for Friday, Saturday, and Sunday because movie attendance, and therefore the identifying variation for our analysis, is concentrated on weekends (see Table I). To estimate movie theater attendance, we deflate both the weekend and the daily box-office sales by the average price of a ticket. For the period January 1995 to mid-August 1997 and for all movies that do not make the daily top-ten list, we impute daily box-office revenue (see Appendix I).

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

We define the number of people (in millions) exposed to movies of violence level k on day t as $A_t^k = \sum_{j\in J} d^{j\epsilon k} a_{j,t}$, where $a_{j,t}$ is the audience of movie j on day t, $d^{j\epsilon k}$ is an indicator for film j belonging to violence level k, and J is the set of all movies. The violence level varies between 0 and 10.[1] We define three summary measures for movies with differing levels of violence. The measure of exposure to strongly violent movies on day t is the audience for movies with violence levels between 8 and 10, $A_t^v = \sum_{k=8}^{10} A_t^k$.

1. The rereleases of *Star Wars V* and *VI* in 1997 were not rated because the original movie predates kids-in-mind.com. We assigned them the violence rating 5, the same rating as for the other *Star Wars* movies. To deal with the small number of remaining movies with missing violence ratings, we assume ratings are missing at random with respect to the level of violence in a movie, and inflate each day's exposure variables A_t^k accordingly. The average share of missing ratings is 4.1% across days.

TABLE I
SUMMARY STATISTICS

	Assaults (per day)			
	Entire day (1)	6 A.M. to 6 P.M. (2)	6 P.M. to 12 A.M. (3)	12 A.M. to 6 A.M. (4)
Assault data for all days				
Weekend (Friday–Sunday)	1,454	569	531	354
Friday	1,589	614	543	432
Saturday	1,564	557	558	449
Sunday	1,209	536	491	182
Weekday (Monday–Thursday)	1,293	608	480	205
	Share of weekend assaults in each category			
Assault data for weekends (Friday–Sunday)				
By gender of offender				
Share with male offender	0.779	0.755	0.784	0.811
By age of offender				
Share with offender of ages 18 to 29	0.378	0.340	0.359	0.467
Alcohol-related assaults				
Share with offender suspected of using alc. or drugs	0.170	0.082	0.185	0.290
Share with offender of ages 17 to 20 (underage)	0.133	0.125	0.139	0.138
Share with offender of ages 21 to 24 (over-age)	0.135	0.118	0.123	0.182
Number of observations	N = 1,563 days, 2,272,999 assaults, 1,781 agencies			

TABLE I
(CONTINUED)

	Movie audience (millions of tickets or rentals per day)	
	Theater audience (5)	VHS/DVD rentals (6)
Movie audience data for all days		
Weekend (Friday–Sunday)	6.29	3.92
Friday	5.74	4.13
Saturday	7.90	4.82
Sunday	5.24	2.82
Weekday (Monday–Thursday)	2.00	2.09
Movie audience data for weekends (Friday–Sunday)		
By kids-in-mind.com rating		
Strongly violent movies	0.87	0.64
Mildly violent movies	2.43	1.56
Nonviolent movies	2.99	1.72

Notes. An observation is a day over the years 1995–2004. Assault data come from the National Incident Based Reporting System (NIBRS), and the sample includes agencies that do not have missing data on any crime (not just assaults) for more than seven consecutive days for that year. The movie audience numbers are obtained from the-numbers.com and are daily box-office revenue divided by the average price per ticket. The ratings of violent movies are from 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. VHS/DVD rental data come from *Video Store Magazine*.

Similarly, exposure to mildly violent A_t^m and nonviolent A_t^n movies on day t are defined as the aggregated audiences for movies with a violence level between 5–7 and 0–4, respectively.

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

Figure Ib plots the corresponding information for the measure of mild movie violence, A_t^m. Because 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 sizable fraction of the U.S. population. Over a weekend, strongly violent and mildly violent blockbusters attract up to 4% and 8%, respectively, of the U.S. population (roughly 300 million). This extensive exposure provides the identifying variation in our setup.

III.B. Violent Crime Data

Our source for violent crime data is the NIBRS, chosen for two important features. First, it reports violent acts known to police, such as verbal intimidation or fistfights, which do not necessarily result in an arrest. Second, it reports the date and time of the crime, allowing us to match movie attendance and violent crime at the daily level. Alternative large-scale data sets on crime, such as the Uniform Crime Report and the National Crime Victimization Survey, do not contain this same type of detailed information at the daily level.

The NIBRS data collection effort is a part of the Uniform Crime Reporting Program. Submission of NIBRS data is still voluntary, and over time the number of reporting agencies has increased substantially. In 1995 (the first year of NIBRS data), only 4% of the U.S. population was covered, but by August 2005, there were 29 states certified to report NIBRS data to the FBI, for a coverage rate of 22% of the U.S. population (reporting is not always 100% within a state). This 22% coverage represents 17% of the nation's reported crime, which reflects the fact that NIBRS coverage is more heavily weighted toward smaller cities and counties (where crime rates are lower). One limitation of NIBRS is that it does not cover crime in the nation's largest cities, although it does include medium-size cities such as Memphis and Cincinnati.

We use data from 1995 to 2004 for NIBRS city and county reporting agencies, which include local police forces and county sheriff offices. Because not all agencies report consistently, in each year we exclude agencies that have missing data on crime (not just assaults) for more than seven consecutive days, where a report of zero counts as nonmissing data. This filter eliminates 12.5% of reported assaults. If no crime is reported on a given day after this filter, we set that day's assault count to zero. Our main violence measure is the total daily number of assaults, V_t, defined as the sum of aggravated assault, simple assault, and intimidation,[2] across all agencies on day t. In some specifications, we separate assaults into four time blocks: 6 A.M.–12 P.M., 12 P.M.–6 P.M., 6 P.M.–12 A.M., and 12 A.M.–6 A.M. We assign assaults occurring between 12 A.M. and 6 A.M. to the previous calendar day to match them to movies played the previous evening.

To provide graphical evidence on this series, we construct the residual of log daily assaults, after controlling for an extensive set of indicator variables for year, month, day-of-week, day-of-year, and holidays as well as weather and TV audience measures (the same set of variables used in our main specification and described in Appendix I). Figure Ic plots the average of the Friday to Sunday residuals (the days with highest movie audience) over time. The residuals behave approximately like white noise. Only 44 weekends differ from the mean by more than 0.05 log points, and just one differs by more than 0.10 log points.

2. Aggravated assault is an unlawful attack by one person upon another wherein the offender uses a weapon or displays it in a threatening manner, or the victim suffers obvious severe or aggravated injury. Simple assault is also an unlawful attack but does not involve a weapon or obvious severe or aggravated bodily injury. Intimidation is placing a person in reasonable fear of bodily harm without a weapon or physical attack.

The figure also labels the top ten weekends for the audience of strongly violent (see Figure Ia) and mildly violent movies (see Figure Ib). Interestingly, Figure Ic offers an indication of a negative relationship between violent movies and crime. For both mildly violent and strongly violent movies, seven of the top ten weekends have residuals below the median. (One of the positive residuals is for *Passion of the Christ*, an atypical violent movie, both for its target audience and its potential effect on crime.) In addition, out of twenty weekends with a residual more negative than −0.05 log points, two are among the top ten weekends for strongly violent movies, and two are among the top ten weekends for mildly violent movies. We examine the relationship between violent movies and violent crime in detail in the next section.

III.C. Summary Statistics

After matching the movie and crime data, the resulting data set includes 1,563 weekend (Friday through Sunday) observations, covering the time period from January 1995 to December 2004. The data set contains a total of 2,272,999 assaults and 1,781 reporting agencies. Table I reports summary statistics. The average number of assaults on any given weekend day is 1,454. The assaults occur mostly in the evening (6 P.M.–12 A.M.), but are also common in the afternoon (12 P.M.–6 P.M.) and in the night (12 A.M.–6 A.M.). Assaults are highest on Friday and Saturday, and lower on Sundays and other weekdays. Assaults are three times larger for males than for females, and are decreasing in the age of the offender (for ages above 18). The share of assaults where the offender is suspected of using alcohol or drugs is 17.0% over the whole day, with a much larger incidence in the night hours.

Table I also reports summary statistics for movie attendance. The average daily movie audience on a weekend day is 6.29 million people, with a peak on Saturday. The audience for strongly and mildly violent movies is respectively 0.87 million and 2.43 million. The table also presents information on VHS and DVD movie rentals.

