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Media and Crime Perceptions: Evidence from Mexico

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Abstract

This paper examines whether individuals' crime perceptions and crime avoidance behavior respond to changes in crime news coverage. I use data from Mexico, where major media groups agreed to reduce coverage of violence in March 2011. Using a unique dataset on national news content and machine learning techniques, I document that after the Agreement, crime news coverage on television, radio, and newspapers decreases relative to the national homicide rate. Using survey data, I find robust evidence that crime perceptions respond to this change in content. After the Agreement, individuals with higher media exposure are less likely to report that they feel insecure and that their country, state, or municipality is insecure, relative to individuals with lower media exposure. However, I show that these changes in crime perceptions are not accompanied by changes in crime avoidance behavior (i.e. no longer going out at night for fear of being a victim of crime), or at least that effects are much smaller.

Keywords: mass media; persuasion; crime perception

JEL codes: D83, K42, L82

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1 Introduction

Crime is a major concern in Mexico. According to survey data, around 70% of Mexicans say crime is one of the three most important problems in the country. In fact, in the survey, crime is listed as the nation's biggest problem, followed by unemployment and poverty which are the second and third highest [ENSI (2010)].

At the same time, media is a key source of information for learning about crime. Approximately, 88% of people learn about public security in the country and their state from television; while 36% and 28% learn from radio and newspapers. Yet, only 14% of individuals report learning from family, friends, or neighbors [ENSI (2010)].

Given this reliance on the media, policy makers have been worried about the frequent presentation of violence in the news and its potential to increase the salience of crime in individuals' lives. According to former Mexican President Felipe Calderón: "news about high-impact crimes are very alarming (and) often are greatly exaggerated; unlike in other countries..., here (the media) explains in detail how the murder was committed and the type and size of the knife" [Mural (2011)].

In part in response to these concerns, Mexico's major media groups agreed to reduce coverage of violence in March 2011. In this paper, I evaluate the effect of this Agreement on media coverage of crime, crime perceptions, and crime avoidance behavior.

I first investigate whether the Agreement affects news content of the top national circulation newspapers, radio, and broadcast television channels. To address this question, I develop several measures of crime news coverage, for example, the total number of monthly news items on a channel/newspaper using any of the words that the editorial criteria of the Agreement suggested to avoid. Based upon this measure, I find that newspapers, radio, and broadcast television channels reduce their coverage of crime relative to the national homicide rate after the policy. This reduction is large: between 21% and 68% of the average amount of crime news in the pre-policy period. Moreover, for radio and newspapers, all of these findings persist when I use measures based on reporting of violent crime or drug trafficking.

Given this change in content, I then investigate whether or not crime perceptions change due to the Agreement. I first use a set of cross-sectional annual surveys with information on the respondent's frequency of news consumption (in 2010), crime perceptions, and some respondent's behavioral responses due to the fear of being a victim of crime. Using the frequency of the individuals' news consumption, I predict a "treatment intensity" based on socioeconomic characteristics. I then use a monthly rotating panel survey that includes questions on the respondent's crime perceptions and sociodemographic characteristics during the period April 2009 to September 2012 to estimate the effect of the Agreement on crime perceptions. I compare crime perceptions between individuals with higher treatment intensity, which corresponds to a higher frequency of news consumption, and individuals who were less treated, before and after the policy. In the monthly data, this strategy allows me to control for both household fixed effects and metro area-specific shocks so that all time-invariant differences across households—such as risk of crime in the neighborhood or anxiety of crime by household members—and metro area changes over time—such as changes in risk factors are controlled for. In the annual data, it allows me to control for victimization experience at the household level, which might be an important determinant of crime perceptions.

Using the above data and strategy, I find that crime perceptions respond to the Agreement. After the Agreement, individuals with higher treatment intensity are less likely to report that they feel insecure (personal crime perception), that their country is insecure (country crime perception), and that their state or municipality is insecure, relative to individuals with lower treatment intensity. My preferred point estimates indicate that a 1.00 standard deviation increase in treatment intensity yields a .66 standard deviation decrease in the personal crime perception index and a .38 standard deviation decrease in the country crime perception index following the Agreement.

I do not, however, find evidence that these changes in perceptions translate into changes in avoidance behavior. Individuals with higher treatment intensity are equally likely to report that they no longer go out at night for fear of being a victim of crime after the policy relative to less treated individuals. Regarding the magnitudes, I'm not able to reject a negative coefficient as big as .01 of a standard deviation, which is much smaller than the effect in perceptions.

My study contributes to the growing literature on the effects of mass media on attitudes and behavior [i.e. Gentzkow and Shapiro (2004); DellaVigna and Kaplan (2007); Olken (2009); Jensen and Oster (2009); Enikolopov, Petrova and Zhuravskaya (2011); La Ferrara, Chong and Duryea (2012)]. I add to this literature by providing evidence of the impact of media on particular types of perceptions and behaviors: those associated with the fear of being a victim of crime. My results suggest that although media can have large effects on reported crime perceptions, this is not accompanied by changes in behavior, or at least the effects are much smaller than the effects on crime perceptions.

Particularly, my findings speak to the large sociological, criminological, and media literature on the role of media in shaping attitudes towards crime, most of which identifies the effect of media using cross-sectional variation in media use.[1] My analysis relates most closely to recent work by Mastrorocco and Minale (2016) who investigate the influence of television on crime perceptions in Italy. They exploit region-specific idiosyncratic deadlines due to the introduction of digital TV and implement a difference-in-difference design that compares crime perceptions of individuals within the same region, before and

[1] See Grabe and Drew (2007) and Heath and Gilbert (1996) for an extensive review of the literature.

after the switch to digital signal occurred. They find that reduced exposure to crime related news decreased the national perceived level of crime for older individuals who, on average, watch more television and use alternative sources of information (such as the Internet, radio, and newspapers) less frequently. However, contrary to my findings, they don't find an immediate effect on perceptions about the level of local crime. My paper employs a different source of variation to this study and examines the effects of media on a much larger scale (not restricted to television). In addition, I add to the literature by studying behavioral responses.

The remainder of the paper is organized as follows. Section 2 provides background on the Mexican media market and the Agreement on the Coverage of Violence, while section 3 outlines the conceptual framework. Section 4 documents the effect of the Agreement on news content. Section 5 describes the data and empirical strategy. Section 6 presents the results on crime perceptions and avoidance behavior. Section 7 provides robustness checks. Finally, section 8 offers concluding remarks.

2 Agreement on the Coverage of Violence

The 24th of March of 2011, 46 Mexican media groups signed the Agreement on the Coverage of Violence (ACIV).[2] The purpose of the Agreement was to propose common editorial criteria for the coverage of violence due to organized crime to avoid spreading terror among the population. These editorial criteria suggested that outlets avoid using the vocabulary or jargon of criminals such as armed group, drug-trafficking bosses, drug lord, execution/executions/executed, *encajuelado* (a body dumped in the trunk of a car), *encobijado* (a person found wrapped in blankets after being assassinated by drug traffickers or their associates), *levantón/levantan/levantado* (the kidnapping of one or more members of a rival gang, or other enemy; unlike traditional kidnappings, the point is to torture and kill), mass grave, *narco-anything* (*narco* can refer to a trafficker or the entire illegal drug trade), hit man, and lieutenant (*prohibited words* from here onwards). Additionally, they recommended avoiding disseminating information in audio, video, and banners from organized crime.

