SCREEN VS SCENE: IMPACT OF NEWS AND TV ON BELIEF FORMATION NOTA BENE: PRELIMINARY RESULTS

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Abstract. This study examines the influence of news and television on belief formation. We analyze public beliefs about serial killing crimes using data from two consecutive online surveys of US residents, comparing the results with both current and historical news as well as content from popular media. We explicitly model belief updating and estimate the causal effect of a movie premiere on beliefs about the typical profiles of victims, killers, and crime locations. Additionally, we examine its impact on individuals' confidence in holding accurate beliefs and their perceived risk of victimization. We find that long-term high consumption of crime news or crime entertainment media in isolation significantly affects beliefs related to the victims' gender. On the margin, we find that a single exposure to a crime-themed film significantly influences certain beliefs about serial killing, resulting in shifts of 0.24 standard deviations in the belief that victims are female, 0.44 standard deviations in the belief that crimes occur in rich counties, and 0.27 standard deviations in the belief that crimes occur in counties with no prior history of serial killing. We do not find evidence of a boost in people's confidence in holding accurate beliefs or an increase in their perceived risk of victimization. This research highlights the role media plays in shaping beliefs, especially in contexts such as terrorism, military conflicts, and international relations, where personal experiences are scarce and access to credible information is limited, often due to national security concerns.

1. Introduction

Nowadays, we are exposed to an overwhelming array of channels through which we receive information—from official news outlets to social media platforms, and from traditional media sources to popular entertainment. This raises important questions: How do we evaluate the credibility of this information, and what role does the medium play in shaping our beliefs? Do we discount less credible sources, or do they influence our perceptions as strongly as more traditional ones?

In this paper, we examine the role of both traditional news and popular entertainment media in shaping beliefs about rare events, particularly in the absence of firsthand experiences or access to credible sources. Specifically, we focus on belief formation around serial killing crimes. The beliefs we investigate concern the typical profile of victims

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and perpetrators, measured by age, race, and gender, as well as characteristics of a typical crime location, such as the level of urbanization, median income, and any history of serial killings.

Studying serial killings is a means to an end: understanding how beliefs are formed in contexts that share key traits—events that are infrequent or perceived as such, carry significant societal impact, and lack accessible, reliable information. Similar characteristics are evident in events like terrorism, military conflicts, human trafficking, organized crime activities, nuclear incidents, space debris impacts. These events,though rare, are highly sensationalized, often dominating traditional crime reporting and popular entertainment media. They captivate public interest despite limited dependable data and minimal opportunities for individuals to form beliefs based on personal experience.

Serial killings and other rare events profoundly impact society. Their rarity makes them particularly shocking, capturing public curiosity and concern. This heightened awareness often leaves lasting effects, as such incidents are perceived as watershed moments that prompt reflection on issues of security, safety, and societal values. Politicians frequently capitalize on these events as rallying points, framing them as urgent matters requiring decisive action. In doing so, they drive policy changes and justify new or more restrictive laws, sometimes setting precedents with far-reaching implications. Rare events often catalyze rapid shifts in areas like surveillance, immigration, or public health policy, as leaders seek to reassure the public and demonstrate their responsiveness to perceived threats.

The limited access to information issued by government agencies in the context of aforementioned events is primarily driven by national security concerns. Releasing sensitive information could compromise defense strategies or expose vulnerabilities, particularly in cases involving terrorism, where public knowledge of tactics might endanger safety. Privacy and sensitivity are also critical; governments, more than media, prioritize the dignity and privacy of victims, avoiding graphic details that could cause trauma or infringe on privacy rights. Ensuring fair trials is another consideration, as premature or detailed information about suspects could bias public opinion and jeopardize legal proceedings. Preventing public bias and panic is equally significant, as governments often limit details to avoid disproportionate reactions and maintain social stability. Ethical considerations further guide authorities in withholding information to respect those affected and prevent public desensitization to violence. Lastly, operational integrity in investigations requires law enforcement to restrict information about ongoing cases to preserve strategies, protect evidence, and avoid alerting suspects, thereby ensuring the effectiveness of investigative and public safety efforts.

In many cases, information about certain events is simply unavailable to the public, either due to insufficient monitoring or a lack of centralized reporting systems. For instance, landslides, despite their potentially devastating impacts, are often monitored far less comprehensively than more prominent natural disasters like earthquakes or floods. This disparity is particularly pronounced in remote or under-resourced regions, where infrastructure for data collection and reporting is minimal. As a result, crucial information about the frequency, scale, and impact of landslides often goes unrecorded or remains inaccessible to the broader public, making perceptions of these events more susceptible to media influence.

Similarly, incidents involving animal attacks, such as shark bites or encounters with venomous snakes, are rarely documented in centralized databases. The lack of standardization in reporting these events across regions and jurisdictions exacerbates the issue, leaving substantial gaps in our understanding of their prevalence and patterns. Without comprehensive and accessible information, the public's perception of these events is often shaped by sensationalized media portrayals, such as Jaws (1975), Anaconda (1997), The Shallows (2016), and 47 Meters Down (2017), rather than by reliable data, further distorting awareness and understanding.

In this paper, we conduct two analyses aimed at investigating the role of both traditional news and popular entertainment media in forming beliefs about serial killing crime. In the first analysis, we estimate the role of news and entertainment media in shaping average beliefs using a standard Gaussian updating model. This allows us to estimate the "prior" beliefs individuals hold about serial killer crimes, which are then updated based on signals received from either traditional media or popular entertainment media or both. By comparing these updated beliefs with the prior estimates among people who report high levels of consumption, we can assess the extent to which media sources influence the public's perceptions of crime characteristics. With a prior belief estimated at 61.8 percent of victims being female, we find that media consumption influences two distinct groups: those who consume high amounts of news and those who consume high amounts of entertainment media. Among respondents in the top 10 percent for news consumption who report no entertainment media consumption, the posterior belief is 58.3 percent. In contrast, for respondents in the top 10 percent for popular media consumption who report no news consumption, the posterior belief is 64.2 percent. This creates a 2.5 percentage point decrease for the first group and a 3 percentage point increase for the second group. These differences align with the signals conveyed by news and popular media about the victim's gender: on average, news outlets report a lower percentage of female victims, leading to lower posterior beliefs among heavy news consumers. Conversely, popular media emphasizes a higher percentage of female victims, resulting in higher posterior beliefs among those who primarily consume popular media.

In our second analysis, we investigate the causal impact of watching a serial killer-themed film on individuals' beliefs, confidence in those beliefs, and perceptions of personal safety through a field experiment. The experiment involved conducting two identical surveys on Prolific, each time with different individuals: the first survey was administered one before the film's release, and the second was conducted two weeks after the opening weekend. To estimate the treatment effect, we compared the beliefs of those who watched the movie with individuals in the control group, selected based on observable characteristics as those who would have likely watched the movie if they had been given the opportunity, while controlling for a wide range of covariates. The treatment group consists of 131 individuals from the second survey who reported watching the film, while the control group includes 2,780 individuals from the first survey, matched to the treatment group on similar characteristics using propensity scores derived from an adaptive Lasso logistic regression with over 330 variables. This matching approach ensured close alignment between the control and treatment groups on relevant observable characteristics, such as media consumption habits and familiarity with crime themes. Our findings indicate that watching the film significantly influenced certain beliefs about serial killing. Specifically, individuals who watched the film reported a 6.52 percentage point increase in the belief that victims are female, a 10.89 percentage point increase in the belief that crimes occur in affluent (rich) counties, and a 7.27 percentage point increase in the belief that crimes occur in counties with no prior history of serial killing. These effects correspond to 0.24, 0.44, and 0.27 standard deviations, respectively, indicating moderate shifts in specific demographic beliefs due to exposure to the film. We find no effect on participants' perceptions of their own safety or confidence in these beliefs, suggesting that while the film influenced certain demographic perceptions about serial crime, it did not impact broader safety concerns or belief certainty.

Our analysis relies on four main data sources: (i) online surveys, (ii) the Serial Killer Database, (iii) regional printed newspapers, and (iv) popular entertainment content from Netflix. The online survey consists of two rounds of identical surveys conducted on Prolific in the summer of 2024, capturing responses from 5,686 participants. These surveys collect detailed information on public beliefs about serial killer crimes, personal risk perceptions, and media consumption patterns. The Serial Killer Database provides a comprehensive record of serial killings in the US from the 20th century onwards. It includes key information about the perpetrators, victims, and locations of crimes, serving as a baseline for understanding how public beliefs compare to actual crime data. Printed newspapers from regional publications are used to measure media coverage of serial killings. Finally, Netflix content is analyzed for its portrayal of serial killers, including demographic details of both victims and perpetrators, as well as the location of the crimes. This diverse set of data allows us to explore how different types of media—both news and entertainment—shape public perceptions of rare crimes like serial killings.

The rest of this paper is organized as follows. For the reminder of this section we discuss the related literature. In Section 2, we describe the data. In Section 3, we briefly outline the Gaussian updating model and discuss our identification strategy for causal inference, focusing on computing the propensity score and matching treated and control individuals. In Section 4, we present our results. Finally, Section 5 concludes.

1.1. **Literature.** This paper contributes to several strands of economic literature on the role of news, popular culture, and belief formation.

The most relevant literature explores belief formation in contexts where private information and official statistics are scarce, but media access is available. Gentzkow and Shapiro (2004) analyze how media exposure and education influence beliefs about the 9/11 attacks in predominantly Muslim countries, demonstrating that different media sources can lead to significantly divergent beliefs. This underscores the critical role of information sources in shaping beliefs about rare events—a concept central to our study, which examines how media influences beliefs about another rare but highly significant event in the public's eyes. Similarly, research on the Iraq War by Kull, Ramsay, and Lewis (2013) shows how media-driven misperceptions, such as beliefs about weapons of mass destruction, can impact political attitudes, highlighting the powerful role of misinformation. In both cases, individuals, aside from those directly involved in 9/11 or stationed in Iraq, lacked private information, while official data remain restricted due to national security concerns.