IV. EMPIRICAL RESULTS

IV.A. Theater Audience—Daily

To test for the short-run effects of exposure to violent movies, we focus on same-day exposure, 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. Although the number of assaults is a count variable, specifying explicitly the count process (as in a Poisson regression) is not key because 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 that follows from the model developed in Section II is

$$\ln V_t = \beta^v A_t^v + \beta^m A_t^m + \beta^n A_t^n + \Gamma X_t + \varepsilon_t. \tag{6}$$

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

The variables X_t are a set of seasonal control variables: indicators for year, month, day-of-week, day-of-year, holidays, weather, and TV audience. Because 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 II we begin by estimating equation (6) with only year controls included. The year controls are necessary because the cities and counties in the sample vary year-to-year. In this specification, exposure to media violence appears to increase crime. However, we also obtain the puzzling result that exposure to nonviolent movies increases crime significantly, suggesting that at least part of this correlation is due to omitted variables. Einav (2007) documents seasonality in movie release dates and underlying demand, with the biggest ticket sales in the beginning of the summer and during holidays. Because assaults are also elevated during summers and holidays, it is important to control for seasonal factors. In columns (2) and (3), we include indicators for month-of-year and for day-of-week. Although introducing these coarse seasonal variables increases the R^2 substantially, from .9344 to .9846, these variables do not control for additional effects

TABLE II
EFFECT OF MOVIE VIOLENCE ON SAME-DAY ASSAULTS

Specification:	OLS regressions						IV regressions
Dep. var.:	Log (number of assaults in day t)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Audience of strongly violent movies	0.0324	0.0005	−0.0061	−0.0051	−0.0072	−0.0091	−0.0106
(millions of people in day t)	(0.0053)***	(0.0053)	(0.0033)*	(0.0033)	(0.0033)**	(0.0026)***	(0.0031)***
Audience of mildly violent movies	0.0246	0.0017	−0.0084	−0.0042	−0.0056	−0.0079	−0.0102
(millions of people in day t)	(0.0030)***	(0.0029)	(0.0020)***	(0.0026)	(0.0027)**	(0.0022)***	(0.0028)***
Audience of nonviolent movies	0.0082	−0.0164	−0.0062	−0.0023	−0.0029	−0.0035	−0.0050
(millions of people in day t)	(0.0029)***	(0.0030)***	(0.0021)***	(0.0024)	(0.0026)	(0.0024)	(0.0029)*
Control variables							
Year indicators	X	X	X	X	X	X	X
Day-of-week indicators		X	X	X	X	X	X
Month indicators			X	X	X	X	X
Day-of-year indicators				X	X	X	X
Holiday indicators					X	X	X
Weather and TV audience controls						X	X
F-test on additional controls	1,934.02	1,334.31	88.56	13.37	15.05	18.58	
Audience instrumented with predicted audience using next weekend's audience							X
R^2	0.9344	0.9711	0.9846	0.9904	0.9912	0.9931	
N	1,563	1,563	1,563	1,563	1,563	1,563	1,563

Notes. An observation is a Friday, Saturday, or Sunday over the years 1995–2004. Assault data come from the National Incident Based Reporting System (NIBRS), where the sample includes agencies that do not have missing data on any crime (not just assaults) for more than seven consecutive days for that year. The movie audience numbers are obtained from the-numbers.com and are daily box-office revenue divided by the average price per ticket. The ratings of violent movies are from 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 assaults occurring in day t) as the dependent variable. The specification in column (7) instruments the audience numbers with the predicted audience numbers based on next weekend's audience. Details on the construction of the predicted audience numbers are in the text. Robust standard errors clustered by week are in parentheses.

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

such as the Christmas season in the second half of December or for holidays such as Independence Day. In columns (4) and (5), we therefore add 365 day-of-year indicators (dropping February 29 in leap years) and holiday indicators (see Appendix I), raising the R^2 further to .9912. As we add these variables, the coefficients β^v and β^m on the violent movie measures flip sign and become *negative*, significantly so in column (5). This suggests that the seasonality in movie releases and in crime biases the estimates upward.

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

Second, we instrument for movie audience on day t using information on the following weekend's audience for the same movie. This instrumental variable strategy exploits the predictability of the weekly decrease in attendance. At the same time, it removes the effect of any shocks that affect violence and attendance in week $w(t)$, but are not present in week $w(t)+1$. Examples include one-time TV events or transient weather shocks that are not already captured in our TV and weather controls. This procedure, detailed in Appendix II, generates predictors for the audience of strongly violent, mildly violent, and nonviolent movies on day t. Panel B in Table III shows that these predictors are strongly correlated with the actual audience numbers they are instrumenting for. In the first stage for the audience of strongly violent movies (column (1)), the coefficient on the predicted audience for strongly violent movies is highly significant and close to 1 (.9145), as predicted. The other two coefficients in this regression are close to 0, though also significant. We obtain similar first stages for the audience of mildly violent movies (column (2)) and nonviolent movies (column (3)).

Column (7) in Table II presents the IV estimates, where we have instrumented for the movie audience variables with their

TABLE III
EFFECT OF MOVIE VIOLENCE ON SAME-DAY ASSAULTS BY TIME OF DAY

A. Benchmark results				
Specification:	Instrumental variable regressions			
Dep. var.:	Log (number of assaults in day t in time window)			
	(1)	(2)	(3)	(4)
Audience of strongly violent movies	−0.0050	−0.0030	−0.0130	−0.0192
(millions of people in day t)	(0.0066)	(0.0050)	(0.0049)***	(0.0060)***
Audience of mildly violent movies	−0.0106	−0.0001	−0.0109	−0.0205
(millions of people in day t)	(0.0060)*	(0.0045)	(0.0040)***	(0.0052)***
Audience of nonviolent movies	−0.0033	0.0016	−0.0063	−0.0060
(millions of people in day t)	(0.0060)	(0.0046)	(0.0043)	(0.0054)
Time of day	6 A.M.–12 P.M.	12 P.M.–6 P.M.	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day
Control variables				
Full set of controls	X	X	X	X
Audience instrumented with predicted audience using next week's audience	X	X	X	X
N	1,563	1,563	1,563	1,562

TABLE III
(CONTINUED)

	B. First stage		
Specification:	IV regression, first stage		
Dep. var.:	Audience of strongly violent movies (1)	Audience of mildly violent movies (2)	Audience of nonviolent movies (3)
Pred. audience of strongly violent movies	0.9145	−0.1431	−0.1694
(millions of people in day t)	(0.0196)***	(0.0210)***	(0.0281)***
Pred. audience of mildly violent movies	−0.0399	0.8532	−0.1817
(millions of people in day t)	(0.0101)***	(0.0255)***	(0.0296)***
Pred. audience of nonviolent movies	−0.0480	−0.1363	0.8138
(millions of people in day t)	(0.0097)***	(0.0195)***	(0.0309)***
Control variables			
Full set of controls	X	X	X
F-test on instruments	1,050.89	889.02	730.85
N	1,563	1,563	1,563

Notes. See notes to Table II. The number of observations in column (4) of Panel A is one fewer than in columns (1)–(3) of Panel A because we are missing the assault data for January 1, 2006, for the hours between 12 A.M. and 6 A.M.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

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

IV.B. Theater Audience—Time of Day

Table II implies that exposure to violent movies diminishes crime in the short run. To clarify this potentially puzzling result (relative to the findings in the laboratory experiments), we separately examine the effect of violent movies on violent crime by time of day. In these and all subsequent specifications, we include the full set of controls X_t and instrument for the actual audiences A_t^v, A_t^m, and A_t^n using the predicted audiences.

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

During the evening hours (column (3)), we find, instead, a significant negative effect of exposure to violent movies. An increase in the audience of mildly violent movies of one million decreases violent crime by 1.09%. Exposure to strongly violent movies has a slightly larger effect. Exposure of one million additional people reduces assaults by 1.30%. Exposure to nonviolent movies is negatively correlated with violent crime, but the point estimate is smaller than for violent movies, and not significant. Over the night hours following exposure to a movie (column (4)), violent movies have an even stronger negative impact on violent crime. Exposure to mildly and strongly violent movies for one million people decreases violent crimes by, respectively, 2.05% and 1.92%. The impact of nonviolent movies is also negative but substantially smaller and not significantly different from 0.

To put these estimates into perspective, on an unseasonably cold day (20–32 degrees Fahrenheit) assaults go down by 11% in the evening hours and 8% in the night hours.[3] In comparison, the blockbuster strongly violent movie *Hannibal* (with an audience size of 10.1 million on opening weekend) is predicted to account for a 4.4% reduction in assaults in the evening hours and a 6.5% reduction in the night hours (see footnote 14 for details on this calculation). In Section V, we provide interpretations of these findings.

IV.C. Theater Audience—Timing of Effects

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

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

One Week, Two Weeks, and Three Weeks Later. In the following specifications, we estimate the impact one, two, and three weeks after the original exposure, controlling for contemporaneous exposure. Separate identification is made possible by new releases occurring after the initial exposure. Lagged movie attendance is instrumented using a similar methodology as for the

3. These are coefficients from the baseline IV regression, with 33–79 degrees Fahrenheit as the omitted category.

TABLE IV
MEDIUM-RUN EFFECT OF MOVIE VIOLENCE

Specification:	OLS regressions							
Timing:	Next Monday and Tuesday		Next week		Two weeks later		Three weeks later	
Dep. var.:	Log (number of assaults on Monday and Tuesday in time window)		Log (number of assaults in day t in time window)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience of strongly violent movies (millions of people in day t)			−0.0127 (0.0045)***	−0.0081 (0.0060)	−0.0142 (0.0051)***	−0.0209 (0.0067)***	−0.0136 (0.0051)***	−0.0199 (0.0063)***
Audience of mildly violent movies (millions of people in day t)			−0.0061 (0.0031)**	−0.0087 (0.0043)**	−0.0096 (0.0042)**	−0.0194 (0.0056)***	−0.0114 (0.0041)***	−0.0199 (0.0052)***
Audience of nonviolent movies (millions of people in day t)			−0.0027 (0.0033)	0.0030 (0.0050)	−0.0050 (0.0046)	−0.0079 (0.0061)	−0.0070 (0.0044)	−0.0076 (0.0056)
Lagged audience of strongly violent movies (millions of people in day t)	0.0019 (0.0058)	−0.0004 (0.0087)	0.0046 (0.0042)	−0.0017 (0.0054)	−0.0028 (0.0047)	0.0020 (0.0062)	0.0017 (0.0044)	−0.0065 (0.0056)
Lagged audience of mildly violent movies (millions of people in day t)	−0.007 (0.0050)	−0.0146 (0.0076)*	−0.0018 (0.0026)	0.0001 (0.0037)	−0.0061 (0.0037)	−0.0056 (0.0049)	0.0002 (0.0031)	−0.0105 (0.0045)**
Lagged audience of nonviolent movies (millions of people in day t)	0.0012 (0.0054)	−0.0065 (0.0074)	−0.0007 (0.0028)	0.0031 (0.0041)	−0.0060 (0.0042)	0.0012 (0.0055)	0.0011 (0.0036)	−0.0049 (0.0048)