A Council was in charge of assuring that the Agreement criteria were being followed. The Council consisted of a diverse group of academics and journalists that issued periodic reports about the coverage of violence. If one of the media outlets that had signed the Agreement was not following one or more Agreement criteria, the Council would warn them in a private meeting. For example, the Council published the following summary of a meeting held with the Editorial Board of one Mexican media outlet due to the transmission of a video in which a group of people, possibly members of organized crime,

[2]The text on the Agreement can be found here.

torture and murder two members of the Armed Forces:

> *"The Editorial Board of Milenio agreed to strengthen their deliberative process about the dissemination of violent images from organized crime. Some members of the Council suggested that overall, the logic of the process would be that in the case of doubt about the information value of certain images, the criteria should be not to publish them... Councilors added that that does not mean failing to report the incident involving such images..."* Observatorio y Monitoreo Ciudadano de Medios, A.C. (2011)

Additionally, according to an interview with a member of the Council:

> *There was awareness of the owners of media outlets, editors, ..., there was an order not to transmit the heads of the hanged, not to transmit explicit images ... but there was no information about how to spread the message ... then we had suddenly some reporters saying you are censoring me.* Regina Nuñez, Member of the Executive Council (January 2016).

Although the Agreement didn't prohibit reporting crime incidents, there's quantitative evidence suggesting that media outlets could have stopped publishing crime news. For example, an extract from the seventh report of the Council states:

> *...the newspaper Imagen de Zacatecas announced that "they will no longer publish on the front page news and photos related to criminal acts and clashes between criminal groups"... "The perception of Zacatecas is that we are a state dominated by violence, shootings, assaults, and kidnappings and that image hurts us all Zacatecas because many investors do not want to come to the state and many tourists neither, by the false image that exists about the entity", said President and Chief of the Imagen, Luis Enrique Mercado Sanchez. "That is not the reality of Zacatecas, as it is not true that you can't travel on Zacatecas' roads, or that our towns and cities are taken by crime", said Mercado Sanchez.* Observatorio de los Procesos de Comunicación Pública de la Violencia (2013)[p. 31]

Since major Mexican media groups signed the Agreement and considering that broadcast and print media are a key source of information for learning about crime (see figure 1), this industry-driven policy might have induced a big change in Mexicans' exposure to crime news.[3] Two television networks—Televisa and TV Azteca—own 94% of all national and local commercial broadcast stations [COFETEL (2011)]; both signed

[3]The full list of media outlets that signed the Agreement is here.

the Agreement. Five radio groups have a presence in almost all cities of Mexico; four out of these five groups signed it. Finally, more than half of the national circulation newspapers (seven out of thirteen) signed it. In section 4, I provide quantitative evidence on the change in crime news coverage induced by the policy.

3 Theoretical Framework

In this section, I present a simple model to guide the empirical work. In this framework, individuals know that nature's parameter θ, the level of crime, is chosen randomly according to a normal distribution $\mathcal{N}(\bar{\theta}, \frac{1}{\rho_\theta})$. Individuals receive private reports from a media sector and update their beliefs using Bayes Rule.

I assume that the media sector receives signals, indexed as m, which are equal to the true value θ plus a noise:

$$\theta_m = \theta + \epsilon_m \tag{1}$$

The noise terms ϵ_m are independent across signals and normally distributed $\mathcal{N}(0, \frac{1}{\rho_\epsilon})$. If the media sector reports a signal without bias, then $r_m = \theta_m$. Define this reporting strategy as r.

I assume that there are two types of individuals. For ease of exposition, let's assume that type I individuals watch, listen, or read one report r_m from the media sector. Type II individuals get two reports r_m and r'_m.

The posterior belief of type I individual after getting report r_m is given by:

$$\theta^{post}_{typeIi} = \bar{\theta}\frac{\rho_\theta}{\rho_\epsilon + \rho_\theta} + r_m \frac{\rho_\epsilon}{\rho_\epsilon + \rho_\theta} \tag{2}$$

Similarly, the posterior belief of a type II individual after getting reports r_m and $r_{m'}$ is given by:

$$\theta^{post}_{typeIIi} = \bar{\theta}\frac{\rho_\theta}{2\rho_\epsilon + \rho_\theta} + r_m \frac{\rho_\epsilon}{2\rho_\epsilon + \rho_\theta} + r_{m'} \frac{\rho_\epsilon}{2\rho_\epsilon + \rho_\theta} \tag{3}$$

I assume the media sector unexpectedly changes his reporting strategy from r to R such that $R_m = \theta_m + b$ for every signal reported. Define $\Delta\theta^{post}_i = \theta^{post}_{i\mathbf{R}} - \theta^{post}_{i\mathbf{r}}$ as the change in agent i posterior belief from reporting strategy r to R conditional on a given realization of the signals. Given that the change in the media sector reporting strategy is unexpected, I assume that individuals do not account for b when they update their posterior beliefs. Thus, posterior beliefs of type I and type II agents change as follows:

$$\Delta\theta^{post}_{typeIi} = b\frac{\rho_\epsilon}{\rho_\epsilon + \rho_\theta} < \Delta\theta^{post}_{typeIIi} = b\frac{2\rho_\epsilon}{2\rho_\epsilon + \rho_\theta} \tag{4}$$

An individual who is more exposed to media (type II) responds more to changes in b of the media sector.[4]

Based on this framework, in the following sections, I first investigate whether the Agreement changes b. Second, I investigate, if individuals that watch, listen, or read news more frequently and consume more reports from the media sector, decrease their posterior beliefs on the level of crime (crime perceptions), relative to individuals less exposed after the policy.

4 Content Analysis

4.1 Data sources and methods

To investigate whether the Agreement had an effect on the evolution of crime news coverage by Mexican media outlets, I use news items collected by the private firm "Eficiencia Informativa". Eficiencia Informativa is a leading firm in media monitoring in Mexico and has a database that consists of more than 15 million news items.[5] The data includes detailed transcripts or summary of transcripts of the top national broadcast television and radio channels and news items from national and Mexico City metro area newspapers. All of the content analysis in this section is conducted in Spanish and translated to English for ease of exposition.