Additionally, it relates to belief formation in contexts with limited private exposure but access to statistics and official data, such as immigration. Recent years have seen a growing aversion to immigration globally, along with the radicalization of public opinion on the issue. Agovino, Carillo, and Spagnolo (2022) examine the relationship between media coverage and individual attitudes toward immigration, finding that pro-immigration attitudes are negatively correlated with media coverage and tone, with stronger effects for those who trust the media. For those with low media trust, increased coverage with a negative slant polarizes views, further entrenching prior beliefs.

This paper also connects to the literature on the role of subjective beliefs in decision making. Koszegi (2006) develops a model of overconfidence, showing how subjective beliefs about one's abilities affect decision-making and task selection. Bentez-Silva and Dwyer (2005) find that individuals generally predict uncertain events like retirement well, although health shocks and job changes are harder to anticipate. Hamermesh (1985) shows that people extrapolate past improvements in longevity when they determine their subjective horizons, and they are fully aware of levels of and movements within today's life tables. The subjective distribution has greater variance than its actuarial counterpart; and the subjective variance decreases with age. Post and Hanewald (2013) demonstrate that while people are aware of longevity risk, they do not adjust their savings behavior accordingly. Unlike these studies, our research focuses on belief formation driven by external media sources, where individuals cannot cross-validate information with personal or national data.

Our paper also relates to the literature on media's influence on behavior, including crime, education, and voting. Dahl and DellaVigna (2009) show that violent crime decreases on days with high attendance at violent movies, primarily because individuals who might otherwise engage in violent behavior are occupied during the screenings. Gentzkow and Shapiro (2008) study the effect of preschool television exposure on standardized test scores during adolescence. The authors' preferred point estimate indicates that an additional year of preschool television exposure raises average adolescent test scores by about 0.02 standard deviations, and that the positive effects are largest for children from households where English is not the primary language, for children whose mothers have less than a high school education, and for nonwhite children. In the political sphere, DellaVigna and Kaplan (2007) find that Fox News increased the Republican vote share in towns where it was introduced, highlighting how media bias can significantly affect voting behavior. Similarly, Gentzkow (2006) shows that the introduction of television led to a decline in voter turnout, likely due to reduced political coverage in other media.

Finally, this paper also contributes to research in sociology on the fear-inducing effects of media, particularly sensationalized crime reporting and entertainment content (Glassner, 2010). When individuals perceive heightened risks to their personal safety, they may limit social activities, avoid public spaces, or even increase gun ownership as a form of self-protection (Carlson, 2015). The psychological impact of crime-focused media can lead to what has been termed a "culture of fear" (Altheide, 2002), where perceptions of danger are amplified, even if actual crime rates remain unchanged. This is further supported by criminology research showing that fear of victimization is more pronounced among women and the elderly (Warr, 1984), and that fear of crime can reduce community engagement and social trust, leading individuals to become more isolated and less trusting of others in their neighborhoods (Hinkle, 2015), which can have long-term social consequences.

2. Data

This paper relies on four main data sources: (i) online surveys, (ii) the Serial Killer Database, (iii) printed regional newspapers, and (iv) the content of Netflix movies and TV shows.

2.1. **Survey data.** The survey data come from two identical online surveys released on Prolific in the summer of 2024, approximately three weeks apart.[1,2] Approximately 56,000 registered Prolific users aged 18+ and more were eligible to participate in each survey.[3] Participation was restricted to those currently residing in the US, who were born in the US., and who spent most of their time before turning 18 in the US. Thus, the survey targeted current US. residents who were born and raised in the country. Furthermore, respondents who participated in the first survey were prohibited from taking part in the second survey. Respondents were paid \$2 for participation (which corresponds to an average hourly rate of \$12) and had the opportunity to earn additional bonus payments based on the accuracy of their responses, up to \$2.25. To ensure the quality of the responses, participants were only allowed to take the survey on a tablet or computer. Each time, we collected 3,000 responses, balanced by gender. After eliminating responses that did not pass the quality check, we were left with 2,853 responses from the first survey and 2,833 responses from the second survey, resulting in a combined sample of 5,686 observations.[4,5] In each survey, we collected information on people's definitions of serial killing, their beliefs about serial killing crime statistics in the US post-WWII, their perceived chances of becoming a victim, general knowledge on the topic, exposure to both news and entertainment media, and a range of socio-economic characteristics.[6]

2.2. **Serial Killer Database.** The second main data source is the Serial Killer Database, the largest non-governmental database of serial killings in the US. We use this database as a reference point to assess whether public beliefs align with the "truth" and to determine whether media portrayals of serial crime are biased.

[1]The first survey was conducted on July 11, 2024, and the second on July 29, 2024. Both surveys were completed within 24 hours of their release. The median completion time across both surveys averaged 12.5 minutes.

[2]The survey was partially funded by the Department of Economics at Copenhagen Business School.

[3]Prolific distributes the study to eligible participants, who complete it on a first-come, first-served basis.

[4]For interested readers, Figure A.1 in Online Appendix A presents the distribution of respondents by demographic and socio-economic characteristics for each survey.

[5]We eliminated responses from participants who failed at least one of two attention checks or whose answers timed out.

[6]See Online Appendix B for details about the information collected in the online surveys.

The database is a collaborative effort by members of Radford University, Florida Gulf Coast University (FGCU), and the Serial Homicide Expertise and Information Sharing Collaborative (SHEISC), who have been involved in collecting, updating, and continuously revising the data since 1992.[7] The database covers both closed and open cases from the early 20th century to the present day. All information in the database is sourced from publicly available, officially released records.[8]

Because the database includes only publicly available information, it is unclear how much it may differ from the confidential data collected and managed by the FBI. However, this aspect works to our advantage, as it reflects the information most accessible to the general public, providing the largest publicly available dataset likely to influence and shape public beliefs about serial killings.

The database includes a wide array of characteristics related to perpetrators, such as their socio-economic background, demographic details, education, employment history, family situation, and mental and physical health. It records individual cases that meet even the broadest definition of serial killer, defined as a person committing at least two murders on separate occasions, and it allows for subsetting by other definitions. Notably, it contains information on whether the perpetrator was affiliated with a criminal organization. The database also includes names and pseudonyms of perpetrators, which, after further research, allowed us to classify them into those identified as serial killers by the media and those who, despite meeting the general FBI definition, were never referred to as serial killers by the media.

In addition to perpetrator information, the database provides key information about victims, along with data on crime locations and crime scene details. Although the dataset offers a broad range of variables, it does contain a significant number of missing observations. However, this is not a concern for our study, as the database offers comprehensive coverage of the variables most relevant to our research—specifically, the sex and race of both the perpetrator and the victim, the perpetrator's age at the time of the crime, the victim's age, and the county where the crime occurred. Additionally, it is reasonable to assume that if any of this information is missing from the dataset, it is also likely unavailable to the general public from other sources.

For this project, we include all crimes identified as serial killings that occurred in the US after World War II, where both the year and county of the offense are known.[9] The data comprises 2,778 killers and 10,281 victims.

Our dataset includes serial killings committed by a single serial killer as well as cases involving multiple serial killers. We include both closed and open cases, where open cases refer to killings that have been linked by authorities as part of a single killing series but where the perpetrator remains unknown. We include e cases confirmed through

[7]The version of the database used here was retrieved in September 2021.

[8]These sources include, but are not limited to, online prison records; state birth, death, marriage, and divorce records; Social Security information; individual-level Census data; journal articles; newspaper articles; books—both scholarly and popular—as well as dissertations and theses.

[9]This excludes any killings that took place before World War II or outside the US, even if they are linked to a series of murders within the US.

conviction or confession, as well as suspected series that could not be resolved due to the death of the suspect, lack of sufficient evidence for indictment, or instances where further investigation was deemed unnecessary by the authorities.

2.3. **Traditional news media.** The third main data source comprises printed newspapers. We use printed newspapers as a proxy for all news media to determine whether a particular serial killing received media coverage. We conduct our search for articles using Newspapers.com.[10] The search is conducted for every victim listed in the Serial Killing Database using the victim's first and last name.[11]

We begin by searching newspapers from the county where the current crime took place, starting from the day of the crime. For counties involved in previous killings in the same series, we also search newspapers from those counties, but the search starts from the day the current crime occurred, not from the day of the earlier crimes. This approach ensures that we do not capture premature reports on individuals who had not yet fallen victim to the crime and were mentioned in the media for other reasons. Additionally, we search newspapers from counties where any future killings in the series occurred, with the search in these counties beginning only from the day those future crimes happened. This prevents the inclusion of premature reports from these counties before their involvement in the crimes, ensuring that the coverage is relevant to the ongoing series. Each search runs up to one month after the series concludes. We consider this time frame to account for the fact that media coverage often begins only after a number of crimes have been linked together, meaning that the first or even second victim may not receive any coverage until authorities inform the press about the presence of a serial killer. Moreover, for each of the counties involved in our search, we extend the search to include newspapers from all counties within a 3-mile radius of the respective county boundaries. This helps to cover counties that may not have their own newspapers, relying instead on regional publications from adjacent areas for news reporting.[12]

Our dataset on traditional news media coverage of serial killings is derived from a subset of the Serial Killer Database. It includes all victims who received at least one news mention (4,492 victims) and all killers who were associated with at least one victim mentioned in the news (2,217 killers).

[10]Newspapers.com is the largest online archive of newspapers, encompassing more than 840 million pages from over 24,000 newspapers, most of which are local to the US.

[11]We enter victim's name in the format first-name + last-name, replace all uppercase letters with lowercase letters, ignore middle names, and delete victim's entry with fully or partially missing first and/or last names.

[12]For example, if the first victim, Joe Doe, was killed in June 1981 in Pittsburgh, Pennsylvania, and the second victim, John Doe, was killed in November 1985 in Cleveland, Ohio, which ended the series, we would conduct the following searches. For Joe Doe, we would search newspapers from Allegheny County (where Pittsburgh is located) and all neighboring counties starting in June 1981, when the crime occurred, and continue until December 1985, which is one month after the last killing in the series. Additionally, we would search newspapers from Cuyahoga County (where Cleveland is located) and its neighboring counties from November 1985 to December 1985. For John Doe, we would search newspapers from both Allegheny and Cuyahoga Counties and their neighboring counties starting in November 1985, when John Doe was killed, and continue until December 1985.