TABLE IV
(CONTINUED)

Specification:	OLS regressions							
Timing:	Next Monday and Tuesday		Next week		Two weeks later		Three weeks later	
Dep. var.:	Log (number of assaults on Monday and Tuesday in time window)		Log (number of assaults in day t in time window)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag specification	Lag: weekend before		Lag: 7 days before		Lag: 14 days before		Lag: 21 days before	
Time of day	6 P.M.– 12 A.M.	12 A.M.– 6 A.M. next day	6 P.M.– 12 A.M.	12 A.M.– 6 A.M. next day	6 P.M.– 12 A.M.	12 A.M.– 6 A.M. next day	6 P.M.– 12 A.M.	12 A.M.– 6 A.M. next day
Control variables								
Full set of controls	X	X	X	X	X	X	X	X
Audience instrumented with predicted audience using following week's audience	X	X	No	No	X	X	X	X
N	1,041	1,041	1,559	1,558	1,556	1,555	1,553	1,552

Notes. See notes to Table II. The specifications are IV regressions with the log(number of assaults occurring in day t) as the dependent variable. The specifications in columns (3) and (4) are not instrumented, because the predictors for the audience of the previous week are highly collinear with the contemporaneous audience.

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

other movie attendance variables, except for the one-week lag (columns (3) and (4)). In this specification, we report the OLS results, because the instrument for lagged exposure would be essentially collinear with contemporaneous exposure. Across the three specifications (columns (3)–(8)), we find no evidence of a delayed effect of movie exposure. Of eighteen coefficients for lagged exposure, only one is significant (negative) at the 5% level. At the same time, we find strong evidence of a negative impact of contemporaneous exposure to violent movies, as in our benchmark specifications. These results suggest that there is no medium-run effect of exposure to movie violence due to either imitation or intertemporal substitution.

IV.D. Theater Audience—Robustness

Before discussing how to interpret the results, in Table V we assess the robustness of the benchmark estimates of Table III, reproduced in column (1).

In column (2), we use a different set of instruments for movie attendance—information on the production budget and the number of theaters in which a movie is playing in week $w(t)$ (see Appendix II for details). Production budgets are decided far in advance, whereas the number of screens is finalized one or two weeks in advance (Moretti 2008). These instruments, like our baseline instruments, should purge the estimates of short-term shocks affecting both attendance and crime. We supplement these instruments with an additional instrument for total movie audience size, based on our standard procedure.[4] The results are remarkably similar to the benchmark IV results.

Column (3) uses the standard instrument but includes all seven days of the week instead of just the weekend (column (3)). Many of the point estimates for the effect of movie violence in the evening and night (Panels B and C) become more negative, including the estimate for nonviolent movies, which is now significant. The latter finding may reflect an impact of nonviolent movies for the same reasons as for violent movies (with smaller magnitudes),

4. We supplement with total movie audience size because the new instruments do not predict overall movie audience well. This is because total number of theaters is essentially fixed in any given week, and production budgets do not provide much identifying variation. The joint F-tests for the first stages of this instrument set range from 280 to 378, with most of the power coming from the variables for the number of theaters.

TABLE V
ROBUSTNESS

Specification:	Instrumental variables regressions						OLS reg.	Poisson reg.
Dep. var.:	Log (number of violent crimes in day t in time window)							No. of assaults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Effects in morning and afternoon (6 A.M.–6 P.M.)								
Audience of strongly violent movies (millions of people in day t)	−0.0037	−0.0046	0.0005	0.0005	−0.0075	−0.0047	−0.0096	−0.0081
	(0.0046)	(0.0045)	(0.0039)	(0.0037)	(0.0056)	(0.0044)	(0.0035)***	(0.0029)***
Audience of mildly violent movies (millions of people in day t)	−0.003	−0.0046	−0.0006	−0.0006	−0.0028	−0.003	−0.0088	−0.0102
	(0.0041)	(0.0042)	(0.0033)	(0.0033)	(0.0039)	(0.0040)	(0.0027)***	(0.0023)***
Audience of nonviolent movies (millions of people in day t)	0.0003	−0.0012	−0.0012	−0.0012	−0.0013	0	−0.0079	−0.0098
	(0.0041)	(0.0042)	(0.0035)	(0.0034)	(0.0044)	(0.0039)	(0.0028)***	(0.0023)***
B. Effects in the evening (6 P.M.–12 A.M.)								
Audience of strongly violent movies (millions of people in day t)	−0.013	−0.0158	−0.0144	−0.0144	−0.0139	−0.0153	−0.0099	−0.0081
	(0.0049)***	(0.0048)***	(0.0046)***	(0.0044)***	(0.0063)**	(0.0044)***	(0.0037)***	(0.0030)***
Audience of mildly violent movies (millions of people in day t)	−0.0109	−0.0107	−0.0165	−0.0165	−0.0109	−0.0119	−0.0065	−0.0075
	(0.0040)***	(0.0042)**	(0.0035)***	(0.0032)***	(0.0039)***	(0.0038)***	(0.0029)**	(0.0023)***
Audience of nonviolent movies (millions of people in day t)	−0.0063	−0.0062	−0.0098	−0.0098	−0.008	−0.0069	−0.0026	−0.003
	(0.0043)	(0.0044)	(0.0040)**	(0.0036)***	(0.0042)*	(0.0040)*	(0.0030)	(0.0024)
C. Effects in the night (12 A.M.–6 A.M.)								
Audience of strongly violent movies (millions of people in day t)	−0.0192	−0.0202	−0.0206	−0.0206	−0.0252	−0.0211	−0.0098	−0.0133
	(0.0060)***	(0.0059)***	(0.0054)***	(0.0055)***	(0.0068)***	(0.0066)***	(0.0052)*	(0.0035)***

TABLE V
(CONTINUED)

Specification:	Instrumental variables regressions						OLS reg.	Poisson reg.
Dep. var.:	Log (number of violent crimes in day t in time window)							No. of assaults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Audience of mildly violent movies (millions of people in day t)	−0.0205 (0.0052)***	−0.0202 (0.0054)***	−0.0245 (0.0040)***	−0.0245 (0.0039)***	−0.0187 (0.0050)***	−0.0205 (0.0052)***	−0.0089 (0.0041)**	−0.0106 (0.0029)***
Audience of nonviolent movies (millions of people in day t)	−0.006 (0.0054)	−0.0047 (0.0056)	−0.0103 (0.0042)**	−0.0103 (0.0041)**	−0.0104 (0.0053)*	−0.0075 (0.0053)	0.0045 (0.0043)	0.0005 (0.0029)
Robustness specification	Benchmark IV specification	IV: Instruments budget and no. theaters	Benchmark + include Mo–Th	Benchmark + include MoTh + Newey-West 28-day corr.	Benchmark + use MPAA measure of movie violence	Benchmark + dep. variable is all crimes against person	OLS regress. (no instruments)	Poisson regression (no instruments)
Control variables								
Full set of controls	X	X	X	X	X	X	X	X
Audience instrumented with predicted audience using following week's audience	X		X	X	X	X		
N	1,563	1,563	3,645	3,645	1,539	1,563	1,563	1,563

Notes. This table presents a series of robustness checks to the results in Table III, reproduced in column (1). Column (2) uses instruments constructed as in the benchmark instruments, but using the number of theaters showing the movie in week $w(t)$ and the production budget (when available) as predictors. This specification also includes the instrument for overall movie audience constructed with the bechmark instruments. (See text for additional details) Column (3) uses data also from Monday–Thursday, in addition to Friday–Sunday. Column (4) uses the same sample as column (3) but with Newey-West standard errors with a 21-day lag. Column (5) presents the results for an alterative measure of movie violence based on the MPAA ratings. The number of observations is smaller because 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 ten weeks in which the rating is available for less than 70% of the movie audience.

In column (6) the definition of crimes against a person, in addition to assaults and intimidation, includes robbery, homicide, and sex offenses. Column (7) presents an OLS specification, and column (8) presents a Poisson regression (also not instrumented). The number of observations in Panel C is one fewer than in Panels A and B because we are missing the assault data for January 1, 2006, for the hours between 12 A.M. and 6 A.M. See also notes to Table II.

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

for example by incapacitating potential criminals. An alternative possibility is that the instrument, which is based on next weekend's audience, does not completely remove the impact of short-term shocks, especially for Wednesdays and Thursdays, which fall immediately before the next weekend.

Column (4) assesses the robustness of the standard errors to autocorrelation. One may worry that violent crime is positively correlated across weeks, even after controlling flexibly for seasonality. In this case, clustering by week (which assumes independence across weeks) may lead to standard errors that are too small. To address this concern, we replicate the specification of column (3) using Newey-West standard errors with a 28-day window.[5] The Newey-West standard errors are on average 5% *lower* than the clustered standard errors, suggesting that autocorrelation is a minor issue.