The sample I use in this analysis covers the period January 2009 and April 2013. Specifically, I focus on 10 national and Mexico City metro area broadcast television channels, which represent 66.5% and 81.8% of the share of the audience of broadcast television in the country and in Mexico City metro area, respectively.[6] Since, all of these media outlets entered into the Agreement, I don't have a non-Agreement sample for broadcast television. I use news items from 21 Mexico City metro area radio channels, which represent more than 97% of the share of the audience of radio in Mexico City metro area and whose programs are usually broadcasted locally.[7] Of these radio channels, 19 entered into the Agreement. Finally, I use news items for 17 national and Mexico City

[4] $\Delta\theta^{post}_{typeII} - \theta^{post}_{typeI} = \frac{\rho_\epsilon\rho_\theta}{(2\rho_\epsilon+\rho_\theta)(\rho_\epsilon+\rho_\theta)} > 0$

[5] This database was also used by the Council of the Agreement to monitor the compliance of the editiorial criteria of the Agreement.

[6] Data on national and Mexico City metro area shares by channel are from the period January-December 2008 and are based on 2008-2009 Nielsen-IBOPE's report on the evolution of Mexican Media market.Available here.

[7] Data on Mexico City metro area shares by radio groups are from the period January-December 2008 and are based on 2008-2009 Nielsen-IBOPE's report on the evolution of Mexican Media market.

newspapers, 9 of which entered into the Agreement. I provide detailed information on the Agreement and non-Agreement media outlets included in my sample in appendix table B.1.

The content analysis I present in this section is mainly based on national news content. As I explained in section 2, most television and radio stations form part of broader regional and national networks. Within networks, entertainment and national news content is bought from or relayed by network providers and is thus identical across stations [Marshall (2015)]. The top channels of these networks are included in my sample. Thus, my analysis focuses on national content.[8] However, local news content might have also changed due to the fact that these stations are part of the major groups that subscribed to the Agreement.

I develop several measures of crime news coverage by media outlets in my sample. The simplest measure is *Use of Prohibited Words*, the total number of monthly non-opinion news items on a channel/newspaper using any of the words that the Agreement suggested avoiding as defined in section 2. This measure reflects the extent to which media outlets stop reporting drug-related news using the vocabulary or jargon of criminals, particularly, of organized crime. To analyze if media outlets report less on crime and the type of the crimes they talk about, I develop a second set of measures. The first is *Crime News*, the total number of monthly non-opinion news items on a channel/newspaper covering violent and drug-related crimes, including accomplishments against perpetrators.[9] The second is *Narco News* or drug-related news, the total number of monthly non-opinion news items on a channel/newspaper covering drug trafficking organizations.

To construct this second set of measures, I use tools of automated text analysis. First, I manually classify a randomly selected subset of news items from both the pre and the post-policy period for each type of media into binary categories: crime-related or not and narco-related or not. The total number of news items I manually classify is 667 for broadcast television, 528 for radio, and 1,070 news for newspapers. Second, I use 70% of this manually classified subset of news to train or supervise a statistical model, a lasso logistic regression, which is known to produce sparse and efficient models [Genkin, Lewis and Madigan (2007)]. Third, I use the remaining 30% of the manually classified subset to validate the classifier's accuracy. Fourth, I use the validated model to classify the rest of the news (around 1.5 million news). Appendix A.1 gives details on the randomization process to select the manually classified subset of news and appendix A.2 explains in more detail the lasso-logistic model I use to create these measures.

Figure 2 presents one-word and two-word phrases with positive lasso coefficients

[8] Many affiliates and regional subdivisions emitting from major cities within each state also provide significant local news content Marshall (2015).

[9] Violent crimes include murder and non-negligent manslaughter, forcible rape, robbery, aggravated assault, and kidnapping.

for each type of media for the crime category. A bigger phrase has a higher coefficient. Among other lessons, it shows that during the period I study, drug-related words ("narco", "cartel", "drug", and "organized crime") are indicative of crime news. Full results, mean error, and the confusion matrix over the test set are provided in tables B.2 to B.7 of the appendix.

In the following subsection, I examine how each of these measures evolves before and after the Agreement was announced. In particular, I estimate the following specification separately for each type of media:

$$Crime\ News\ Measure_{cm} = \beta_{0c} + \beta_1 post + \beta_2 hom_m + \beta_3 sport_{cm} + \alpha_s + \epsilon_{cm} \quad (5)$$

where β_{0c} is a channel/newspaper-specific intercept, *post* is a dummy equal to 1 for months after the announcement of the Agreement, hom_m is the logarithm of the number of homicides in the country per 100,000 inhabitants in month m,[10] and $sport_{cm}$ is the total number of monthly non-opinion news items with the word sport of channel/newspaper c. This control captures structural changes that happen over time within each media outlet, for example, changes in the number of articles. Finally, α_s are calendar month dummies.

The above specification is guided by the theoretical framework in section 3 which assumes that crime news coverage is a function of the level of crime (i.e., the state of nature). However, it is possible that crime reacts to crime news coverage (i.e., if cartels become more violent because the media sector covers their killings). Using pre-period data, I show in appendix A.3 that consistent with my model the direction of causality goes from the homicides rate to crime news coverage.

4.2 Findings

Figure 3 shows the evolution of each of my measures for all newspapers in my sample, weighted by the circulation of each newspaper. Newspapers in my sample tend to have lower coverage of crime after the policy. The same pattern applies to radio and television channels (figure 4 and 5). They tend to have lower coverage of crime after the Agreement and this change doesn't seem to be explained by the evolution of the national homicide rate.

Table 1 shows the results of estimating equation 5 over different subsamples of media outlets. For newspapers, the coefficients on the post-period are large, negative, and statistically significant for all the measures, confirming much lower crime news coverage by newspapers after the policy. This reduction is large and around 13% and 30% of

[10] Similar results are obtained if I use the number of homicides in the country per 100,000 inhabitants or the monthly change in the homicides rate.

the average amount of the crime news measures in the pre-period. The change over the pre-mean for the *Narco News* measure is slightly higher than the change for the *Crime News* measure, suggesting that within crime-related news the emphasis in drug-related news is decreasing.

Next, I compare the magnitude of the reduction of crime news coverage relative to the pre-mean level across Agreement and non-Agreement newspapers. I expect a higher reduction for Agreement versus non-Agreement newspapers if the policy, rather than other factors, are driving this decline. As shown, the reduction in crime news coverage tends to be larger for Agreement versus non-Agreement newspapers, suggesting that the policy is driving the effect, but that non-Agreement media nevertheless were affected by the Agreement.[11]

Turning to radio channels, the coefficients on the post-period are large, negative, and statistically significant for all the measures of crime news coverage for the full sample of radio channels. This suggests a reduction in the coverage of crime of 59% and 68% of the average amount of the crime news measures in the pre-period. Again, the reduction in crime news coverage tends to be larger for the Agreement subsample versus the non-Agreement subsample of radio channels.

For television, all coefficients on the post-period are large, negative, but only statistically significant for the *Use of Prohibited Words* measure and marginally significant for the *Narco News* measure (p-value .056). Although the reduction in crime news coverage seems to be restricted to drug-related news that use the jargon of criminals, this reduction is large and of around 54% of the average amount of this measure in the pre-period.