2.4. **Popular entertainment media.** The fourth main data source comprises movies and TV shows about serial killings available for streaming on Netflix in the US in April 2024. Netflix was selected due to its status as one of the two largest streaming platforms in the US, alongside Amazon Prime. It is assumed that Netflix offers a comparable profile of movies and shows to other platforms like Amazon Prime, Max, and Hulu, making it a suitable representative for streaming content. Given that streaming catalogs are updated monthly, the April 2024 catalog was chosen as the basis for analysis. The volume and type of content available on Netflix each month are influenced by a combination of production schedules, licensing agreements, and seasonal programming strategies, which impact the overall viewing experience.

April was specifically chosen because it provides a balanced snapshot of Netflix's typical offerings. Unlike October and November, which are heavily influenced by Halloween and feature an increased proportion of horror and thriller content, or December through February, dominated by Christmas, New Year's, and Valentine's Day, with a focus on holiday-themed, family-friendly, and romantic content, April is relatively free from these seasonal biases. Positioned equidistant from these major holiday periods, April offers a neutral baseline for examining Netflix's programming strategy without the distortion of seasonal trends.

This choice ensures that the analysis captures a representative cross-section of Netflix's catalog, one that is likely to reflect its core strategy rather than temporary or seasonal fluctuations. While the ideal approach would involve analyzing data from all months to construct a comprehensive view of Netflix's programming choices, resource constraints make this infeasible at present. Nevertheless, focusing on April allows for meaningful insights into Netflix's typical content strategy and provides a strong foundation for understanding how streaming platforms curate their offerings.[13]

We manually constructed the dataset by watching all fictional and non-fictional movies and TV shows, including documentaries, related to serial killings, a process primarily conducted by our research assistants.[14] When defining what constitutes a serial killing

[13]While this paper does not delve into the reasons behind the popularity of serial killing-related movies, after reviewing a random sample of movies, we find the following. Serial killer titles on Netflix have an average IMDb rating of 6.7, an average Rotten Tomatoes score of 62 percent, and were, on average, produced in the year 2019. This suggests that these movies are relatively recent and of above-average quality, traits often associated with higher audience popularity.

[14]Despite the time-consuming nature of this process, we chose to watch each title for several reasons. First, it ensures the collection of high-quality data and minimizes measurement errors, which are difficult to avoid when relying on summaries or other indirect sources. Movie summaries often lack crucial details, such as character demographics and contextual information, and may come from unreliable platforms. Textual analysis of subtitles or audio descriptions was not a viable option either, as they generally omit important information about locations and personal demographics. Furthermore, cast lists proved problematic for two reasons: actors' real ages rarely align with the ages of the characters they portray, and many victims, particularly in documentaries, are referred to indirectly, meaning they are often not listed in the cast. Additionally, employing AI services could present a more efficient method for obtaining these estimates. However, data protection regulations constrain the use of AI for estimating an individual's age or race. Regarding image recognition, ChatGPT clarifies: "I can't determine the age of the person in the image. Inferring someone's age from a photo involves speculation, as appearances can differ greatly among individuals and may not accurately reflect their actual age. Moreover, my functionalities are intentionally

title, we used the broadest definition of serial killing to compile the most comprehensive set—comparable to the Serial Killer Database—from which cases that meet stricter definitions can be subsetted.[15] From each title, we collected information on the sex, age, and race of each victim; the age of the perpetrator at the time of each crime; the perpetrator's sex and race; and the county where the crime occurred. In cases where the age was not provided, we made provisional estimates based on our own judgment.[16] In order to filter out cases that match only stricter definitions of serial killing, we also collected information on whether the perpetrator was a member of an organized crime group, following the definition used in the Serial Killer Database, and whether the term "serial killer" was used throughout the movie in reference to the perpetrator. In addition, we collected information on the number of comments posted by US users on each title's IMDb page. We treat this as a measure of the title's popularity, where popularity increases with the number of comments.

Our data on serial killings portrayed in popular entertainment media consists of 110 titles, covering 202 killers and 897 victims.

3. Methods

In this paper, we conduct two separate analyses: one aimed at rationalizing the observed beliefs using existing theoretical models of belief updating, and the other aimed at identifying the causal effect of exposure to newly released serial killing content.

3.1. **Theoretical model.** To rationalize observed beliefs, we use an off-the-shelf Gaussian updating model t. Let $\theta_k \sim \mathcal{N}(\theta_{0k}, 1)$ represent the underlying distribution of beliefs

designed to uphold privacy and abstain from making personal evaluations or assumptions about people based on their looks."

[15]To ensure we captured all content related to serial killings, even under the broadest definitions, we followed a three-step process. First, we compiled a list of all titles available for streaming in the US as of April 2024 from genres most likely to feature serial killing content, such as *Crime, Action, and Adventure Movies* (Netflix code 9584), *Crime Documentaries* (9875), *Crime Drama Movies* (6889), *Crime Programs* (26146), *Docuseries* (2853), *TV Dramas* (11714), *Gangster Movies* (31851), *Horror Films* (8711), *Horror Programs* (83059), *Mystery Programs* (4366), and *Thrillers* (8933). The process resulted in a list of approximately 2,450 titles. To put this number into perspective, as of July 2023, Netflix offered a total of 6,621 movies, series, and specials for streaming in the US. In the second step, we excluded titles set outside the US without any reference to the US, those set before WWII without any reference to the present, as well as those set in the future or in an alternative universe. For the remaining titles, we conducted a thorough online search to verify whether the title contained any reference to murder. Titles were removed if all sources clearly indicated a lack of any direct or indirect reference. The remaining titles were watched, and approximately 300 were confirmed not to be related to serial killings, while 111 were confirmed as serial-killing content. There are still 45 titles left to be analyzed. In our analysis, we consider episodes from a single umbrella TV series that are unconnected and possess distinct titles as individual TV shows (e.g., see Catching Killers, seasons 1 through 3).

[16]To refine this method, we are preparing a small online survey that will be distributed via mailing lists. Respondents will be asked to estimate the ages of ten individuals based on a set of photographs. These photographs were taken by us during the data collection process and depict individuals whose ages are unknown and need to be estimated. None of the photographs require viewer discretion. To encourage participation, we will offer a $100 Amazon gift card to five participants whose estimates are closest to the average across all respondents. While the responses will not be nationally representative, we are confident they will significantly improve upon our current estimates.

regarding characteristic k. Let $s_{k,m} = \theta_{0k} + \epsilon_{k,m}$ be the signal about characteristic k sent by media source $m \in \{n, p\}$, where n stands for news media and p for popular entertainment media. Each $\epsilon_{k,m}$ follows a normal distribution with mean zero and variance of $1/\rho_{k,m}$. Our objective is to estimate the mean beliefs, $\{\theta_k\}$, which we also refer to as prior beliefs, across all k.

From the joint distribution of $\left[\theta_k, s_{k,n}, s_{k,p}\right]^T$, we derive the conditional expectations of θ_k given the signals. For each characteristic k, this results in three moment conditions, and for all k, a total of 21 moment conditions.[17] We estimate all nine mean beliefs jointly based on these 21 moment conditions using the iterative Generalized Method of Moments (iterative GMM).

3.2. **Causal effect.** To identify the causal effect of exposure to serial killer-related entertainment media on beliefs, we utilize the nationwide release of a serial killer movie titled Longlegs in the summer of 2024.[18] The release of Longlegs was widely publicized in the US and screened across major theater chains, including AMC Theaters (the largest movie theater chain in the US and worldwide), Regal, and Cinemark. At its widest release, the movie was shown in 2,850 theaters across the US.[19] The film opened with $22 million in its first weekend and eventually grossed over $100 million globally, making it the highest-grossing independent horror movie of the year.[20] Despite its recent release, Longlegs has already outperformed several well-known independent films in box office performance.

The plot of Longlegs revolves around two middle-aged serial killers—a white man and a white woman—who, over 30 years, targeted predominantly white families with young daughters aged 10 to 14. The movie is set in the late 1990s or early 2000s, as evidenced by a portrait of President Bill Clinton in the FBI headquarters. The murders occur in Oregon, inferred from the license plates, but the counties mentioned are fictional, leaving their urbanity, wealth, and historical crime rates ambiguous. However, the victims' neighborhoods, including their living standards, and the movie's narrative suggest that they reside in affluent, rural areas, with no indication of prior serial killings..

The movie portrays a specific narrative: serial killers targeting affluent, rural families with young daughters. This narrative aligns with the beliefs reported by the movie goers, suggesting that the movie directly influenced these perceptions. Respondents who watched the movie reported beliefs that victims of serial killers are more likely to be female, live in wealthy counties, and reside in areas with no prior history of serial killing crimes. We will discuss this in more detail in Section 4.

3.2.1. *Identification strategy.* To identify the causal effect of watching Longlegs on beliefs, we conducted two surveys around its premiere. As shown in Figure 1, we ran the first survey one day before the Longlegs release, and the second survey two weekends after the

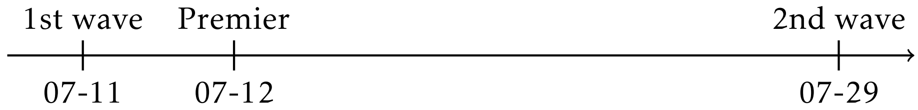
[17] For each characteristic k, we derive three moment conditions: $\mathbf{E}(\theta_k|s_n)$, $\mathbf{E}\left(\theta_k|s_p\right)$, and $\mathbf{E}\left(\theta_k|s_n, s_p\right)$.

[18] The movie premiered in the US on July 12, 2024.