Next, we use an alternative measure of movie violence. In addition to rating movies (R, PG, etc.), the MPAA summarizes in one sentence the reason for their rating. We characterize as mildly violent those movies whose MPAA rating contains the word "Violence" or "Violent," with two exceptions. If the reference to violence is qualified with "Brief," "Mild," or "Some," we classify the movie as nonviolent. If qualified with either "Bloody," "Brutal," "Disturbing," "Graphic," "Grisly," "Gruesome," or "Strong," we classify the movie as strongly violent. The kids-in-mind.com and MPAA-based measures have correlations of .68 (mild violence) and .66 (strong violence).[6] The correlation is also apparent in Table A.1, which lists the violence ratings for blockbuster movies. Using this MPAA-based measure of movie violence yields similar results (column (5)). When we include both measures of violence (not shown), however, the effects on assaults load almost exclusively onto the kids-in-mind.com measures.

We also consider an alternative definition of violent crimes, including any type of crime against a person (column (6)). In addition to assaults and intimidation, this definition includes also robbery, homicide, and sex offenses. The results are very similar

5. We use data for the seven-weekday data rather than the benchmark three-day weekend data because Newey-West standard errors imply a decay that is a function of the temporal distance between observations.

6. These are the correlations of the residuals from OLS regressions on the standard set of control variables appearing in column (6) of Table II, excluding the movie violence measures.

to the benchmark ones.[7] We find qualitatively similar results for the three component categories of our assault measure (intimidation, simple assault, and aggravated assault), for assaults with and without injury, for assaults occurring at home and away from home, and for crimes involving a weapon (see Online Appendix Tables 1 and 4). We find larger effects for assaults against a known person, as opposed to against a stranger. We find small negative but statistically insignificant effects for property crimes (burglary, theft, motor vehicle theft, and vandalism).[8]

Finally, we estimate two specifications that do not instrument for movie audience: OLS (column (7)) and Poisson MLE (column (8)). In these specifications, the effect in the evening and night hours is qualitatively similar to the benchmark estimates, with somewhat smaller effects. Exposure to all types of movies in the morning and afternoon has a negative (significant) effect on violent crime. These small differences are likely due to omitted variables that are correlated with overall movie audience and crime. Indeed, if one considers the differential impact of violent versus nonviolent movies, the results mirror the IV results: no differential effect in the morning and afternoon, and large negative effects in the evening and night.

An Online Appendix presents additional robustness checks, including (i) the use of 52 week-of-year indicators instead of 365 day-of-year indicators, (ii) estimates using only the audience for the first week of release, (iii) estimates for the set of agencies that report consistently for the entire sample, (iv) separate estimates for violence levels 0 through 10, and (v) estimates in two-hour blocks. The pattern of findings is similar in these specifications.

In addition, the Online Appendix includes two placebo tests: one that reassigns movie attendance to the other date in the sample that falls on the same day of year and same day of week, and another that examines whether future exposure, controlling for current exposure, affects violent crime. We find no systematic impact for either set of placebo variables, suggesting that our findings are not due to unobserved seasonal factors.

7. Homicide and sex offenses are relatively infrequent, and not significant individually. Regressions for robbery by itself yield negative estimates that are significant in the evening hours but not in the nighttime hours.

8. Insofar as alcohol plays an important role (Section V.B), the smaller findings for property crimes are consistent with Carpenter and Dobkin (forthcoming) who find a smaller spike around the legal drinking age in property crimes, compared to violent crimes. It is also possible that movie attendance creates additional opportunities for property crimes because property owners may be in the theater.

IV.E. DVD and VHS Rental Audience

While this paper focuses on the effect of movies shown in theaters, a similar design exploits the releases of movie rentals on VHS and DVD. These releases occur several months after the theatrical release, and rentals of newly released VHSs and DVDs peak in the first week of release, with the top one to two movies capturing a substantial share of total rental revenue.

We use data on weekly DVD and VHS rental revenue from *Video Store Magazine* covering the top 25 movies over the period January 1995–December 2004.[9] The average number of rentals on a weekend day is 3.92 million (Table I). Weekend rentals of strongly violent (mildly violent) movies total 0.64 (1.56) million. While rentals are 30% to 40% smaller than the theater attendance, these numbers underestimate the audience reached because multiple people often view a single rented movie. The violent audience size for DVD and VHS rentals is positively correlated to the box-office measure in the corresponding week: the conditional correlation between the two measures of strong (mild) violence is .15 (.39) (see footnote 6).

In columns (1)–(3) of Table VI, we estimate equation (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 rentals. 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 find a large negative impact of exposure to mildly violent movies (a 1.48% decrease in assaults per million rentals), and a smaller, insignificant impact of strongly violent movies. In the night hours (column (3)), we find large negative effects of exposure to rentals of violent movies, but also a significant negative effect of the rental audience of nonviolent movies. These estimates are less precise than the estimates for box-office releases, with standard errors about 30% larger. When we also control for box-office movie audience in the regressions, the results are similar, although with larger standard errors (columns (4)–(6)).

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

TABLE VI
EFFECT OF DVD/VHS MOVIE VIOLENCE ON SAME-DAY ASSAULTS

Specification:	Instrumental variable regressions					
Dep. var.:	Log (number of assaults in day t in time window)					
	(1)	(2)	(3)	(4)	(5)	(6)
DVD/VHS rentals of strongly violent movies	−0.0042	−0.0078	−0.0148	−0.0051	−0.0044	−0.0107
(millions of people in day t)	(0.0058)	(0.0063)	(0.0078)*	(0.0101)	(0.0104)	(0.0120)
DVD/VHS rentals of mildly violent movies	−0.0041	−0.0148	−0.0311	−0.0034	−0.0227	−0.0193
(millions of people in day t)	(0.0059)	(0.0052)***	(0.0071)***	(0.0103)	(0.0092)**	(0.0102)*
DVD/VHS rentals of nonviolent movies	−0.0029	−0.0043	−0.0225	−0.0054	−0.0041	−0.0199
(millions of people in day t)	(0.0066)	(0.0060)	(0.0076)***	(0.0115)	(0.0106)	(0.0114)*
Theater audience of strongly violent movies				0.0017	−0.0098	−0.0192
(millions of people in day t)				(0.0082)	(0.0077)	(0.0089)**
Theater audience of mildly violent movies				0.0034	−0.0119	−0.0202
(millions of people in day t)				(0.0076)	(0.0070)*	(0.0080)**
Theater audience of nonviolent movies				0.0042	−0.0049	−0.0071
(millions of people in day t)				(0.0078)	(0.0070)	(0.0079)
Time of day	6 A.M.–6 P.M.	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day	6 A.M.–6 P.M.	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day
Control variables						
Full set of controls	X	X	X	X	X	X
Rental and theater audiences instrumented with predicted audiences using next week's audiences	X	X	X	X	X	X
N	1,475	1,475	1,475	1,475	1,475	1,475

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

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

The results on DVD and VHS releases are consistent with a negative impact of violent movies on violent crime, especially over the evening hours. The similarity with the results from theater releases is interesting in light of the differences in setting (e.g., alcohol consumption is possible at home but not at the theater).

V. Interpretation and Additional Evidence

We summarize the findings so far as follows: (i) exposure to violent movies lowers same-day violent crime in the evening; (ii) this exposure also lowers violent crime in the night after exposure; (iii) in the night, strongly violent movies have a somewhat smaller effect on crime compared to mildly violent movies; (iv) nighttime hours have larger negative effects compared to evening hours; (v) there is no lagged effect of exposure in the weeks following movie attendance. We now provide interpretations and additional evidence for the first four of these findings (the fifth finding is straightforward to interpret).

We stress that, because of data limitations, the interpretations in this section are based on ecological inference and not individual-level analysis. As such, alternative explanations for the findings are also possible. For example, whereas the decrease in crime in the evening hours has a natural interpretation as incapacitation of criminals, an alternative, complementary interpretation is protection of potential victims.

V.A. Lower Crime in the Evening—Voluntary Incapacitation and Sorting

We interpret the first finding, that violent movies lower crime in the evening hours, as *voluntary incapacitation*. Because it is virtually impossible to commit an assault while in the theater, as movie attendance rises, violent acts fall relative to the counterfactual. Interestingly, as simple as this explanation is, incapacitation has largely been ignored in discussions on the effect of movie violence. This voluntary incapacitation differs from the standard incapacitation in the literature because it is optimally chosen by the consumers, rather than being imposed, as in the case of school closings (Jacob and Lefgren 2003) or incarceration (Levitt 1996).

Although the qualitative findings are consistent with incapacitation, are the magnitudes also consistent with this interpretation? Suppose watching a movie (including time spent buying tickets, waiting in the lobby, and traveling to and from the theater) occupies roughly one-half of the 6 P.M.–12 A.M. time period and fully incapacitates individuals. For the rest of the time block, assume that crime rates are the same as for the alternative activity. Using the framework of Section II, denoting criminals with a y subscript, and assuming no crime is committed by nonviolent individuals ($\sigma_o = 0$) yields $\beta^j = -0.5x^j\sigma_y$. If criminals were equally represented in the audience of a movie with one million viewers, about 1/300th (i.e., 1 million out of a total population of 300 million) of the criminals would be incapacitated, leading to $\beta^v_{\text{equal}} = -0.5 * (1/300) \approx -0.0017$, compared to the observed values $\hat{\beta}^v = -0.0130$ and $\hat{\beta}^m = -0.0109$. This implies violent individuals are overrepresented by about $0.0130/0.0017 = 7.6$ times in strongly violent movies and $0.0109/0.0017 = 6.4$ times in mildly violent movies.