The three measures that I analyze include news items reporting about crime events in a positive, mixed, or negative form. Given a constant number of crime-related news items, a different tone in a crime story can have a different impact on crime perceptions. I investigate this issue by manually classifying into positive, mixed, and negative tone the manually classified crime-related items in the sample described in appendix A.1. In particular, I classify as positive all crime-related news items covering accomplishments on crime (i.e. fewer murders, police solve a crime, etc.); as mixed, all news items that inform about solving a crime and about crimes perpetrated by individuals; and as negative, news items covering a crime story. The result of this exercise shows that 93.4%, 86.4%, and 82% of the newspaper, radio, and broadcast television crime-related news items have either a negative or mixed tone, suggesting that the drop in the measures of crime news coverage that I document above is driven by a drop in negative news.[12] Appendix A.4

[11] Yet only the coefficient on an interaction term for Agreement newspapers and the post-period added to specification in equation 5 is marginally significant for the *Crime News* measure (p-value 0.068).

[12] For broadcast television, which has the highest proportion of positive crime news with respect to any other type of media (18%), a t-test on the difference in the proportion of positive crime-related news items in pre and post-policy period shows an increase in the fraction of crime-related news items with positive tone in the post-period (p-value is 0.012). This suggests that even if I don't find a decrease in

gives examples of news items in each category and details of its distribution across the pre and post-policy period for each type of media.

Taken together, these results suggest that crime news coverage fell after the Agreement. A potential concern is that media outlets are only substituting the words they use to report violent news rather than decreasing the coverage of crime. If this is the case, the decrease in crime news coverage documented by the automated text analysis measures would be partially reflecting that substitution. To address this issue, in Appendix A.5 I show that the above patterns hold using a random sample of manually classified news items and using other measures of coverage of crime (i.e., the fraction of crime-related news items as a proportion of total news items and narco-related news items as a proportion of crime-related news decrease after the Agreement).

Finally, throughout this section, I examine the effect of the Agreement on the evolution of crime news coverage after the announcement of the policy. However, the content analysis results that I present and interviews with academics in charge of monitoring the compliance of the Agreement suggest that media content might have changed before the announcement date. I explore this issue in more detail in section 7 of the paper.

5 Crime Perceptions and Behavior

Given that I have shown that the Agreement is associated with a decline in crime reporting, I turn to the second part of my empirical analysis, where I estimate the effect of this change in content on crime perceptions and crime avoidance behavior. In this section, I explain the data and empirical strategy I use to estimate this effect.

5.1 Data

To study the monthly evolution of crime perceptions, I use the Survey on the Perception of Public Safety (ECOSEP-monthly dataset from here onwards) conducted from April 2009 to September 2012. This is a rotating panel survey containing one person per household age 18 or older.[13] This survey is designed to be representative of the 32 metropolitan areas in the country (one in each state), and includes questions on the respondent's perception of the crime level and other sociodemographic characteristics. From this survey, I use two crime perception measures: Personal Crime Perception and Country Crime Perception. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel

the *Crime News* measure, I do find a change in the intensive margin.

[13]Each household is in the sample for eight months. In the first stage, the household is in the sample for four consecutive months, but then it rests eight months. Then that household is once again in the sample for a second and final stage, which lasts four months.

today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". Similarly, Country Crime Perception is an index constructed from answers to the question: "How do you consider security in the country today as compared to 12 months ago?" The coding of this question is the same as the Personal Crime Perception index.

I complement the monthly dataset with cross-sectional annual data for 2009 and 2010 from the National Survey on Insecurity (ENSI) and for 2011 to 2013 from the National Survey of Victimization and Perception of Public Safety (ENVIPE). Both sets of surveys are administered to people age 18 or older and are designed to be representative at the national, urban national, rural national, and state level.[14] They contain information on the respondent's perception of public safety, the victimization experience of all individuals in the household, and some respondent's behavioral responses due to the fear of being a victim of crime. In 2010, the survey also collects information on the frequency at which an individual watches, listens, or reads news: daily (30), three times per week (12), once a week (4), once a month (1), or never (0). From the annual surveys, I use two crime perception measures: Crime Perception State and Crime Perception Municipality. Crime Perception State (Municipality) is dummy equal to 1 if the answer to the question: "Do you think living in your State (Municipality) ...?" is "Insecure" and equal to 0 if the answer is "Secure". In addition, I analyze a particular behavior associated with the fear of being a victim of crime: no longer going out at night. Individuals are asked: "For fear of being a victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" This measure is equal to 1 if the answer is "Yes" and 0 if the answer is "No".

Finally, I use a bi-annual dataset for 2008-2012 from the AmericasBarometer by the Latin American Public Opinion Project (LAPOP). In this national survey, individuals are asked: "in your opinion, what is the most serious problem of the country?" Crime Concern is a dummy equal to 1 if the answer is crime, drug trafficking, kidnapping, violence or insecurity; and 0 otherwise.

State-level and municipality-level varying characteristics on homicides, unemployment, industrial index, taxes, and GDP are from the National Institute of Statistics and Geography (INEGI). The homicide data are drawn from vital statistics compiled by state government authorities. Population and immigration estimates are from Mexico's National Population Council (CONAPO).

[14] Table B.8 contains detailed information on the survey months and the comparability among the annual and monthly surveys.

5.2 Empirical Strategy

My main estimation strategy follows the same logic as a standard difference-in-difference strategy. I compare the relative change in crime perceptions and avoidance behavior in the post-policy period (when the Agreement was announced) relative to the pre-policy period across individuals with different "treatment intensities". The main differences between my estimates and a standard DD strategy is that I use a continuous measure of treatment intensity and that my treatment intensity measure is a predicted value rather than an observed value.[15]

In my basic estimation strategy, I use a two step procedure. In the first step, I compute a "treatment intensity"' using the frequency of media consumption observed in the annual survey in 2010. Particularly, I estimate a linear regression of the form:

$$Y_{is} = \alpha' X_{is} + u_{is} \tag{6}$$

where Y_{is} is the frequency at which an individual i in state s watches, listens, or reads news. X_{is} is a vector of individual controls that include sex, age, a quadratic in age, educational background, occupational status, an urban dummy, and state dummies. I define $treatment\_intensity_{is} = \hat{\alpha'} X_{is}$. A higher value of the treatment intensity variable corresponds to a higher frequency of news consumption. Tables B.9 and B.10 in the appendix show the results of this regression.[16] Overall, being male, having a higher level of education, living in an urban area, and not working are associated with a higher treatment intensity.

In the second step of my empirical strategy, I use a difference-in-difference design using this predicted "treatment intensity". The primary regression estimated with the crime perceptions monthly data is the following:

$$\begin{aligned} CrimePerception_{ism} = \beta_{0s} + \beta_1 treatment\_intensity_{ism} + \\ \beta_2 post \times treatment\_intensity_{ism} + \delta W'_{ism} + \lambda_{sm} + \epsilon_{ism} \end{aligned} \tag{7}$$

where $CrimePerception_{ism}$ denotes the outcome for individual i in the metro area of state s in month m. β_{0s} is a metro area-specific intercept. The variable $treatment\_intensity_{ism}$ is equal to $\hat{\alpha'_{2010}} X_{ism}$, where $\hat{\alpha'_{2010}}$ are the coefficients estimated with the annual sample in 2010 and X_{ism} are the individual characteristics defined above. The term *post* is a dummy equal to 1 for months after the announcement date (March 2011). W'_{ism} is a vector of individual-level controls that includes dummies for type of occupation, economic activity, and monthly income. These controls exclude the variables in X_{is}. λ_{sm}

[15] Nunn and Qian (2011); Card (1992)are some papers that have used a similar approach.