[19] As of 2022, there were approximately 39,007 movie screens in the US. Assuming an average of seven screens per theater, this equates to roughly 5,572 theaters nationwide. Therefore, Longlegs was screened in approximately 51 percent of US theaters.

[20] For comparison, Hereditary (2018) earned $82 million, while Everything Everywhere All at Once (2022) grossed $141 million.

Figure 1. The timeline of the field experiment



opening weekend, resulting in responses from two repeated cross-sections.[21] Our identification strategy compares beliefs of respondents from the second wave who watched the film (treatment group) with respondents from the first wave who were "most likely to have seen the movie" had it been available. This comparison controls for a wide range of socioeconomic characteristics to attribute observed differences in beliefs specifically to exposure to Longlegs, as opposed to the general exposure to the theme.

We deliberately designed the study with different respondents in each wave. While tracking the same individuals across both waves could allow for a difference-in-differences (DiD) approach, such a design risks bias from an experimental demand effect. Respondents in a longitudinal study might alter their beliefs based on prior survey exposure.

In the survey, we asked about beliefs related to the demographic and geographic characteristics of serial killing crimes, confidence in these beliefs, self-perceived risks of becoming a victim, knowledge about the topic, and familiarity with blockbuster movie content. Answers to non-incentivized questions could be biased due to respondents attempting to please the researchers or as a result of actions taken after the first survey, stemming, for example, from curiosity—such as watching a movie from the list or learning about high-profile cases mentioned in the survey—which could disproportionately affect the treatment group. Similarly, responses to incentivized questions could be biased if some respondents sought out the "correct" answers more diligently than others to claim larger bonuses.

To mitigate these risks, we surveyed different respondents in each wave, thereby avoiding experimental demand bias while introducing the challenge of constructing a valid control group.

Our control group comprises individuals "most likely to see the movie" and is constructed using one-to-many matching with replacement based on propensity scores.[22]

[21] The first survey was published on July 11 at 10:57 AM. All respondents completed the survey by 4:59 PM EST on July 11. The second survey was published on July 29 at 8:03 PM. All respondents completed the survey by 2:10 AM EST on July 30.

[22] We employ caliper matching with a 0.005 caliper, a commonly used threshold in the literature, as introduced by Dehejia and Wahba (1999). This caliper ensures that the difference in propensity scores between matched individuals remains at most 1 percent, reducing bias without significantly reducing the sample size. Allowing multiple matches helps ensure sufficient observations in the control group. Importantly, while control individuals may be matched to multiple treated individuals, each control is only counted once in the analysis. This ensures that the control group is not overrepresented, even when certain control individuals serve as matches for several treated individuals. We are currently in the process of assessing the sensitivity of our results to the choice of this matching method (e.g., comparing it with nearest-neighbor matching without replacement) and the size of the caliper. This analysis will allow us to evaluate whether different matching strategies or caliper values could lead to different conclusions, helping us ensure the robustness of our findings.

We calculate the propensity scores by running an adaptive Lasso logistic regression on respondents from the first survey.[23] The dependent variable is whether a respondent reported seeing the movie. The set of control variables includes 336 variables related to respondents' socioeconomic characteristics (sex, age, ethnicity, race, education, marital status, income, political beliefs, current state of residency), past and current consumption of news and entertainment media, and general awareness of the most prolific serial killers in US history.[24] We identify the optimal lambda using a random sample of 70 percent of first-wave respondents. Once the optimal model is identified, we re-estimate it using all first-wave respondents to arrive at the final set of parameters and propensity scores for individuals in both the first and second surveys.

Once the control group is constructed, we check for balance among the characteristics used to compute the propensity scores between the treatment and control groups. Specifically, we employ standardized bias, also referred to as standardized mean difference (SMD), as discussed by Rosenbaum and Rubin (1983) and further detailed by Imbens and Wooldridge (2009). The SMD compares the difference in means between the treated and control groups, scaled by the pooled standard deviation. To compute the SMD, we weight the observations by their propensity scores. Since the control group could not have received the treatment (as they were surveyed before the movie premiered), the weighting approach ensures comparability by emphasizing the most similar individuals in the control group to those who did receive the treatment. Treated individuals are weighted by the inverse of their propensity score, while control individuals are weighted by the inverse of one minus their propensity score. This weighting is further stabilized by multiplying the weights for the treated group by the fraction of treated individuals and the weights for the control group by the fraction of control individuals. This helps align the characteristics of the control group with those of the treatment group based on the likelihood of receiving the treatment, even though the control group was never at risk of being treated.[25]

In the final step, we estimate the average treatment effects by regressing our outcome variables on the treatment indicator, controlling for the set of all variables used to compute propensity scores with the Lasso logit.

[23] We select adaptive Lasso over traditional $k-$fold cross-validation to prioritize model parsimony, as it allows for a more interpretable final specification.

[24] Lasso logistic regression is particularly suited for high-dimensional data with many covariates, as it applies regularization, reducing overfitting by penalizing less important variables while automatically selecting the most predictive ones. This approach is especially valuable in our context, where we have over 300 variables. By using Lasso, we ensure that only the most relevant variables contribute to the propensity score, thereby improving model performance and reducing multicollinearity. To ensure the performance of the Lasso estimator is not affected by highly correlated variables, we conducted pairwise Pearson correlation tests for binary variables and Cramér's V tests for categorical variables. For more on Lasso's performance in the presence of multicollinearity, see Tibshirani (1996).

[25] The standardized bias test is typically preferred over statistical tests like $t-$tests for balance checks because it does not depend on sample size, making it more suitable for assessing balance in observational studies where sample sizes can vary across subgroups, as is the case with our treatment and control groups.

3.2.2. *Internal validity.* Our identification strategy assumes selection on observables. This is supported by the inclusion of over 330 variables covering socioeconomic characteristics, historical and current media consumption, familiarity with the subject matter, and exposure to similar content.

One potential threat to the internal validity is that advertising materials, particularly teasers and trailers available for viewing before the movie's release, could have contained information pertinent to the profiles of the killers, victims, and locations, potentially influencing first survey participants. Longlegs was marketed by its producers as a serial killer movie in which "in pursuit of a serial killer, an FBI agent uncovers a series of occult clues that she must solve to end his terrifying killing spree." The trailer, which is over two minutes long, primarily focuses on the female lead—an FBI agent on the task force—but does not disclose specific details about the victims, the killer, or the locations. Therefore, while the movie's description and trailer were accessible prior to its premiere, viewers in the first survey group lacked the detailed information necessary to shape their beliefs in the same way as those who watched the movie.

Another concern is the possibility of unauthorized viewing, such as pirated versions accessed via the dark web, before the official release. To address this, we excluded individuals from the first survey who reported seeing the movie. While it remains unclear whether these respondents viewed only the trailer or a pirated version, their removal ensures a more robust analysis.

Lastly, to the best of our knowledge, Longlegs was the only serial killer-themed movie released in theaters during the survey period. While we cannot entirely rule out exposure to similar content via streaming platforms or other media, our findings remain relevant as they reflect the impact of exposure to entertainment media on beliefs. Whether the observed changes are specifically due to Longlegs or other related content, the causal story holds: exposure to serial killer-themed entertainment media influences beliefs.

3.2.3. *External validity.* Our exercise involves comparing beliefs elicited from online surveys conducted on Prolific. Both waves of the survey are balanced by gender but are not nationally representative. In particular, compared to the US population aged 18 and over, our survey respondents are more likely to be young, better educated, single, favor Democratic Party policies, and earn median incomes. Therefore, while our results hold within the surveyed population, we cannot make claims regarding the external validity of the findings.

4. Results

In this section, we first examine the public's beliefs about serial killing crimes. We then compare these beliefs to the truth (as provided by the Serial Killer Database) and to the crime's portrayal in both news and entertainment media.

4.1. **Public beliefs.** By analyzing the distributions of beliefs we find that

Result 1. *There is a large variation in beliefs regarding the profiles of victims, perpetrators, and crime locations.*

Across the three groups of beliefs, we observe the greatest variation in beliefs regarding crime geography and victim profiles (see Figure 2). Specifically, there is a standard deviation of approximately 25 percentage points in beliefs about the percentage of crimes occurring in rich, urban, and previously unaffected counties, as well as in beliefs about the percentage of female victims. For the percentage of Black victims, the standard deviation is around 20 percentage points.

The smallest, yet still notable, variation in beliefs is observed in characteristics of the perpetrators. Focusing on the two characteristics expressed as percentages—the percentage of female perpetrators and the percentage of Black perpetrators—we find a standard deviation averaging 15 percentage points.

4.2. **Public beliefs and data.** In this section, we perform a side-by-side comparison between an average belief of the public and the "empirical truth" as captured by the the Serial Killer Database. To ensure the comparison is robust, we carefully account for variations in how individuals define the term "serial killer." As shown in Figure A.2 in Online Appendix A there is considerable heterogeneity in how people interpret the concept, with some respondents using a more inclusive definition and others imposing more restrictive criteria.[26]

To address this variation, we compute statistics from the Serial Killer Database by applying weights that reflect the distribution of how respondents define the term. This method allows us to adjust the data according to the proportion of the population that holds each definition, ensuring that our comparisons between belief and reality are based on an appropriately weighted version of the crime data.

We find that:

Result 2. *Beliefs about serial killing crimes do not align with the data.*

As shown in the first and second columns of Table 1, we find statistically significant differences between public perceptions and actual data across all nine characteristics studied.[27]

Regarding victims, the public perceives them as younger, more frequently female, and more often Black compared to what the data reveals. For perpetrators, the public believes they are slightly younger—a difference that is statistically significant—overestimates the share of female perpetrators, and underestimates the proportion of Black perpetrators.

[26] Close to 50 percent of respondents understand the term serial killer as "anyone recognized by law enforcement for committing several murders." This definition abstracts away from a fixed threshold in the number of victims and instead focuses on the idiosyncratic features of the crime known to law enforcement, who then, on a case-by-case basis, decide which string of crimes qualifies as serial killings and which do not. Only about 5 percent of respondents understand the term serial killer the way it is defined by the FBI. Most respondents who define a serial killer based on a specific number of victims tend to choose three as the threshold and exclude members of organized crime groups from this category. Additionally, the figure clearly shows that, regardless of the chosen threshold, the majority of respondents do not classify individuals involved in organized crime as serial killers.