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

For each day t in the years 1995–2004, we compute the share of interviewed households that watch a movie at the theater, $\text{share}_t^{\text{CEX}}$. We regress this share on shares of the population attending movies of different violence levels according to our primary movie attendance data[10]:

$$(7)\quad \text{share}_t^{\text{CEX}} = \alpha + \beta^v \frac{A_t^v}{\text{Pop}_t} + \beta^m \frac{A_t^m}{\text{Pop}_t} + \beta^n \frac{A_t^n}{\text{Pop}_t} + \Gamma X_t + \varepsilon_t,$$

where Pop_t is the U.S. population in year t (Table VII). Because $\text{share}_t^{\text{CEX}}$ and A_t^j/Pop_t are both measures of the share of the population attending a movie on day t, we expect, and indeed find, that the estimated regression coefficients β^j are statistically indistinguishable from 1 when we include all demographic groups (column (1)).

10. The regressions include Friday, Saturday, and Sunday and are weighted by the number of households reporting consumption expenditures for day t, which averages 157.88. We include the standard set of controls X_t. We obtain similar results when using an imputed individual-level measure of movie attendance, and similar, but less precisely estimated, results if we instrument for movie attendance.

TABLE VII
PATTERNS OF MOVIE ATTENDANCE BY DEMOGRAPHICS (CEX DATA)

Specification:	OLS regressions				
Dep. var.:	Share of households interviewed watching a movie at the theater in day t				
	(1)	(2)	(3)	(4)	(5)
Share of audience of strongly violent movies	0.9469	2.094	1.146	0.4323	2.7751
(in share of U.S. population in day t)	(0.1883)***	(0.5602)***	(0.3328)***	(0.2580)*	(1.4550)*
Share of audience of mildly violent movies	0.7736	1.4642	1.4499	0.1259	2.7825
(in share of U.S. population in day t)	(0.1419)***	(0.4407)***	(0.2623)***	(0.1711)	(1.3110)**
Share of audience of nonviolent movies	0.7614	1.0786	1.1555	0.392	0.4031
(in share of U.S. population in day t)	(0.1440)***	(0.4652)**	(0.2491)***	(0.1741)**	(1.2926)
Demographic groups (by head of household)	All	Ages 18–29	Ages 30–44	Ages 45+	Single males age 18–29
Full set of controls	X	X	X	X	X
Regressions weighted by number of households interviewed in day t	X	X	X	X	X
Average number of households in demographic group interviewed on day t	157.88	22.61	53.94	81.29	3.96
N	1,563	1,558	1,560	1,563	1,474

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 shares are obtained from daily box-office revenues divided by the average price per ticket and then divided again by the U.S. population. Because both the dependent variable and the independent variables are measures of attendance to the theater in shares, the coefficients in column (1) should be close to 1. The coefficients in columns (2)–(4) indicate the degree of self-selection of different demographic categories into movies of different violence levels. See also notes to Table II.

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

Although different types of movies should have the same impact on overall attendance, we expect differential sorting when we split the data by demographics (columns (2)–(5)). Indeed, younger households (heads ages 18 to 29, column (2)) have larger estimated coefficients, indicating that they attend the movies more often than older people. Younger households also select disproportionately into violent movies: they are $2.094/0.9469 = 2.2$ times oversampled in strongly violent movies and $1.4642/0.7736 = 1.9$ times oversampled in mildly violent movies, but only $1.0786/0.7614 = 1.4$ times oversampled in nonviolent movies. Middle-age households (heads ages 30 to 44, column (3)) and especially older households (heads over 45 years, column (4)) attend the movie theater less and display a flatter attendance pattern with respect to the violence content of movies. The age groups with higher crime rates (Table I), therefore, select into violent movies, a result consistent with selective incapacitation.

Because men also have higher assault rates compared to women (Table I), it would be useful to differentiate by gender. Although this is generally problematic in the CEX data (which only report purchases at the household level), we can consider single men ages 18–29. In this group (column (5)), we find even greater evidence of selection. Single young males are $2.7751/0.9469 = 2.9$ times oversampled in strongly violent movies and $2.7825/0.7736 = 3.6$ times oversampled in mildly violent movies. Although the estimates for this small group should be taken with caution given the large standard errors, they indicate substantial sorting into violent movies.[11]

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

V.B. Lower Crime after Exposure—Sobriety

The second result is that exposure to movie violence also lowers violent crime in the night. We interpret this to mean that an evening spent at the movies leads to less dangerous activities in

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

the night hours following exposure (i.e., $\alpha^i < \sigma$ in expression (4)). This could be because a visit to the movie theater involves less alcohol consumption, disrupts and alters an evening's activities, or places potential criminals in relatively safer environments once the movie is over. This is not a trivial finding, because attendance at movie theaters could have provided a meeting point for potential criminals, leading to an increase in crime.

Alcohol is a prominent factor that has been linked to violent crimes, and assaults in particular (Carpenter and Dobkin forthcoming). Alcohol is banned in almost all movie theaters in the United States, so a mechanism for reduced crime in the nighttime could well be sobriety. To test this explanation, we examine whether the displacement is larger for assaults involving alcohol or drugs (columns (1) and (2) of Table VIII) than for assaults not involving such substances (columns (3) and (4)). Indeed, although the negative impact of movie violence on assaults is present in both samples, the estimates are on average 1.5 times larger for assaults involving alcohol or drugs. We also find large displacement effects in the night hours for assaults in bars and nightclubs and for arrests for drunkenness, although these estimates are imprecise (Online Appendix Table 3).

To further test the impact of alcohol, in columns (5)–(8) we separately estimate the effect for offenders just under the legal drinking age (ages 17–20) and offenders just over the legal drinking age (ages 21–24). If the effect is due to alcohol consumption, it should be larger for the latter group, because the younger group is less likely to drink as part of their displaced alternative activity. Indeed, the effect of violent movies is two to three times larger for the over-age group.

Finally, to provide direct evidence that movie attendance lowers alcohol consumption, we use data from the CEX time diaries. We examine whether exposure to violent movies reduces the share of respondents consuming alcohol away from home (column (9)). We find suggestive evidence that violent movies may have reduced alcohol consumption, though the estimates are not significantly different from zero.

V.C. Nonmonotonicity in Violent Content—Arousal

The third finding is that the negative effect in the night hours is not monotonic: strongly violent movies have a slightly smaller effect than mildly violent movies (−.0192 versus −.0205). This at

TABLE VIII
TEST OF SOBRIETY: EFFECT OF ALCOHOL CONSUMPTION

Specification:	Instrumental variable regressions								Reg. (CEX data)
Dep. var.:	Log (number of assaults of a type in day t in time window)								Share consuming alcohol away from home
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Audience of strongly violent movies (millions of people in day t)	−0.012	−0.0287	−0.0137	−0.0164	−0.0239	−0.0376	−0.0125	−0.0058	−0.3303
	(0.0080)	(0.0109)***	(0.0056)**	(0.0070)**	(0.0103)**	(0.0115)***	(0.0114)	(0.0149)	(0.2696)
Audience of mildly violent movies (millions of people in day t)	−0.0183	−0.025	−0.0088	−0.0197	−0.0229	−0.0338	−0.0112	−0.0171	−0.1921
	(0.0071)**	(0.0107)**	(0.0046)*	(0.0059)***	(0.0084)***	(0.0107)***	(0.0100)	(0.0133)	(0.2077)
Audience of nonviolent movies (millions of people in day t)	−0.0068	−0.0102	−0.0057	−0.0039	−0.02	−0.0213	0.0065	0.0011	−0.0271
	(0.0076)	(0.0114)	(0.0048)	(0.0060)	(0.0089)**	(0.0110)*	(0.0106)	(0.0139)	(0.1993)
Type of crime	Assaults involving alcohol or drugs		Assaults not involving alcohol or drugs		Assault by offender ages 21–24 (over drinking age)		Assault by offender ages 17–20 (under drinking age)		Alcohol consumption away from home
Time of day	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day	6 P.M.–12 A.M.	12 A.M.–6 A.M. next day	6 A.M.–12 A.M.	12 A.M.–6 A.M. next day	Same day
Control variables									
Full set of controls	X	X	X	X	X	X	X	X	X
Audience instrumented with predicted audience using next week's audience	X	X	X	X	X	X	X	X	
N	1,563	1,560	1,563	1,562	1,563	1,562	1,563	1,561	1,563

Notes. The specifications are in IV regressions for specific types of assaults using NIBRS data in columns (1)–(8). Column (9) uses the CEX data used in Table VIII; the dependent variable is the share of the households in the diary CEX sample that reported consuming alcohol away from home. In column (9), the movie exposure variables are in share of the total population. See also notes to Table II.

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

first is puzzling, because strongly violent movies attract more potential criminals, and the additional selection should render the effect more negative. As discussed in Section II, however, this puzzle can be explained if strongly violent movies have a differential direct impact.

We estimate the differential impact of strongly violent movies, $\alpha^v - \alpha$, under the assumptions used to derive expression (5). Estimation of $\alpha^v - \alpha$ requires information about the selection of potential criminals x^j into different movies. Although this selection is unobservable, we do observe selection along dimensions that correlate with criminal behavior, age, and gender. As Table I indicates, crimes are committed disproportionately by young males. We make the assumption that the selection of potential criminals into movie theaters, x^j, is an affine transformation of the selection of young males, y^i; that is, $x^j = \lambda_0 + \lambda_1 y^i$. We can then estimate expression (5) by substituting the term $(y^v - y^n) / (y^m - y^n)$ for the unobserved $(x^v - x^n) / (x^m - x^n)$.