[16] The specification in table B.10 is implemented in the bi-annual dataset due to differences in the measures of education background.

are month-year-metro area dummies that capture common shocks per month such as the level of crime. Since I'm controlling for metro area dummies, identification comes from comparing changes in individuals with different treatment intensities before and after the policy within metro-areas as opposed to average changes across metro-areas. The coefficient of interest $\hat{\beta}_2$ measures the additional change in the outcome of interest experienced by individuals whom more frequently watch, listen, or read news (relative to those who do so less frequently) after the policy was announced (relative to before). $\hat{\beta}_2$ captures the reduced form effect of the Agreement under the following assumptions: i) the model in equation 7 is correctly specified; ii) the error term is on average zero; and iii) the error term is uncorrelated with the other variables in the equation, in particular, $cov(\epsilon_{ism}, treatment\_intensity_{ism} \times post) = 0$. That is, there is no other policy that could have differentially affected individuals with different "treatment intensities" conditional on the controls defined by the model. I discuss this in more detail below.

I also study two other specifications. The first replaces the $treatment\_intensity_{ism}$ variable in equation 7 by a dummy variable equal to 1 for individuals above median treatment intensity. I use this specification to operationalize a simple counterfactual in which I set the key coefficient (β_2) equal to zero to see how crime perceptions would have evolved, according to my model, if media had not have affected perceptions. The second specification exploits the rotating panel structure of the data by including household fixed effects in equation 7. Since usually the same individual is interviewed in the household this is equivalent to having individual fixed effects. This specification controls for any household time-invariant characteristics that could bias the results, for example, the risk of crime in the neighborhood, providing further evidence that the effects observed are driven by the policy.[17]

The primary regression estimated with the annual data is similar to the monthly estimation, but exploits the availability of municipality level identifiers:

$$\begin{aligned} Outcome_{icy} = \beta_{0c} + \beta_1 treatment\_intensity_{icy} + \\ \beta_2 post \times treatment\_intensity_{icy} + \delta W'_{icy} + \gamma Z'_{cy} + \lambda_y + \epsilon_{icy} \quad (8) \end{aligned}$$

where $Outcome_{icy}$ denotes the outcome for individual i in municipality c in survey year y. β_{0c} is a municipality-specific intercept. As defined above, $treatment\_intensity_{icy}$ is equal to $\widehat{\alpha'_{2010}} X_{icy}$. The term *post* is a dummy equal to 1 for survey years 2011 to 2013. W'_{icy} is a vector of individual controls that includes dummies for type of occupation, number of vehicles per household as a proxy for income, number of individuals living in the same dwelling, and victimization risks controls. Z'_{cy} is a vector of municipality-

[17]Identification in this specification comes from households that are interviewed in both the pre and the post-policy period. Due to the rotating panel nature of my dataset, this implies that 35% of the sample identifies my effect of interest. Appendix figure C.1 shows the distribution of the fraction of periods in the post-policy period of individuals in the monthly data.

varying controls that includes the number of homicides in the municipality c one calendar year before survey year y and income taxes raised at the municipality level as a proxy for the municipality's GDP. λ_y are year dummies. In this specification, I am comparing changes in individuals with different treatment intensities before and after the policy within municipalities.

Finally, the regression estimated with the bi-annual data is the following:

$$Outcome_{icy} = \beta_{0s} + \beta_1 treatment\_intensity_{icy} + \beta_2 post \times treatment\_intensity_{icy} + \delta W'_{icy} + \gamma Z'_{cy} + \lambda_y + \epsilon_{icy} \quad (9)$$

where $Outcome_{icy}$ denotes the outcome for individual i in municipality c in survey year y. β_{0s} is a state-specific intercept. $treatment\_intensity_{icy}$ is equal to $\widehat{\alpha'_{2010}} X_{icy}$. The term *post* is a dummy equal to 1 for 2012. W'_{icy} is a vector of individual controls that include the number of vehicles per household, dummies for the availability of durable goods (i.e., television, refrigerator, phone, cellphone, washing machine, etc.) as proxies for income, and a dummy equal to one if the individual has been a victim of crime. Z'_{cy} is a vector of municipality-varying controls that includes the average number of homicides in the municipality c twelve months before the survey date and income taxes. λ_y are year dummies.

The coefficient $\hat{\beta}_2$ in both the annual and bi-annual specification captures the reduced form effect of the Agreement under similar assumptions as above, but conditional on the controls defined by their respective equations. In all specifications, standard errors are bootstrapped to account for the fact that the treatment intensity variable is an estimated regressor.

6 Results: Crime Perceptions and Behavior

I start by analyzing the effects of the Agreement on crime perceptions. Figures 6 and 7 a) show the monthly evolution of personal and country crime perceptions broken down by individuals that are above and below median treatment intensity. The vertical line corresponds to the announcement of the Agreement. Personal and country crime perceptions tend to be higher for individuals with higher treatment intensities in the pre-policy period, but crime perceptions fall relatively more for the more intensely treated individuals after the policy. Figures 6 and 7 b) show the fitted values of the model defined by equation 7 of the main text but with the $treatment\_intensity_{ism}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity.[18] Figures 6 and 7 c) simulate a counterfactual in which I set the key coefficient (β_2) equal to zero

[18] Appendix table B.11 shows the results of this specification.

to see how crime perceptions would have evolved, according to my model, if media had not have affected perceptions. As shown, the gap between both treated and non-treated individuals would have been more or less constant if media had not affected perceptions: this gap would not have closed as it is observed with the fitted values. Finally, while the model in figure 6 b) replicates well the patterns of the data, the evolution of country crime perceptions (figure 7 a) suggests that the convergence of crime perceptions across individuals with different treatment intensities happens several months after the policy comes into effect, which is not captured by figure 7 b). I explore this issue in more detail in section 7 of the paper.

Table 2 turns to the results from the difference-in-difference regression of the form in equation 7. Columns (1) and (3) show the crime perceptions results, which are consistent with the previous graphs. The effect of the policy is negative and statistically significant. In terms of the magnitudes, the effect is large: a one standard deviation increase in the treatment intensity yields a .66 standard deviation decrease in the personal crime perception and a .38 standard deviation decrease in the country crime perception index. Columns (2) and (4) add household fixed effects to equation 7. The coefficient of interest is negative and significant for both the personal and country crime perception measures.