[27] p-values from two-sided tests on means are reported in Table A.1 in Online Appendix A.

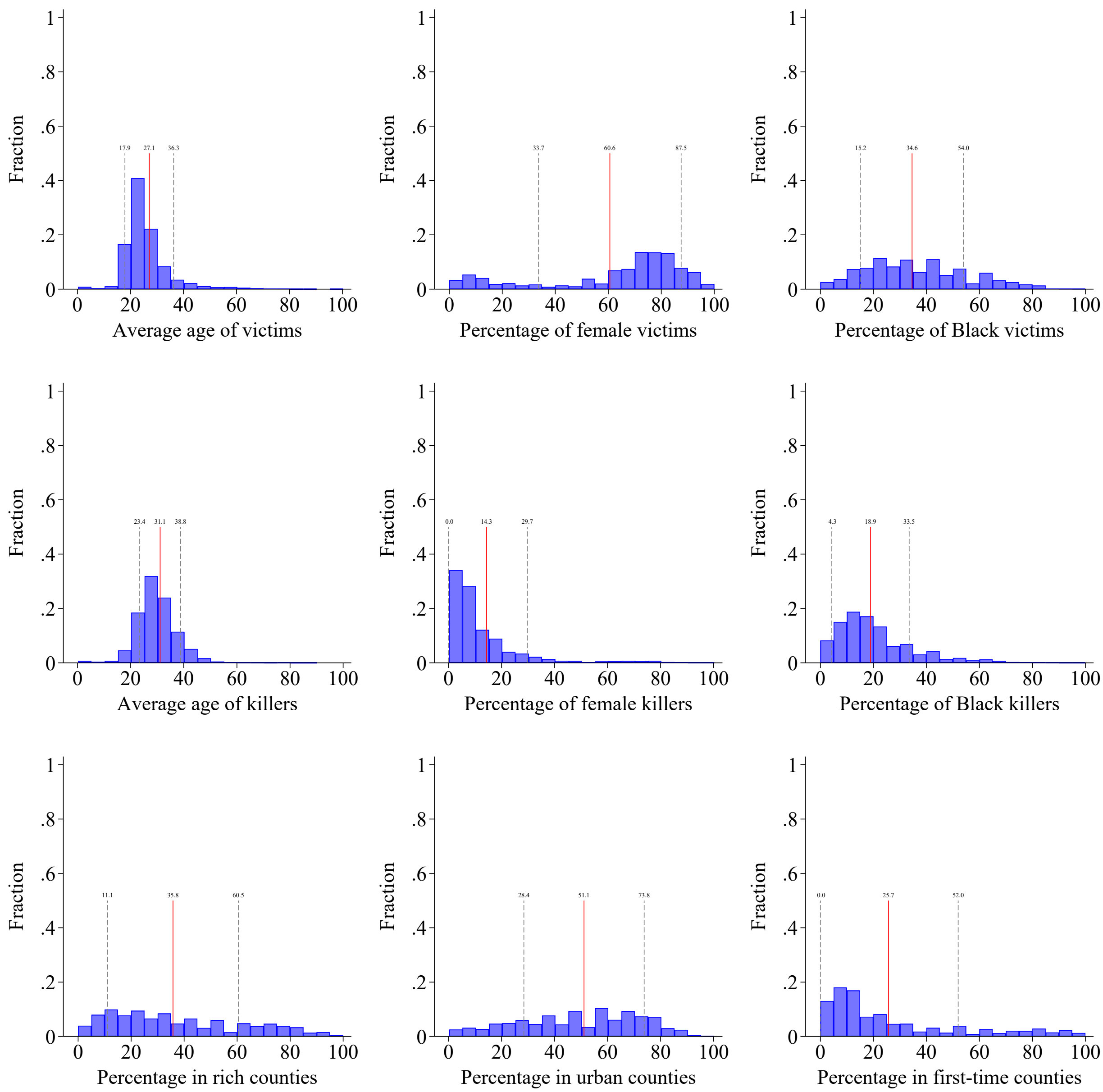


FIGURE 2. Distribution of respondents by beliefs about serial killing crimes

Note: The vertical solid red lines depict the mean. The two vertical dashed gray lines depict ± standard deviation from the mean. Distribution of respondents by beliefs about percentage of female serial killers are statistically different across the two waves.

The public also misjudges the geographic distribution of serial killings. On average, Americans believe these crimes primarily affect poor counties, occur equally in urban and rural areas, and happen in counties with no prior history about one in every four times. In reality, the data paints a different picture: most serial killings occur in wealthy,

Table 1. Representation of serial killings by source

Outcome	Survey data	Radford database	News media	Popular media
Panel A: Victims				
Average age	27.1	34.7	34.4	34.2
	(9.2)	(19.8)	(19.7)	(19.7)
	5,686	9,824	4,395	729
% of women	60.6	55.3	54.2	60.5
	(26.9)	(49.7)	(49.8)	(48.9)
	5,686	10,200	4,466	1,190
% of Blacks	34.6	27.3	24.3	12.5
	(19.4)	(44.6)	(42.9)	(33.1)
	5,686	9,124	4,057	853
Panel B: Killers				
Average Age	31.1	31.6	31.3	37.4
	(7.7)	(9.7)	(9.5)	(9.6)
	5,686	10,413	4,495	2,018
% of women	14.3	5.7	4.4	9.0
	(15.4)	(23.3)	(20.4)	(28.6)
	5,686	2,778	2,127	196
% of Blacks	18.9	40.2	39.2	7.3
	(14.6)	(49.0)	(48.8)	(26.1)
	5,686	2,760	2,114	193
Panel C: Locations				
% of affluent counties	35.8	85.8	87.2	98.0
	(24.7)	(34.9)	(33.4)	(14.0)
	5,686	10,281	4,492	1,832
% of urban counties	51.1	41.4	40.3	78.1
	(22.7)	(49.2)	(49.0)	(41.4)
	5,686	10,281	4,492	1,823
% of first-time counties	25.7	12.3	14.3	10.4
	(26.3)	(32.9)	(35.0)	(30.5)
	5,686	10,281	4,492	1,855

Note: The numbers are presented as the mean, with the standard deviation in parentheses, followed by the count of non-missing observations. Due to missing values, the number of observations may differ across sources. The datasets may include more observations for calculating the average age of killers than for analyzing victim characteristics, as a single victim's death may involve multiple serial killers.

urban counties, and the likelihood of such crimes reoccurring in a given county is more than twice as high as the public believes.[28]

[28]We summarize the direction in which the public over- or underestimates the given proportions and averages in Figure A.3, where an upward arrow indicates overestimated beliefs and a downward arrow indicates

4.3. **Public beliefs and media.** Our first step in understanding why an average belief does not align with the data is to compare the beliefs with the image of the crime created by other sources of information, in our case, news and entertainment media. If public beliefs were formed primarily through news coverage, for instance, we would expect them to closely match the way serial killings are portrayed in news outlets. The same would apply to entertainment media, such as fictional portrayals in television shows or films, as well as true-crime documentaries.

As shown in the last three columns of Table 1, none of the media channels alone can fully explain how the crime is perceived by an average respondent. In other words, neither news media nor entertainment media, by itself, offers a portrayal that aligns with an average belief of the public about serial killings. This indicates that the public's understanding is likely shaped by a combination of various media sources, along with other external influences.[29]

To explore whether the media plays a role in shaping beliefs, we divide the respondents into four categories based on their reported consumption of crime news and crime-related entertainment media.[30] A respondent is classified as a consumer of a given medium if their reported consumption falls within the top 10 percent. Regarding popular media, we impose no restrictions on the form of consumption, whether it be through books, podcasts, movies, or TV shows. For news media, no restrictions are made with respect to the reported media channel.[31]

We start by testing whether there are statistically significant differences in the distribution of beliefs across the different groups. Here, we compare standardized distributions of beliefs after controlling for respondents' socio-demographic characteristics and their definition of the term "serial killer." Using the Kolmogorov-Smirnov test, we find evidence of significant differences.[32] While this effect is not observed for all groups or crime characteristics, it is significant in several cases, such as beliefs about the victim's gender and the killer's race.

To provide further evidence supporting the role of media in shaping beliefs, we estimate the Gaussian updating model described in Section 3. Here, we find that media plays an

underestimated beliefs. The bars provide further insight into the alignment between public beliefs and actual data, showing the fraction of respondents who provided an answer within a predetermined range to qualify for the bonus: either a correct answer or an answer within 5 units of the correct value. For most characteristics (approximately two-thirds), fewer than 25 percent of respondents were able to align their beliefs closely enough with the real data to qualify for the bonus.

[29]As with the analysis using the Serial Killer Database, the statistics obtained from both news media and entertainment media are computed by accounting for weights that reflect how respondents define the term "serial killer."

[30]We define crime-related entertainment media as a combination of mystery, thriller, and true crime genres.

[31]The first category consists of respondents who fall into the top 10 percent of crime news consumption but report no crime-themed entertainment media consumption; the second category includes respondents who are in the top 10 percent of entertainment media consumption but report no news consumption; the third category comprises respondents who are in the top 10 percent for both news and entertainment media; and the fourth category consists of all other respondents. The fractions and counts for each group can be found in Table A.2 in Online Appendix A.