To estimate the sorting of young males, we turn to an auxiliary source of data, the IMDb.[12] IMDb maintains a popular website for movie-goers, which invites its users to rate movies. A typical blockbuster movie is rated by tens of thousands of viewers. IMDb displays, for each movie, statistics on the rating for each combination of gender (male, female) and four age groups (under 18, 18 to 29, 30 to 44, and over 45). As a measure of the attractiveness of a movie to potential criminals, we use the share of raters that are male and are ages 18 to 29, a group disproportionately likely to commit crimes (see Table I). Figure II shows that the share of young male reviewers is fairly linear in the 0 to 10 violence ratings for movies from kids-in-mind.com. The extent of selection is substantial: while the fraction of raters of nonviolent movies that are young males, y^n, is 0.459, the corresponding fraction for strongly violent movies, y^v, is 0.546. These data allow us to estimate $(y^v - y^n) / (y^m - y^n)$ as 1.718.

Figure III displays both the actual impact of movie violence $\hat{\beta}^j$ (solid lines) and the predicted impact purely due to sorting (dotted lines). The two estimates are very close for crime in the evening hours, and one cannot reject the hypothesis that they are the same. This is to be expected, because a large share of the evening is

12. The CEX data used in Table VIII also indicate substantial selection: young households (with heads ages 18–29) select into strongly violent movies at a rate that is 43% higher compared to mildly violent movies. We use the IMDb data because they provide a substantially more precise estimate.

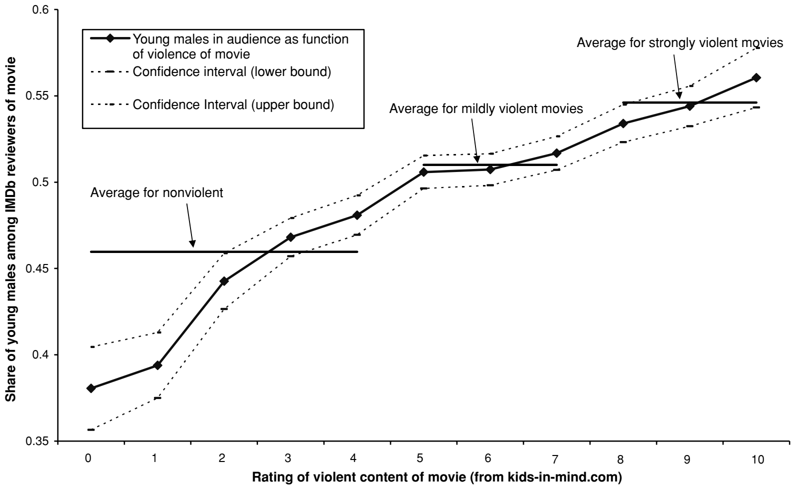

FIGURE II

Share of Young Males in Audience as Function of Movie Violence (Internet Movie Database Data)

This plot employs IMDb rating data to provide a measure of the attractiveness to young males of movies of varying degrees of violence (0 is least violent, 10 is most violent). The measure of attractiveness to young males is the share of raters of a movie that report being male and ages 18 to 29. The plotted variable is the average share across all movies of a given violence level, weighted by the number of raters for the movie. The violence rating of movies is from kids-in-mind.com. The dotted lines are pointwise 95% confidence intervals.

spent inside the movie theaters, which mechanically implies $\alpha^v \approx \alpha \approx 0$. In the night hours, instead, the observed impact of movie violence is substantially larger than the predicted impact because of selection, and the difference is marginally significant (p-value of .08).[13] The estimated differential impact of movie violence $\widehat{\alpha^v - \alpha}$ is sizable (.011) and equal to about one-third of the predicted impact of strongly violent movies because of sorting.

We therefore detect some evidence that, after accounting for selection, violent movies induce *more* violent crime relative to nonviolent movies, consistent with an arousal effect. This may occur for the same reasons as in the laboratory—an emotional effect of arousal, or short-term imitation of violent acts. As in the laboratory, we find no evidence of a cathartic effect, which would have made the effect of strongly violent movies even more negative. Our field evidence, hence, provides a natural comparison of the size of

13. Bootstrap standard errors take into account the sampling variability associated with $(y^v - y^n)/(y^m - y^n)$.

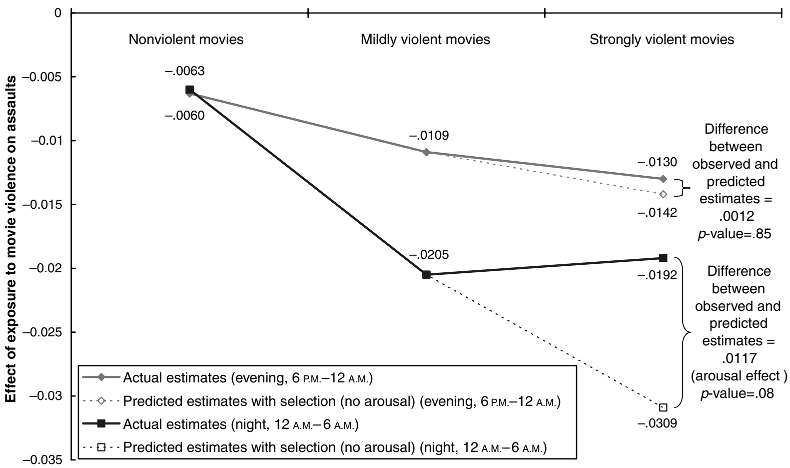

FIGURE III

Effect of Movie Violence on Assaults: Selection and Arousal Effects

This figure displays both the actual impact of movie exposure on violent crime (solid lines) and the predicted impact with linear selection (dotted lines) by type of movie (nonviolent/mildly violent/strongly violent) and by time block (evening 6 P.M.–12 A.M./night 12 A.M.–6 A.M.). The estimates of the actual impact (solid lines) are reproduced from columns (3) and (4) of Table III, Panel A, and can be interpreted as the percent change in violent crime due to the exposure of one million people to movies of type j in time period t. For example, an increase in one million of the audience of mildly violent movies lowers violent crime by 1.09% in the evening time block and by 2.05% in the nighttime block. The estimates of the predicted impact with linear selection (dotted lines) are computed using the estimates for nonviolent and mildly violent movies, taking into account the increased selection of criminals into strongly violent movies and assuming that all types of movies have the same direct effect on violent crime. The (unobserved) selection of criminals into movies is assumed to be related linearly to the (observed) selection of young males into movies. The comparison between the predicted and the actual effect of violent movies provides an estimate of the differential effect of strongly violent movies relative to mildly violent and nonviolent movies. The figure shows a marginally significant difference in the actual and predicted impact for the nighttime block: compared to the predicted impact, strongly violent movies cause more crime, consistent with an arousal effect of strongly violent movies. Details on the calculations of the difference are in the text.

the arousal effect to the other main impact of movie violence, time use. Although the estimated arousal effect on violence is sizable, it is one-third as large as the foregone violence associated with the alternative activity.

We also point out that this evidence should be considered suggestive, given the assumptions involved. Other explanations for this nonmonotonic pattern are also possible. For example, a potential offender may attend a mildly violent movie with a girlfriend and a strongly violent movie with drinking buddies. This could have an independent effect on the level of violence.

V.D. Larger Nighttime Estimates—Compositional Effects

The fourth finding is that, in the night hours following movie exposure (12 A.M.–6 A.M.), the impact of movie violence on assaults is higher than in the evening hours (6 P.M.–12 A.M.). This finding might seem puzzling, because the highest decrease in crime should occur when potential criminals are in the movie theater, when committing crimes is nearly impossible.

However, the composition of crimes in the two time periods is different, making a direct comparison of the size of the effects difficult. For example, assaults involving alcohol or drugs and assaults committed by offenders just over the legal drinking age are much more common in the night hours than in the evening hours (Table I). As previously noted, alcohol-related assaults respond more to violent movie exposure (Table VIII). Hence, the decrease in alcohol consumption, a primary mechanism for the effects, is likely to prevent a higher fraction of violent crimes in the night (when inebriation would have the most impact) compared to the evening. The activities prevented by movie attendance in the night hours are more dangerous (in the model, have a larger σ) than the activities prevented in the evening hours.

Broadly speaking, we obtain similar compositional differences in the pattern of assaults by demographics (shown in Online Appendix Table 5). The impact of exposure to violent movies is larger (i.e., more negative) for male offenders than for female offenders, especially in the night hours, and male offenders commit a higher share of the assaults at night than in the evening hours (Table I). We also find a relatively monotonic decrease of the effect sizes by age (with the exception of the 45–54 age group), which contributes to explaining the findings, because the younger age group also contributes disproportionately to nighttime assaults (Table I).

V.E. Additional Evidence on Selection

In both the evening and the night hours, violent movies lower crime more than nonviolent movies. Our explanation for these facts is selection: violent movies are more likely to attract potential criminals. We now test another implication of selection, that movies that draw young men tend to decrease violent crime, even if the movies are not violent.

We divide movies into thirds based on the fraction of young men rating a movie in the IMDb (see Figure II), and label the categories as Not Liked, Liked, and Highly Liked by young males. Table IX reports information on the blockbusters within the three categories, holding constant the kids-in-mind.com violence rating. Among nonviolent movies, *Runaway Bride* is not liked by young males, while *Austin Powers in Goldmember* is highly liked. For mildly violent movies, *Save The Last Dance* and *Spider-Man* are best sellers in the Not Liked and Highly Liked categories, respectively. Among strongly violent movies, there are essentially no blockbusters that are not liked by young males, because movie violence and liking by young males are highly correlated. However, the IMDb information distinguishes between movies in the middle group such as *Passion of the Christ* and movies in the top group such as *Hannibal*.