I provide additional evidence on the impact of the Agreement on crime perceptions using the cross-sectional annual datasets. The annual datasets have some advantages relative to the monthly data. First, these surveys provide information on both rural and urban households, rather than only highly urban metro areas, which is valuable for checking if crime perception results are valid in a more general context. Second, they include information on individual and household victimization risks. By controlling for these variables, I alleviate the possible concern that groups with different treatment intensities might have differential victimization risks. Third, they also include information on avoidance behavior. Thus, I can analyze the effect of the Agreement on both crime perceptions and avoidance behavior.

Figures 8 and 9 mimic the format of figures 6 and 7 and show the effects of the Agreement on state and municipality crime perceptions. Although the annual data are noisier, I see roughly the same pattern. State and municipality crime perceptions tend to be higher for individuals with higher treatment intensities in the pre-policy period (2009-2010), and the difference between the two types of individuals decreases after the policy. Again, similar counterfactuals as those done with the monthly data, show that the gap between both treated and non-treated individuals would have been more or less constant, according to my model, if media had not have affected perceptions.[19]

Table 3 turns to the results from the difference-in-difference regression of the form in

[19] Results of this specification are shown in appendix table B.12.

equation 8. Columns (2) and (4) show the perceptions results, which are consistent with the previous graphs. The effect of the policy is negative and statistically significant. In terms of the magnitudes, the effect is quite large: a one standard deviation increase in the treatment intensity yields a .43 standard deviation decrease in the state crime perception index and a .54 standard deviation decrease in the municipality crime perception index. Columns (1) and (3) show that results aren't sensitive to the exclusion of victimization risk controls, which documents that the results of the monthly specification are robust. Additionally, table B.13 of the appendix shows that the crime perceptions results are robust to the inclusion of municipality-year fixed effects, which controls for any type of differential trends across municipalities.

Finally, table 4 shows that a similar pattern is found using the bi-annual dataset. Additionally, column (1) and (3) show that the coefficient is robust to the use of short-term versus long-term homicides controls i.e., the average monthly number of homicides in the municipality one month before the survey date versus the average monthly number of homicides in the municipality three years before the survey date.

Having established that the policy changed crime perceptions and the crime concern at the national level, and not only for the metro areas represented in the monthly data, I turn to the effects of the policy on a particular behavior: no longer going out at night for fear of being a victim of crime. I look at this measure because is, perhaps, the most likely place to see an effect of a policy aimed at reducing coverage of drug violence. According to a national survey Benítez Manaut (2012), 61% of Mexicans say they no longer go out at night because they worry about being victims of drug trafficking violence. Figure 10 imitates the format of the state and municipality crime perception figures. Consistent with those, individuals with higher treatment intensities are more likely to report they no longer go out at night because of fear of being victims of crime. However, in contrast with the crime perception measures the difference between the two types of individuals doesn't decrease after the policy (2011 and 2012 in the figures).

Table 11 shows the results from the difference-in-difference regression of the form in equation 8. Although the coefficient is positive, it isn't statistically significant. In terms of the magnitudes, I'm not able to reject a negative coefficient as big as .012 of a standard deviation, which is much smaller than the effect in perceptions. That is, although the policy decreased crime perceptions, this was not accompanied by changes in behavior.

7 Robustness Checks

7.1 Testing for Structural Break in *Use of Prohibited Words*

My estimation strategy in section 5 examines the reduced form effect of the Agreement on crime perceptions and avoidance behavior after the announcement of the policy in March 2011. As explained above, interviews with academics in charge of monitoring the compliance of the Agreement suggest that media content might have changed before the announcement.

To address this issue, I examine whether any shift in the number of news using words prohibited by the policy seems to correspond to the announcement date (*Use of Prohibited Words* measure as defined in section 4).

More concretely, using methods analogous to those from the econometrics literature on unknown structural breaks, I locate for the pooled sample of media outlets the single break in *Use of Prohibited Words* for which the model best fits the data.[20]

I estimate the following model for all possible break dates j and choose the date that minimizes the sum of squared residuals:

$$Use\ of\ Prohibited\ Words_{cm} = \beta_{0c} + \beta_1 \mathbb{1}(m \geq j) + \beta_2 hom_m + \beta_3 sport_{cm} + \alpha_s + \epsilon_{cm} \quad (10)$$

where $\mathbb{1}(m \geq j)$ is a dummy equal to 1 for months after date j. The other variables are defined as in equation 5 that formed the basis for my baseline estimator in section 4. Thus, this model generates the most likely date in which the *Use of Prohibited Words* differentially jumps from its mean once I control for possible determinants of this variable.

To estimate the most likely break date, I use news between January 2009 and April 2013.[21] As shown in figure C.2 of the appendix the sum of squared residuals for the subsample of Agreement media outlets is minimized by choosing February 2011, one month before the announcement of the Agreement, as the break date. Choosing May 2011 as the break date minimizes the model for the full sample of media outlets. It is important to note that for the full sample of media outlets, the figure shows a local minima around the announcement date.[22]

[20] See Hansen (2001) for a review of the literature on testing for structural breaks.

[21] Following standard techniques, I trim 15% of the observations on each side and thus allow for all possible break dates between September 2009 and August 2012, for a total of 36 months.

[22] As shown by table B.14 both coefficients capturing the size of the break (β_1) are significant at conventional levels.

7.2 The Impact of the Agreement with Alternative cut-offs

Having established that the break in *Use of Prohibited Words* occurred within a window of 4 months from February to May 2011, I evaluate the sensitivity of my results to alternative cut-offs.

For the crime perceptions monthly data, I estimate the baseline specification from equation 7 at each of the two possible break dates, defining the post-policy period as the months after each of the break dates. Panel A of Table 5 reports estimates for the Agreement sample break date in February 2011 with a post indicator variable that equals 1 for March 2011 onwards.[23] While Panel B report estimates for break date of the full sample of media outlets. I find negative and statistically significant coefficients for $post \times treatment\_intensity$ in all specifications.

For the annual data, I estimate the baseline specification from equation 8 defining the post-policy period as the 2012 and 2013 survey years, instead of 2011-2013. Survey interviews for 2011 occurred between March 14th and April 22nd of 2011. Thus, in this specification, I'll be capturing the effects of the policy after the estimated full sample break-date (in May 2011). I find negative and statistically significant coefficients for $post \times treatment\_intensity$ in the crime perceptions specification (table 6) and again, no effect on avoidance behavior (table 12). The effects are also less negative than those in the baseline specification.

7.3 Flexible Estimates. Monthly Data

The evolution of the country crime perception measure in figure 7 a) of the paper suggests a delayed effect of the policy. To examine whether this is the case, I estimate a fully flexible estimating equation that takes the following form:

$$CrimePerception_{ism} = \beta_{0s} + \beta_1 treatment\_intensity_{ism} + \sum_{m=May2009}^{Sept2012} \beta_m month \times treatment\_intensity_{ism} + \delta W'_{ism} + \lambda_{sm} + \epsilon_{ism} \quad (11)$$

where all variables are defined as in equation 7. The only difference from equation 7 is that in this equation, rather than interacting the treatment intensity variable with a post-announcement indicator, I interact the treatment intensity variable with each of the time period fixed effects. That is, *month* is a dummy equal to 1 for each month in the period

[23] In this specification, if this break date is accurately identifying the break in content, all of the years in the post-period coincide with the post-policy period. Therefore, I expect the estimates to capture all of the effects of the Agreement, and to be equal (if the effects of the change in content take time to materialize or if there's no effect at all) or larger than the estimates in Panel B which capture only some of the effects of the policy. Results are consistent with this hypothesis.