[32]For more details, see Table 1 in Online Appendix A.

important role in shaping beliefs about the victim's gender. As shown in Table 2, with a prior belief estimated at 61.8 percent of victims being female, media consumption affects two groups of respondents: those who consume high amounts of news or high amounts of entertainment media. Specifically, the posterior belief among those who rank in the top 10 percent of news consumption, while reporting no entertainment media consumption, is 58.3 percent. In contrast, the posterior belief among those who rank in the top 10 percent of popular media consumption, while reporting no news consumption, is 64.2 percent. Hence, we observe a 2.5 percentage point difference in beliefs for the first group and a 3 percentage point difference for the second group. This is consistent with the signals we observe from news and popular media regarding the victim's gender. On average, news outlets convey a lower percentage of female victims, leading to lower posterior beliefs among those who consume more news. In contrast, popular media portrays a higher percentage of female victims, which corresponds with higher posterior beliefs among those who primarily consume popular media.[33]

Table 2. GMM regression results: Estimates of prior beliefs

Outcome	Prior beliefs	Posterior beliefs		
	GMM	News media	Popular media	Both media
Panel A: Victims				
Average age	23.9	25.9	26.2	27.1
% of women	61.8	58.3	64.2	61.1
% of Blacks	35.6	35.4	35.7	35.4
Panel B: Killers				
Average Age	30.6	30.2	31.1	30.3
% of women	14.6	14.7	13.8	14.9
% of Blacks	20.3	19.2	19.2	21.1
Panel C: Locations				
% of affluent counties	34.7	35.4	34.4	35.0
% of urban counties	50.1	48.5	50.6	50.2
% of first-time counties	23.9	25.7	24.6	23.3

[33]For the estimation, we use the Gradient-based Newton-Raphson optimization method with the initial weighting matrix set to the identity matrix. A heteroskedasticity-consistent estimator is used for the weighting matrix, and robust standard errors are applied to the parameter estimates. We calibrate the variance of each signal $s_{k,m} = \frac{1+\rho_{k,m}}{\rho_{k,m}}$ before running GMM by setting it equal to the observed variance. The p-value of Hansen's test for over-identifying restrictions is equal to 0.6900.

Based on this evidence, we conclude that:

Result 3. *High consumption of either crime news media or crime-themed entertainment media affects beliefs about the percentage of female victims.*

4.4. **The effect of movie release.** To identify the causal effect of the movie release, we compare the beliefs of treated individuals with those in the control group while controlling for a wide range of observable characteristics. For more details, see Section 3.

The treatment group is composed of 131 individuals who watched the movie, while the control group consists of 2,780 individuals from the first survey who match closely on propensity scores.

Out of an initial pool of 331 variables, Lasso logit identified a model with 11 key predictors. Notably, none of these selected variables were demographic in nature. Instead, all 11 variables pertain to respondents' media habits and familiarity with serial killing topics. This selection emphasizes that media consumption patterns and prior engagement with serial killing content are stronger predictors of treatment likelihood than traditional demographic factors like age, gender, or socioeconomic status. This alignment strengthens the focus of our study, as the selected variables directly relate to the kind of content that could shape beliefs about serial killing.

As shown in Table 3, the balance between the treatment and control groups on these selected characteristics is mostly within 0.1 standard deviations, with three variables slightly exceeding this range (0.1–0.15 standard deviations). This level of balance confirms that our matching approach has effectively aligned the control and treatment groups on relevant observable characteristics, ensuring that any differences in beliefs can be attributed to exposure to the movie.

Table 4 presents the estimated treatment effects across various belief-related outcomes, including perceptions of the age, race, and gender of victims and perpetrators. Statistically significant effects were found in several belief variables. Specifically, individuals who watched the movie reported a 6.52 percentage point increase in the belief that victims are female, a 10.89 percentage point increase in the belief that crimes occur in affluent (rich) counties, and a 7.27 percentage point increase in the belief that crimes occur in counties that had never before been subject to serial killing. These effects correspond to 0.24, 0.44, and 0.27 standard deviations, respectively, indicating a moderate but meaningful influence of the movie on these specific beliefs.

All in all, we find that:

Result 4. *Exposure to the movie led viewers to associate serial killings more with female victims, affluent counties, and locations with no prior history of serial crime.*

Tables A.4 and A.5 In Online Appendix show no significant treatment effects in areas related to personal safety concerns or confidence in one's beliefs. This indicates that while exposure to the movie altered certain perceptions about victim and crime characteristics, it did not notably affect respondents' personal sense of safety or their confidence in these beliefs.

Table 3. Standardized bias test

Covariate	μ(C)	μ(T)	SMD
Number of known movies in the top 16	6.210	5.611	0.149
Film: Zodiac	0.333	0.295	0.081
Film: Maxxxine	0.036	0.054	0.089
Film: The Batman	0.482	0.429	0.107
Killer: The Scorecard Killer	0.054	0.031	0.116
Killer: The Nightstalker	0.521	0.473	0.096
Low consumption of action-driven themes	0.048	0.042	0.030
Low consumption of drama-driven themes	0.017	0.011	0.051
No consumption of horror-driven themes	0.375	0.361	0.030
High consumption of horror-driven themes	0.093	0.120	0.086
High consumption of CNN news channel	0.010	0.014	0.030

5. Conclusion

In this study, we conduct two complementary analyses on the role of media in shaping public beliefs and perceptions about crime. The first analysis uses a Gaussian updating model to explore how individuals' average beliefs are influenced by their media consumption patterns, while the second analysis examines the causal effect of a single media exposure on beliefs.

We find that media consumption plays an important role in shaping beliefs about the gender of victims. Our findings show that news media tends to portray a lower percentage of female victims, leading to lower posterior beliefs among those who consume high amounts of crime news. Conversely, popular entertainment media often portrays a higher percentage of female victims, which correlates with higher posterior beliefs among those who primarily consume such content. These differences, estimated through a Gaussian updating model, highlight the critical role of media as a signal through which individuals update their beliefs about crime.

The second analysis investigates the causal effect of exposure to a single piece of crime-related entertainment: a highly publicized serial killer movie. The findings reveal that watching the film significantly influenced specific beliefs about serial killing. Individuals who viewed the movie exhibited moderate shifts in demographic perceptions, with effect sizes of 0.24 standard deviations for the belief that victims are female, 0.44 standard deviations for the belief that crimes occur in affluent counties, and 0.27 standard deviations for the belief that crimes occur in counties with no prior history of serial killing. Importantly, there was no observed effect on participants' perceptions of their own safety or their confidence in these beliefs. This suggests that while the movie shaped certain demographic perceptions about serial crime, it did not influence broader concerns about personal safety or the certainty of these beliefs.

Taken together, these findings underscore the powerful influence of both traditional news and popular entertainment media in shaping public perceptions. While traditional news outlets play a critical role in informing the public, popular media, including films and

Table 4. Average treatment effect on beliefs

Panel A: Victims

ATE	Victim		
	Age	Female	Black
Treatment	-0.206	6.535**	1.849
	(0.877)	(2.553)	(2.191)
Observations	2,911	2,911	2,911
Controls	336	336	336

Panel B: Killers

ATE	Killer		
	Age	Female	Black
Treatment	-0.162	2.724	2.256
	(0.739)	(2.774)	(1.564)
Observations	2,911	2,911	2,911
Controls	336	336	336

Panel C: Locations

ATE	Location		
	Rich	Urban	First-time
Treatment	10.667***	4.395	7.185**
	(2.854)	(2.690)	(3.574)
Observations	2,911	2,911	2,911
Controls	336	336	336

Note: Robust standard errors in parentheses. Treated individuals are weighted by the inverse of their propensity score, and control individuals by the inverse of one minus their propensity score, stabilized by multiplying each group's weights by their respective population fractions.

television, can have an equally significant impact, especially when individuals lack direct experience or access to reliable information.

Our findings also have important implications for public policy and societal dynamics. Political campaigns or interest groups could strategically release content to shape public opinion before elections or referenda. Entertainment media often relies on emotional storytelling, which can influence voters' decisions by evoking fear, hope, or anger, potentially swaying opinions even without factual accuracy. To address this, regulators might consider stricter oversight of entertainment media releases during election periods to prevent indirect voter manipulation through biased or strategically timed content.

To combat misinformation, governments and NGOs could use these findings to support the development of educational programs that highlight how media shapes beliefs, encouraging critical thinking and media literacy to mitigate manipulation. Public institutions could also proactively counter biased or fear-inducing narratives in entertainment media by disseminating accurate, compelling, and relatable content.

This research underscores the need for transparency in the funding and production of entertainment media, particularly when such content aligns with political or corporate agendas. Introducing content advisories or disclaimers for media dealing with politically or socially sensitive topics could help viewers contextualize the material and reduce undue influence.

These findings are also relevant to stereotype formation. Entertainment media often shapes perceptions of marginalized or stigmatized groups (e.g., immigrants, specific religions). Our findings could inform policies aimed at limiting harmful stereotypes that influence public opinion or voting on issues like immigration reform.

On a more positive note, while media can manipulate beliefs, it can also be used ethically to shape positive public perceptions on important issues, such as public health and environmental protection. These findings could guide campaigns to use entertainment media responsibly for public awareness initiatives.

Future research could explore potential heterogeneity in these effects to determine whether specific subgroups, such as individuals with varying levels of prior media exposure or distinct demographic characteristics, exhibit more pronounced shifts in beliefs. Additionally, examining whether the effects associated with a movie release are short-lived or persist over a longer period would be valuable. Insights into the duration of these effects could reveal how temporary versus sustained media exposure influences public perceptions.