To estimate the impact of movie attendance on violence within each of the nine cells, we estimate $\ln V_t = \sum_{j=1}^{9} \beta^j A_t^j + \Gamma X_t + \varepsilon_t$, where $j = 1, \ldots, 9$ denotes the nine cells. We adopt the full set of controls and use the baseline instrument. Table IX reports within each cell the coefficients for the evening time block and for the night time block. Moving down within a column shows that more violent movies are generally associated with lower crime, even holding constant the liking by young males (except for movies not liked by young males, where the violent movie category is very sparse and hence the estimates very noisy). For example, among the movies highly liked by young males, the estimated parameters $\hat{\beta}^j$ are $-.0090$ (nonviolent), $-.0111$ (mild violence), and $-.0140$ (strong violence) for the evening hours. These patterns are broadly consistent with the interpretations discussed in Sections V.A–V.D.

More important for a test of selection, moving along a row the coefficients also generally become more negative. In nine of twelve pairwise comparisons, the estimates become more negative as the liking by males increases (seven of ten if we exclude the bottom-left group, which is very sparse). Movies that attract more young males, therefore, appear to lower the incidence of violent crimes more, even holding constant the level of violence in a movie. These results underscore the importance of selection. Exposure to movies that attract more violent groups (along observable lines) is associated with lower rates of violent crime.

TABLE IX
MOVIE BLOCKBUSTER BY IMDB RATING AND VIOLENCE

Violence rating (1)		Blockbuster movies not liked by young males (date, millions of people) (2)	Blockbuster movies liked by young males (date, millions of people) (3)	Blockbuster movies highly liked by young males (date, millions of people) (4)
0–4 Nonviolent movies	Top 1	*Harry Potter and the Chamber of Secrets* (11/16/02, 15.2)	*Shrek 2* (5/22/04, 17.4)	*Austin Powers in Goldmember* (7/27/02, 12.6)
	Top 2	*Harry Potter and the Chamber of Secrets* (11/23/02, 7.3)	*Harry Potter and the Sorcerer's Stone* (11/17/01, 15.9)	*Incredibles* (11/6/04, 11.3)
	Top 3	*Runaway Bride* (7/31/99, 6.8)	*Shrek 2* (5/29/04, 11.8)	*Bruce Almighty* (5/24/03, 11.2)
	Top 4–6	*Sweet Home Alabama, America's Sweethearts, Erin Brockovich*	*Finding Nemo, Toy Story 2, Monsters Inc.*	*Ace Ventura: When Nature Calls, Waterboy, Big Daddy*
	Effect on crime	−0.0041 (0.0062) (6 P.M.–12 A.M.) 0.0049 (0.0071) (12 A.M.–6 A.M.)	−0.0035 (0.0042) (6 P.M.–12 A.M.) −0.0057 (0.0055) (12 A.M.–6 A.M.)	−0.0090* (0.0053) (6 P.M.–12 A.M.) −0.0079 (0.0063) (12 A.M.–6 A.M.)
5–7 Mildly violent movies	Top 1	*Double Jeopardy* (9/25/99, 4.6)	*Harry Potter and the Prisoner of Azkaban* (6/5/04, 15.1)	*Spider-Man* (5/4/02, 19.8)
	Top 2	*Save The Last Dance* (1/13/01, 4.1)	*Mummy Returns* (5/5/01, 12.4)	*Matrix Reloaded* (5/17/03, 15.2)
	Top 3	*Double Jeopardy* (10/2/99, 3.3)	*Planet of the Apes* (7/28/01, 12.3)	*Lost World: Jurassic Park* (5/24/97, 14.3)
	Top 4–6	*Absolute Power, Random Hearts, Unfaithful*	*Day after Tomorrow, Independence Day, Pearl Harbor*	*Spider-Man 2, X2: X-Men, Star Wars 2*
	Effect on crime	0.0049 (0.0111) (6 P.M.–12 A.M.) −0.0268 (0.0141*) (12 A.M.–6 A.M.)	−0.0099** (0.0047) (6 P.M.–12 A.M.) −0.0177*** (0.0057) (12 A.M.–6 A.M.)	−0.0111*** (0.0039) (6 P.M.–12 A.M.) −0.0179*** (0.0052) (12 A.M.–6 A.M.)

TABLE IX
(CONTINUED)

Violence rating (1)		Blockbuster movies not liked by young males (date, millions of people) (2)	Blockbuster movies liked by young males (date, millions of people) (3)	Blockbuster movies highly liked by young males (date, millions of people) (4)
8–10	Top 1	*Missing* (11/29/03, 1.8)	*Passion of the Christ* (2/28/04, 13.5)	*Hannibal* (2/10/01, 10.1)
Strongly violent	Top 2	*Nurse Betty* (9/9/00, 1.3)	*Passion of the Christ* (3/6/04, 8.5)	*Jurassic Park 3* (7/21/01, 9.1)
movies	Top 3	*Copycat* (11/4/95, 1.2)	*Air Force One* (7/26/97, 7.9)	*Scary Movie* (7/8/00, 8.2)
	Top 4–6	*Jade, In Dreams, A Rich Man's Wife*	*Ransom, Sleepy Hollow, General's Daughter*	*Bad Boys 2, Troy, Terminator 3*
	Effect on crime	0.0625 (0.0384) (6 P.M.–12 A.M.)	−0.0084 (0.0082) (6 P.M.–112 A.M.)	−0.0140*** (0.0047) (6 P.M.–12 A.M.)
		0.0526 (0.0549) (12 A.M.–6 A.M.)	−0.0252*** (0.0087) (12 A.M.–6 A.M.)	−0.0150** (0.0061) (12 A.M.–6 A.M.)

Notes. We divide movies into thirds using the fraction of IMDb raters of a movie that are male and of ages 18–29. Movies not liked by young males are defined by movies in the bottom third of this distribution, movies liked by young males are in the middle third, and movies strongly liked by young males are in the top third. The ratings of movie violence are from kids-in-mind.com. The table divides movies into nine categories defined by the interaction of how liked the movie is by young males and the violence level. The top three movies with the highest weekend audience are reported for each category, along with the next three largest distinct blockbuster movies. The "Effect on crime" rows report the coefficients on the audience sizes for each of the nine categories from two separate regressions for the evening (6 P.M.–12 A.M.) and nighttime hours (12 A.M.–6 A.M.), where the dependent variable is log(number of assaults occurring in day t in the specified time block) and the independent variables are the audiences in millions of people for movies in each of the nine categories. See also notes to Table II.

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

VI. Conclusion

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

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

These findings appear to contradict evidence from laboratory experiments that document an increase in violent behavior following exposure to movie violence. However, the field and laboratory findings are not contradictory. Exposure to movie violence can lower violent behavior relative to the foregone alternative activity (the field finding), even if it increases violent behavior relative to exposure to nonviolent movies (the laboratory finding). In fact, we document suggestive evidence that, after accounting for selection, violent movies induce more violent crime relative to nonviolent movies, consistent with an arousal effect. This example suggests that other apparent discrepancies between laboratory and field studies (see Levitt and List [2007]) might be reconciled if differences in treatment and setup are taken into account. In addition, the field evidence provides a bound for the laboratory finding of an arousal effect, which we estimate in the field to be one-third as large as the time-use effect.

Given that movie attendance occupies a significant portion of leisure time use, our findings imply first-order welfare effects. We can calculate the change in assaults that would occur if the audience of violent movies did not go to the movies but instead engaged in their next best alternative. The total number of evening and nighttime assaults prevented is 997 assaults per weekend, adding up to almost 52,000 weekend assaults prevented yearly.[14] With an estimated (in year 2007 dollars) direct monetary cost of \$2,217 and an estimated intangible quality-of-life cost of \$11,154 per assault (Miller, Cohen, and Wiersema 1996), this implies a benefit of roughly \$695 million each year. Our estimates suggest that a strongly violent blockbuster movie such as *Hannibal* (with 10.1 million viewers on opening weekend) reduced assaults by 1,056 on its opening weekend, which amounts to a 5.2% decrease in assaults, about half the impact of the reduction in crime due to a cold day. This substantial short-term impact of violent movies had been overlooked by the previous literature.

Of course, if strongly violent movies were banned as a matter of public policy, our estimated short-term effects could be offset partly if studios respond by producing more mildly violent movies. The degree to which this would temper our findings depends on how substitutable strongly and mildly violent movies are for each other. This substitution, however, is likely to be imperfect; a regression of strongly violent movie attendance on mildly violent movie attendance (including all the baseline controls of Table III) yields a coefficient of −.196 (s.e. .028). This implies that there will be substantial substitution to other nonmovie activities as well, and our empirical results suggest that these nonmovie activities are more conducive to violent behavior.

In the paper, we find no impact of violent movies in the days and weeks following exposure. Still, our design (like the laboratory experiments) cannot address the important question about the long-run effect of exposure to movie violence. As such, this paper does not provide evidence on the long-term effects of a policy limiting the level of violence allowed in the media. However, it does indicate that in the short run these policies will likely increase violent crime, because they induce substitution toward more dangerous activities.

Finally, a central point of our paper is that the merits of any particular activity must be viewed relative to the next best activity in utility terms. As such, our findings are relevant beyond

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

the case of movies. For example, violent video games may well increase aggression, but they also incapacitate potential offenders for a substantial period of time. More generally, we hypothesize that other activities with a controlled, alcohol-free environment that attract young men, such as Midnight Basketball, should also reduce crime in the short run.