I study. Figure 11 plots the point estimates of β_m and the bootstrapped 95% confidence intervals for the personal and country crime perceptions measures. These coefficients must be measured relative to the baseline time-period, or omitted month which I take to be April 2009. Consistent with the data, this model suggests a discontinuity in the pattern for the personal crime perception measure around the time the policy was announced, while the country crime perception measure suggests a discontinuity several months after the policy was implemented. Since the point estimates of the coefficients are more or less stable in the pre-period, this test provides some evidence of no existing pre-trends in the monthly data, which I corroborate in the following subsection.

7.4 Testing for the Parallel Trends Assumption

I test statistically for the possibility of pre-trends by using a "placebo test". More concretely, for the monthly data, I estimate the baseline specification from equation 7 using a window of 16 months from April 2009 to July 2010, defining the last eight months as the "placebo" post-policy period. As shown in table 7, not only the coefficient estimates for $post \times treatment\_intensity$ are not statistically significant, but the point estimates are very small, and in most cases are statistically different from the effect of the Agreement (i.e estimated at any cut-off), so we can reject that any changes observed after the policy was in effect are the continuation of preexisting trends.

For the annual data, I estimate the baseline specification from equation 12 using survey years 2009 and 2010, defining 2010 as the "placebo" post-policy period. As shown in table 8, the parallel trends assumption is violated. Since the coefficients are positive, the evidence indicates that in relative terms, crime perceptions were increasing for individuals with higher treatment intensities, the opposite of what I would be concerned with. However, this raises concerns about the ability of the difference-in-difference strategy to produce unbiased estimates of the policy. To address this concern, I also include a separate time trend for different levels of treatment intensity by estimating:

$$Outcome_{icy} = \beta_{0c} + \beta_1 f(t) + \beta_2 f(t) * treatment\_intensity_{icy} + \beta_3 treatment\_intensity_{icy} + \beta_3 post + \beta_5 post \times treatment\_intensity_{icy} + \delta W'_{icy} + \gamma Z'_{cy} + \epsilon_{icy} \quad (12)$$

where $f(t)$ is a third degree polynomial in time $(t + t^2 + t^3)$. The rest of the terms are equal to the baseline specification in equation 8. As shown in table 10, the estimated effects get more negative when I include group-specific time trends, and in all specifications, except for the behavior data, coefficients are statistically different from zero. However, we should be cautious in interpreting these results since there are only two periods of pretreatment data that are used to pin down the group-specific trends.

Finally, regarding the bi-annual data, table 9 shows no evidence of pre-trends.

8 Conclusion

This paper investigates the effect of crime news coverage on crime perceptions and avoidance behavior in the context of Mexico. I find that the Agreement on the Coverage of Violence in March 2011 signed by major media groups is associated with a decrease in crime news coverage, measured as the number of monthly news items on a channel/newspaper using any of the words the Agreement suggested avoiding. I also find that crime perceptions respond to these changes in media content. Individuals with higher treatment intensity (i.e. with a higher frequency of news consumption) are less likely to report that they feel insecure and that their country, state, or municipality is insecure relative to individuals with lower treatment intensity following the Agreement. Despite the large effects in crime perceptions, these changes are not accompanied by decreases in avoidance behavior, or at least the effects are much smaller than the effects on crime perceptions.

Taken together, these results demonstrate that the frequent presentation of violence in the media does make individuals more fearful, but that individuals do not necessarily respond to this fear by changing avoidance behavior. Yet, another type of behaviors might respond to these changes in crime perceptions. Exploring the potential implications of these changes in crime perceptions for voting behavior are left for future work.

Given my focus on the Mexican context and the type of violence portrayed in the news, a key question involves the generalizability of my results. However, this situation is, in fact, common across Latin American countries, where media coverage of organized crime is a central issue in policy discussions (see Bridges (2010)). Thus, while my empirical results are derived specifically from Mexican data, the lessons to be learned from these findings are more general.

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Table 1: Crime News Coverage

Variables	Use of Prohibited Words			Crime News			Narco News		
	Full Sample	Agreement	Non-Agreement	Full Sample	Agreement	Non-Agreement	Full Sample	Agreement	Non-Agreement
Panel A				**Newspapers**					
post	-29.742***	-32.790**	-24.022**	-17.047**	-22.097**	-8.522	-21.530***	-21.047**	-21.434***
	(0.002)	(0.02)	(0.002)	(.012)	(.038)	(.388)	(.006)	(.036)	(.002)
Observations	884	468	416	884	468	416	884	468	416
R-squared	0.850	0.873	0.817	0.852	0.884	0.799	0.770	0.804	0.701
Mean Dependent-Pre	140.4	125.7	156.9	132.4	115.6	151.2	70.87	62.64	80.14
% Change over Pre-Mean	-21%	-26%	-15%	-13%	-19%	-6%	-30%	-34%	-27%
Panel B				**Radio**					
post	-74.356***	-76.789***	-53.604	-94.067***	-97.466***	-62.536	-44.885***	-46.371***	-30.018
	(0.002)	(.002)	(0.45)	(.002)	(.002)	(0.528)	(.002)	(.002)	(.506)
Observations	1,092	988	104	1,092	988	104	1,092	988	104
R-squared	0.707	0.710	0.670	0.746	0.751	0.578	0.653	0.658	0.480
Mean Dependent-Pre	109.6	112	86.52	159.3	164.3	110.9	68.28	70.11	50.81
% Change over Pre-Mean	-68%	-69%	-62%	-59%	-59%	-56%	-66%	-66%	-59%
Panel C				**Television**					
		Agreement			Agreement			Agreement	
post		-32.071***			-21.865			-14.634*	
		(0.002)			(.218)			(.056)	
Observations		520			520			520	
R-squared		0.580			0.590			0.561	
Mean Dependent-Pre		59.64			105.9			45.74	
% Change over Pre-Mean		-54%			-21%			-32%	

Notes. This table shows the coefficients on the post-period of equation 5 in the main text estimated using the full sample, or the subsample of Agreement or non-Agreement media outlets. All regressions include a channel/newspaper-specific intercept, a *post* dummy equal to 1 for months after the announcement of the Agreement, the logarithm of the number of homicides in the country per 100,000 inhabitants, the total number of monthly non-opinion news items with the word sport of channel/newspaper as proxy for number of articles, and calendar month dummies. Wild bootstrapped p-values clustered at the channel/newspaper level are reported in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 2: The Impact of the Agreement on the Coverage of Violence (ACIV) on Crime Perceptions, Monthly data