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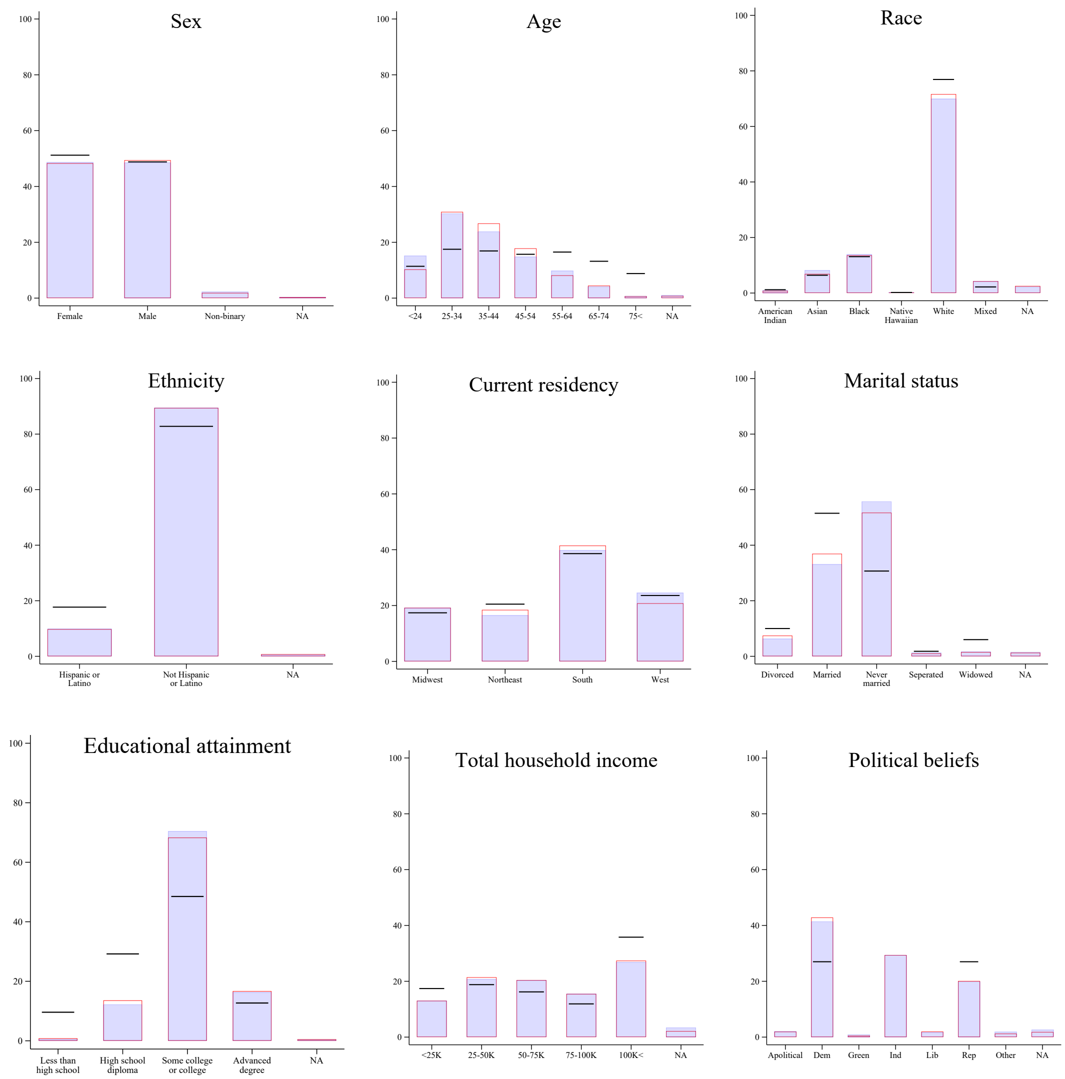
Appendix A. Additional tables and figures



Note: The bars present percentages of respondents by socio-ecoomic status. The filled blue bars represent respondents from the first wave, and the unfilled bars with a red border represent respondents from the second wave. The black horizontal lines represent the corresponding percentages for the US population aged 18 or older. Population data regarding sex, age, marital status, educational attainment, and total family income are sourced from the US Census Bureau, Current Population Survey, Annual Social and Economic Supplement, 2022 (Internet release date: August 2023) (https://www.census.gov/data/tables/2022/demo/age-and-sex/2022-age-sex-composition.html). Population data on political beliefs are derived from annual averages of Gallup telephone survey interview data for 2023 (https://news.gallup.com/poll/548459/independent-party-tied-high-democratic-new-low.aspx). Population data on race and ethnicity come from the US Census Bureau, Population Division, the National Population Estimates for 2022 (https://www.census.gov/data/tables/time-series/demo/popest/2020s-national-detail.html). Distributions of respondents by region, marital status, and age bracket are statistically different across the two waves (chi-squared test).

Figure A.1. Respondent demographics across the two surveys

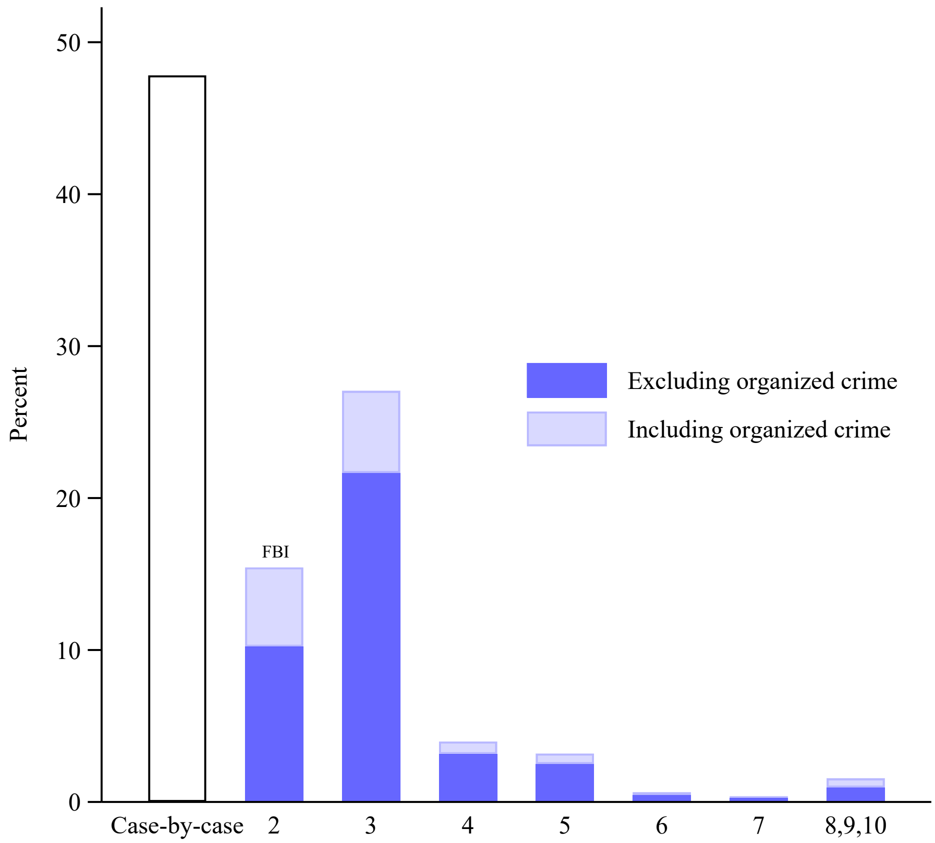


Figure A.2. Distribution of respondents by a serial killer definition

Note: Bar labeled as "case-by-case" represents percentages of respondents who define a serial killer as "anyone recognized by law enforcement for committing several separate murders. The classification depends on the specifics of the crimes, with each situation evaluated individually." Bars labeled with numbers represent the percentage of respondents who define a serial killer as anyone who has committed at least the given number of separate murders. Here, the dark blue bars represent the percentages of respondents who exclude from this definition those in organized crime groups.

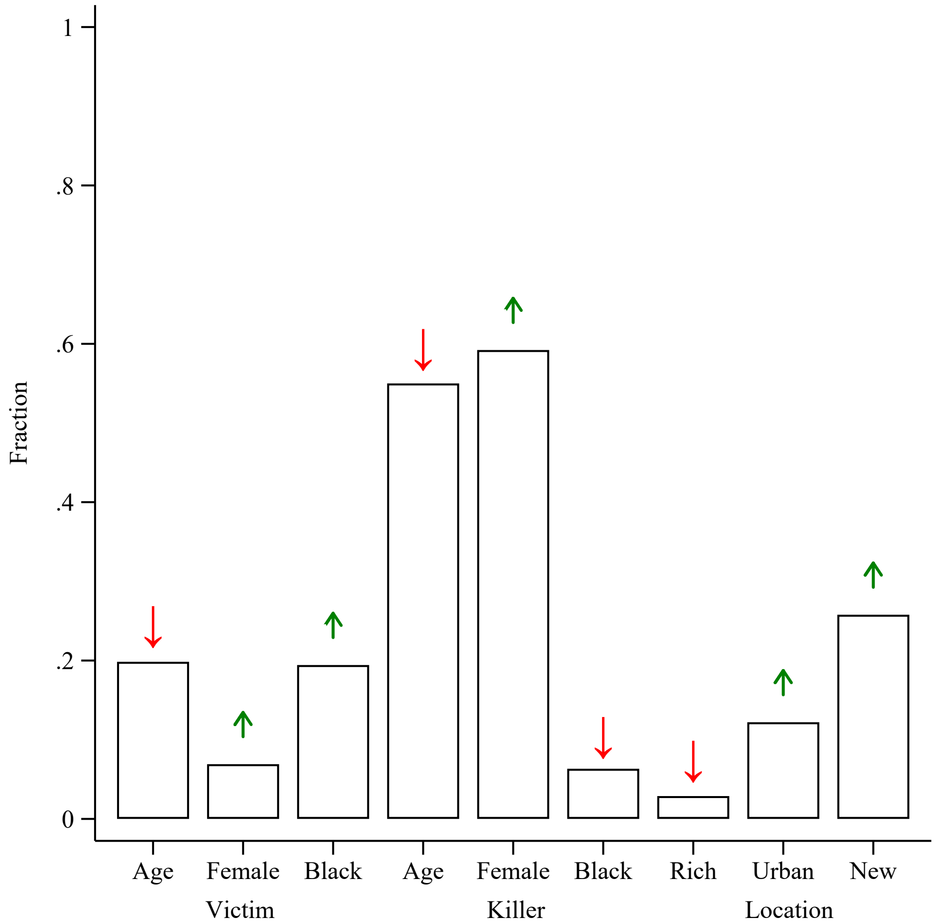


Figure A.3. Alignment of public beliefs with actual data

Note: Upward-pointing green arrows indicate characteristics that were overestimated by respondents, while downward-pointing red arrows indicate those that were underestimated. The bars represent the fraction of respondents who qualified for a bonus by providing an answer within 5 units of the correct value.