APPENDIX I: DATA APPENDIX

A. *Imputation of Daily Box-Office Audience*

The daily box-office movie revenue for the ten highest-selling movies is available starting in September 1997. To extend coverage to January 1995–August 1997 and to movies that do not make the daily top-ten list, we make use of weekend revenue for the fifty highest-selling movies, because this is available throughout the whole sample. We take advantage of the regularity in the within-week pattern of sales and impute the daily data, whenever missing, using the weekend box-office data for the same movie in the same week. 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. (Because 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 is allowed to depend on a set of controls Y, $s(Y)$: $a_{j,t} = s(Y)\, a^w_{j,w(t)}$. In logs, the model can be written as $\ln\left(a_{j,t}\right) = \ln(s(Y)) + \ln(a^w_{j,w(t)})$. The most important control for the share $\ln(s(Y))$ is the set of day-of-week indicators d^d_t, because different days of the week capture a different share of the overall revenue (Table I). In addition, we use the following controls $X_{j,t}$ for the weekday share: month indicators (in the summer the Monday–Thursday audience is larger), a linear time trend, indicators for the level of violence (nonviolent versus mildly violent versus strongly violent), indicators for rating type (G/PG/PG-13/R/NC-17/Unrated/Missing Rating), indicators for week of release (up to week 26), and indicators for audience size in week $w(t)$ (audience $<$0.5M, $\geq$0.5M and $<$1M, $\geq$1M and $<$2M, $\geq$2M and $<$5M, $\geq$5M). This set of controls X is interacted with the day-of-week dummies, as well as being present in levels. Finally, we control for a set of holidays H_t, described below. We estimate

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

and obtain the predicted daily audience $\hat{a}_{j,t}$ using $\hat{a}_{j,t} = \exp[\ln(a^w_{j,w(t)}) + \widehat{\ln(a_{j,t}) - \ln(a^w_{j,w(t)})}]$. The final daily box-office audience is defined as the actual box-office data $a_{j,t}$ whenever available, and the predicted value otherwise. In the subsample, where both the daily and the weekend data are available, a regression of predicted daily revenue on actual daily revenue yields a slope coefficient of .9559 and has an R^2 of .9590.

B. Holiday Controls

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

C. TV Audience Controls

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

D. Weather Controls

The source for the weather variables is the "Global Surface Summary of Day Data" produced by the National Climatic Data

TABLE A.1
MOVIE BLOCKBUSTERS BY VIOLENCE LEVEL

Violence rating (1)	Title of blockbuster (2)	Weekend date (3)	Weekend theater audience (4)	MPAA violence rating (5)	Liking by young males (6)
0	*Birdcage*	3/9/1996	4,026,083	Low	Low
	You've Got Mail	12/19/1998	3,925,587	Low	Low
	You've Got Mail	12/26/1998	3,855,011	Low	Low
1	*Runaway Bride*	7/31/1999	6,771,654	Low	Low
	Erin Brockovich	3/18/2000	5,178,850	Low	Low
	Notting Hill	5/29/1999	4,355,314	Low	Low
2	*Liar Liar*	3/22/1997	6,709,569	Low	High
	Toy Story	11/25/1995	6,599,610	Low	Medium
	Sweet Home Alabama	9/28/2002	6,135,755	Low	Low
3	*Shrek 2*	5/22/2004	17,397,404	Low	Medium
	Shrek 2	5/29/2004	11,838,217	Low	Medium
	Finding Nemo	5/31/2003	11,650,366	Low	Medium
4	*Harry Potter and the Sorcerer's Stone*	11/17/2001	15,953,113	Low	Medium
	Harry Potter and the Chamber of Secrets	11/16/2002	15,207,829	Medium	Low
	Austin Powers in Goldmember	7/27/2002	12,576,592	Low	High
5	*Harry Potter and the Prisoner of Azkaban*	6/5/2004	15,086,532	Medium	Medium
	X2: X-Men United	5/3/2003	14,188,845	Medium	High
	Star Wars 2: Attack of the Clones	5/18/2002	13,774,151	Medium	High
6	*Spider-Man*	5/4/2002	19,766,628	Medium	High
	Spider-Man 2	7/3/2004	14,195,850	Medium	High
	Planet of the Apes	7/28/2001	12,297,262	Medium	Medium
7	*Matrix Reloaded*	5/17/2003	15,219,637	Medium	High
	Lost World: Jurassic Park	5/24/1997	14,255,579	Medium	High
	Mummy Returns	5/5/2001	12,467,726	Medium	Medium

TABLE A.1
(CONTINUED)

Violence rating (1)	Title of blockbuster (2)	Weekend date (3)	Weekend theater audience (4)	MPAA violence rating (5)	Liking by young males (6)
8	*Jurassic Park 3*	7/21/2001	9,104,505	Medium	High
	Scary Movie	7/8/2000	8,240,157	Medium	High
	Scream 2	12/13/1997	8,188,454	High	High
9	*Bad Boys 2*	7/19/2003	7,715,185	High	High
	Saving Private Ryan	7/25/1998	6,500,639	Medium	High
	Sleepy Hollow	11/20/1999	5,751,378	High	Medium
10	*Passion of the Christ*	2/28/2004	13,484,402	High	Medium
	Hannibal	2/10/2001	10,114,135	High	High
	Passion of the Christ	3/6/2004	8,531,673	High	Medium
Missing	*A Perfect Murder*	6/6/1998	3,545,842	Medium	Missing
	A Perfect Murder	6/13/1998	2,404,994	Medium	Missing
	A Cinderella Story	7/17/2004	2,207,419	Low	Low

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

Center and available from ftp://ftp.ncdc.noaa.gov/pub/data/gsod. Weather information is collected for the capital of each state in our sample (except Kentucky, where Lexington is used because of data issues). We then average these variables, using as weights the state-year-specific NIBRS population. The variables used are maximum and minimum daily temperature measured in Fahrenheit, heat index, wind speed measured in knots (in Beaufort scale), rainfall, and snow. Before averaging, the variables are categorized as dummy variables for the maximum daily temperature falling in one of three categories (>80 and ≤ 90, >90 and ≤ 100, >100), the minimum daily temperature falling in one of three categories (≤ 10, >10 and ≤ 20, >20 and ≤ 32), the heat index falling in one of three categories (>100 and ≤ 115, >115 and ≤ 130, >130), the wind speed falling in one of two categories (>17 and ≤ 21, >21), any rain, and any snow.

Appendix II: Instruments

A. Benchmark Instrument

Our set of instruments uses information on the following weekend's audience for the same movie to predict movie attendance, and then aggregates these predictors across all movies of a given violence level. The procedure is similar to the imputation procedure described in Appendix I. We assume the daily audience of movie j on day t, $a_{j,t}$, is a share of the weekend audience in the same week $w(t)$, where the share is allowed to depend on a set of controls. In addition, we assume that the weekend audience decays each week at a rate that is also a function of the controls. This specification allows the decay rate to vary by weekday and differentially so for different types of movies. We use the same controls (including interactions with day of week) as for the imputation procedure described in Appendix I with three differences: (i) the indicators for audience size refer to week $w(t)+1$ (as opposed to week $w(t)$); (ii) we add two indicators for slow releases, that is, indicators for the cases in which the weekend audience for week $w(t)$ is less than 3 and less than 5 times smaller than in week $w(t)+1$; (iii) we add 365 day-of-year indicators $\eta_{d(t)}$ (not interacted with day of week). As in Appendix I, we estimate a log model, with $\ln(a_{j,t}) - \ln(a^w_{j,w(t)+1})$ as the dependent variable. The regression uses observations with nonimputed movie audience and is weighted by next weekend's audience $a^w_{j,w(t)+1}$. We obtain the predicted daily audience using $\hat{a}_{j,t} = \exp[\ln(a^w_{j,w(t)+1}) + \ln(a_{j,t}) - \widehat{\ln(a^w_{j,w(t)+1})}]$. To generate the predicted audiences $\hat{A}^n_t$, $\hat{A}^m_t$, and $\hat{A}^v_t$, we aggregate across movies in the relevant violence category.

We note that a coarser, but simpler, approach is to use as instruments the audience in week $w(t) + 1$ of all movies in a category (strongly violent, mildly violent, and nonviolent). The empirical results using this approach are similar, although somewhat noisier (see Online Appendix Table 1).

B. *Instrument for DVD / VHS Rentals*

The instrument for DVD and VHS rentals is constructed similarly to the benchmark instrument, except that *Video Store Magazine* only publishes the DVD and VHS rental at the weekly level. Hence, we estimate the equivalent of the predictive specification for the benchmark instrument, but without day-of-week dummies and day-of-week interaction variables. The regression is weighted by the next week's rentals $a^w_{j,w(t)+1}$. The set of controls, as for the standard instrument, includes month indicators, a linear time trend, indicators for the level of violence, indicators for rating type, and indicators for rentals in week $w(t) + 1$. The holiday controls are separate indicators for whether the week $w(t)$ includes any of the holidays described in Appendix I, and whether the week $w(t) + 1$ includes any of these holidays. The predicted values from the regressions are used to generate the predicted weekly rentals $\hat{a}_{j,t}$. These predicted rentals are then apportioned to each day of week using the within-week shares of rentals from the CEX time diaries.

C. *Theaters and Budget Instrument*

The estimates in column (2) of Table V use instruments based on the number of theater screens on which a movie plays and its production budget (Moretti 2008). We use data from the-numbers.com and renormalize the number of screens and budget by the corresponding 90th percentile of each variable for that year. We use the number of screens in levels and take the log of production budget (setting it equal to zero for missing production budgets and adding an indicator variable for missing production budgets). Because the predictability of audience using number of screens and budget varies with both the weekday and the number of weeks a movie has been out, we interact these screen and budget variables with indicators for day of week as well as number of weeks out (0 weeks, 1 week, 2–4 weeks, 5–9 weeks, 10–19 weeks, 20–26 weeks, >26). We estimate a log model, with $\ln(a_{j,t})$ as the dependent variable, using observations with nonimputed movie audience and weighting by the number of screens next week. The set of controls is the same as for the standard instrument, except that we do not use information on the audience next week.

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