Table A.1. Comparison of average beliefs to reported mean values

Outcome	Radford database	News media	Popular media
Panel A: Victims			
Average age	0.000	0.000	0.000
% of women	0.000	0.000	0.987
% of Blacks	0.000	0.000	0.000
Panel B: Killers			
Average Age	0.001	0.290	0.000
% of women	0.000	0.000	0.009
% of Blacks	0.000	0.000	0.000
Panel C: Locations			
% of affluent counties	0.000	0.000	0.000
% of urban counties	0.000	0.000	0.000
% of first-time counties	0.000	0.000	0.000

Note: The table presents p-values from two-sided tests on whether the average beliefs are the same as the means reported by various sources. The first column contains p-values for testing the null hypothesis that the average belief in the population is equal to the mean value in the Radford data set. The second column contains p-values for testing the null hypothesis that the average belief in the population is equal to the mean value portrayed in newspapers. The third column contains p-values for testing the null hypothesis that the average belief in the population is equal to the mean value in popular media.

Table A.2. Distribution of respondents by reported media consumption

Source	Percentages	Counts
News	1.8	102
Fiction	4.3	244
Both	8.4	477
None	85.5	4,863
Total	100.0	5,686

Table A.3. Comparison of average beliefs by the type of signal received

Signal	Victim			Killer			Location		
	Age	Female	Black	Age	Female	Black	Rich	Urban	First-time
{N} vs. {F}	0.476	0.294	0.484	0.821	0.858	0.752	0.154	0.468	0.995
{N} vs. {N,F}	0.998	0.692	0.619	0.680	0.751	0.232	0.608	0.795	0.948
{N} vs. {∅}	0.892	0.592	0.173	0.577	0.423	0.610	0.680	0.382	0.980
{F} vs. {N,F}	0.151	0.406	0.851	0.856	0.996	0.275	0.131	0.999	0.621
{F} vs. {∅}	0.171	0.039	0.845	1.000	0.898	0.962	0.079	0.679	0.523
{N,F} vs. {∅}	0.940	0.111	0.295	0.446	0.326	0.041	0.796	0.600	0.197

Note: The table presents the $p-$values of the Kolmogorov-Smirnov test for equality of distributions. The distributions are compared for standardized data after accounting for respondents' socio-demographic characteristics and their definition of the term "serial killer."

Table A.4. Average treatment effect on safety and confidence levels

ATE	Safety concern		Likelihood of occurance	
	Discrete (0-10)	Binary (0/1)	Prob (0-1)	Binary (0/1)
Treatment	-0.146	0.002	2.866	0.027
	(0.245)	(0.054)	(2.373)	(0.064)
Observations	2,911	2,911	2,911	2,911
Controls	336	336	336	336

Note: Robust standard errors in parentheses.

Table A.5. Average treatment effect on safety and confidence levels

ATE	Confidence		
	Victims (0-10)	Killers (0-10)	Locations (0-10)
Treatment	-0.141	0.056	-0.061
	(0.222)	(0.245)	(0.220)
Observations	2,895	2,908	2,904
Controls	336	336	336

Note: Robust standard errors in parentheses.

Appendix B. Online survey experiment

In each of our two online surveys, we collected information on people's definitions of serial killings, their beliefs about serial killing crime statistics in the US post-WWII, their perceived chances of becoming a victim, general knowledge on the topic, historical and current exposure to both news and entertainment media, familiarity with the most prominent and blockbuster serial killer content, and their socio-economic characteristics. The blocks were displayed in the order listed above.

B.1. **Definition.** To investigate how the public defines a serial killer, we began our survey by asking participants to choose the definition that most closely aligned with their understanding of the term. Respondents were provided with a total of 19 definitions, grouped into three sets for readability.

The first set defined a serial killer as anyone, *including* those involved in organized crime groups, who has committed at least a certain number of murders. Respondents could select any number between 2 and 10. The second set defined a serial killer as anyone, *excluding* those involved in organized crime groups, who has committed at least a certain number of murders, with respondents again able to choose a number between 2 and 10. The third set offered a broader approach, with just one definition that did not rely on a fixed threshold. In this set, a serial killer was defined as anyone recognized by law enforcement as committing multiple murders, with classification determined on a case-by-case basis.

Respondents were instructed to use their chosen definition of the term to complete the remainder of the survey. This question was mandatory, but their responses were not incentivized, and the question was not timed.

B.2. **Beliefs.** To collect participants' beliefs about the crime, we asked them about the demographic characteristics of a typical victim, a typical perpetrator, and about the population characteristics of a typical region where the crime occurs. Specifically, we inquired about the average age of the victim, the percentage of victims who are female, the percentage of victims who are African American, the average age of the perpetrator at the time of the crime, the percentage of perpetrators who are female, the percentage of perpetrators who are African American, the percentage of crimes that occur in wealthy counties, the percentage of crimes that occur in urban counties, and the percentage of crimes that occur in counties that have never previously experienced a serial killing.

Respondents were instructed to consider serial killings in the US from the end of World War II in 1945 to the present day, using the definition they provided earlier in the survey. Questions were grouped into three blocks, with each block focusing on beliefs about victims, perpetrators, or crime locations. The questions were randomized both within blocks (shuffling the order of questions within each topic) and across blocks (shuffling the sequence in which blocks were presented) to minimize order effects.

After answering the questions in each block, participants were asked to rate their confidence in their responses on a scale from 0 (no confidence) to 10 (complete confidence). Confidence ratings were not incentivized.

We emphasized the importance of this section and expressed our appreciation for their responses. Monetary incentives of $0.25 were offered for answers within 5 percentage points for percentages and within 5 years for ages of the correct values. The bonus amount was fixed and did not vary within the range. Respondents were informed that serial killing statistics, typically unavailable, had been shared with us specifically for this study and would be used to assess the accuracy of their responses and determine bonus eligibility.

Each block was timed, with participants given two minutes to answer. If questions were left unanswered, the survey automatically advanced to the next page. The time limit was implemented to minimize the possibility of external influences, such as participants consulting others, searching for information online, or engaging in discussions that could compromise the integrity of their individual responses

B.3. **Perceived risk.** To assess participants' perceptions of the risk of a serial killing in their vicinity, we asked about the likelihood of a serial killing occurring in their neighborhood within the next 10 years, their concern level for their personal safety due to the possibility of a serial killing, and what activities they engage in, if any, to reduce the chances of falling victim to such a crime.

These questions were mandatory; however, responses were not incentivized, and the questions were not timed.

B.4. **General knowledge.** To evaluate participants' knowledge on the topic, we asked them to identify all known serial killers from a list of 25 names. The list included the 25 most prolific serial killers in the post-World War II history of the US who met the criteria of all provided definitions of a serial killer used in the study. Specifically, these individuals: (i) Had at least 10 confirmed victims; (ii) Were not members of organized crime groups; (iii) Were officially classified as serial killers by law enforcement. This intersection of definitions ensured that only individuals universally recognized as serial killers under the strictest criteria were included. The list ranged from Samuel Little, who had 63 proven victims, to Richard Ramirez, with 15 confirmed victims.

The names were presented in alphabetical order, with media-coined pseudonyms included when applicable. This question was not mandatory, respondents were not incentivized, and the question was not timed.

B.5. **General media exposure.** To assess participants' exposure to popular entertainment media, we asked them to select and rank in order of importance the genres they were exposed to during childhood and adolescence, as well as the genres they favor now. They were provided with a list of seven genres (action/fantasy, comedy, drama, horror, mystery/thriller, true crime, and other) from which they could select any number and rank them in order of importance.

To quantify respondents' current media consumption, we asked them about the average number of books, movies, TV shows, and podcasts they consume. Participants were asked to report how many books they read from start to finish each month, how many movies and TV shows they watch, and how many podcast episodes they listen to each week.

To assess participants' exposure to traditional news media, we asked them to select and rank in order of importance the news categories they were exposed to during childhood and adolescence, as well as the categories they follow now. The list included six categories: business/economy, crime/public safety, society/culture, politics, science/environment, and other. To further quantify current news consumption, we also asked participants to reflect on their average daily time spent watching news channels. The list included CNN, Fox News, MSNBC, Newsmax TV, and other, with consumption divided into five time bins: none, under 30 minutes, 30 minutes to 1 hour, 1 to 2 hours, and over 2 hours.

These questions were not mandatory, respondents were not incentivized, and the questions were not timed.

B.6. **Familiarity with blockbuster movies and TV shows.** To measure respondents' familiarity with prominent serial killer content, we asked them to identify all movies and TV shows they had seen in the past from two lists, comprising a total of 32 titles. The titles were presented with visual aids (posters), basic information (titles), and contextual details (release years) to facilitate identification. The source of the titles was a curated "Serial Killer Movie" list from IMDb, a reliable and well-known media database. Created in 2021, the list has remained actively viewed, with 23,000 total views and an average of 300 views per week. It was chosen because it is updated regularly and continues to attract current engagement, ensuring it reflects both classic and newly released content.

Although not all titles on the list may align with respondents' definitions of who a serial killer is, they are widely recognized as such by the media and audiences, reflecting the general public's interpretation of the term. The movies were not explicitly referred to as "serial killer movies" but simply as "movies" to avoid influencing respondents' beliefs or shaping their choices. To minimize potential bias, this block was placed at the end of the survey.

For the survey, the IMDb list was divided into two separate categories. One focused on fictional content, which included movies and TV shows with fictionalized portrayals of serial killers. The other focused on documentaries and true events, featuring titles based on real-life cases or true crime stories. Each list consisted of 16 titles, selected based on the highest popularity scores as measured by the number of IMDb user comments.

The fictional content list began with Seven, The Silence of the Lambs, and The Batman, and concluded with Don't Breathe, Hannibal, and Red Dragon. The nonfiction/documentary list started with Zodiac, Mindhunter, and Monster, and ended with Night Stalker, Lost Girls, and Maxxxine.

These questions were not mandatory, respondents were not incentivized, and the questions were not timed.