Variables	(1) Personal Crime Perception	(2) Personal Crime Perception	(3) Country Crime Perception	(4) Country Crime Perception
post×treatment_intensity	-0.010***	-0.008**	-0.006***	-0.007**
(post=1 if t>2011m3)	(0.002)	(0.004)	(0.002)	(0.004)
Observations	51,241	51,241	51,192	51,192
R-squared	0.156	0.523	0.098	0.460
Household Fixed Effects	No	Yes	No	Yes
Metro Dummies	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Month*Year*Metro	Yes	Yes	Yes	Yes
Mean Dependent	0.643	0.643	0.663	0.663
Mean Treatment Intensity	25.83	25.83	25.83	25.83

Notes. This table shows the reduced form effect of the Agreement on personal and country crime perceptions in the monthly dataset. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". Similarly, Country Crime Perception is an index constructed from answers to the question: "How do you consider security in the country today as compared to 12 months ago?". Columns (1) and (3) are estimated using the model defined in equation 7 of the main text. Columns (2) and (4) add to that specification household fixed effects. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 3: The Impact of the Agreement on the Coverage of Violence (ACIV) on Crime Perceptions, Annual data

Variables	(1) State Crime Perception	(2) State Crime Perception	(3) Municipality Crime Perception	(4) Municipality Crime Perception
post×treatment_intensity	-0.016***	-0.016***	-0.022***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	204,110	200,084	205,553	201,467
R-squared	0.121	0.136	0.126	0.158
Homicide Control	Yes	Yes	Yes	Yes
Municipality Dummies	Yes	Yes	Yes	Yes
Municipality Time Varying Controls	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Victimization Risks	No	Yes	No	Yes
Mean Dependent	0.703	0.703	0.590	0.590
Mean Treatment Intensity	24.56	24.56	24.56	24.56

Notes. This table shows the reduced form effect of the Agreement on state and municipality crime perceptions in the ENSI and ENVIPE datasets. Crime Perception State (Municipality) is dummy equal to 1 if the answer to the question: "Do you think living in your State (Municipality) ...?" is "Insecure" and equal to 0 if the answer is "Secure". All regressions include the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for survey years equal or after the announcement date (i.e. 2011-2013); individual controls that include dummies for type of occupation, number of individuals living in the household and number of cars owned; taxes collected at the municipality level as a proxy for municipality's income; municipality and year dummies. Columns (2) and (4) include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 4: The Impact of the Agreement on the Coverage of Violence (ACIV) on Crime Perceptions, Bi-annual data

Variables	(1) Crime Concern	(2) Crime Concern	(3) Crime Concern
post×treatment_intensity	-0.019***	-0.018**	-0.017**
	(0.007)	(0.007)	(0.007)
Observations	4,653	4,653	4,653
R-squared	0.074	0.074	0.075
Homicide control	hom_lag1	hom_lag12	hom_lag36
Municipality Time-Varying Controls	Yes	Yes	Yes
Individual Controls & Victimization Risks	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes

Notes. This table shows the reduced form effect of the Agreement on Crime Concern in the bi-annual dataset. Crime Concern is a dummy equal to 1 if the answer to the question "in your opinion, what is the most serious problem of the country?" is either crime, drug trafficking, kidnapping, violence or insecurity; and 0 otherwise. All regressions include a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for 2012; individual controls that include the number of vehicles per household, dummies for the availability of durable goods (i.e., television, refrigerator, phone, cellphone, washing machine, etc.), and a dummy equal to one if the individual has been a victim of crime; taxes collected at the municipality level and year dummies. hom_lag1, hom_lag12, and hom_lag36 are the average monthly number of homicides in the municipality one, twelve, and three years before the survey date. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 5: The Impact of the Agreement on the Coverage of Violence (ACIV) on Crime Perceptions with Alternative cut-offs, Monthly data

Variables	(1) Personal Crime Perception	(2) Country Crime Perception
Panel A Break Agreement		
post×treatment_intensity	-0.010***	-0.005**
(post=1 if t>2011m2)	(0.002)	(0.002)
Observations	51,241	51,192
R-squared	0.156	0.098
Panel B Break Full Sample		
post×treatment_intensity	-0.008***	-0.006***
(post=1 if t>2011m5)	(0.002)	(0.002)
Observations	51,241	51,192
R-squared	0.155	0.098
Household Fixed Effects	No	No
Metro Dummies	Yes	Yes
Individual Controls	Yes	Yes
Month*Year*Metro	Yes	Yes
Mean Dependent	0.643	0.663
Mean Treatment Intensity	25.83	25.83

Notes. This table shows the reduced form effect of the Agreement on personal and country crime perceptions in the monthly dataset. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". Similarly, Country Crime Perception is an index constructed from answers to the question: "How do you consider security in the country today as compared to 12 months ago?". All regressions are estimated using the model defined in equation 7 of the main text, but with the *post* variable being a dummy equal to 1 as explained in the table. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 6: The Impact of the Agreement on the Coverage of Violence (ACIV) on Crime Perceptions with Alternative cut-offs, Annual data

Variables	(1) State Crime Perception	(2) Municipality Crime Perception
post×treatment_intensity	-0.012***	-0.015***
(post=1 if t>=2012)	(0.002)	(0.002)
Observations	200,084	201,467
R-squared	0.135	0.157
Homicide Control	Yes	Yes
Municipality Dummies	Yes	Yes
Municipality Time Varying Controls	Yes	Yes
Individual Controls	Yes	Yes
Year Dummies	Yes	Yes
Victimization Risks	Yes	Yes
Mean Dependent	0.703	0.590
Mean Treatment Intensity	24.56	24.56

Notes. This table shows the reduced form effect of the Agreement on crime perceptions in the annual dataset. All regressions include the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for survey years 2012 and 2013; individual controls that include dummies for type of occupation, number of individuals living in the household, and number of cars owned; victimization risk controls include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality and year dummies.

Table 7: Testing for the Parallel Trends Assumption, Monthly data

Variables	(1) Personal Crime Perception	(2) Country Crime Perception
post×treatment_intensity	0.001	0.000
	(0.003)	(0.003)
Observations	19,978	19,959
R-squared	0.129	0.091
Household Fixed Effects	No	No
Metro Dummies	Yes	Yes
Individual Controls	Yes	Yes
Month*Year*Metro Dummies	Yes	Yes
Mean Dependent	0.641	0.662
Mean Treatment Intensity	25.79	25.79

Notes. This table tests the parallel trends assumption in the monthly dataset. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". Similarly, Country Crime Perception is an index constructed from answers to the question: "How do you consider security in the country today as compared to 12 months ago?" Both regressions are estimated using a window of 16 months from April 2009 to July 2010 and define the later eight months as the "placebo" post-policy period. Both are estimated using the model specified in equation 7 of the main text. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 8: Testing for the Parallel Trends Assumption, Crime Perceptions-Annual data

Variables	(1) State Crime Perception	(2) Municipality Crime Perception
post×treatment_intensity	0.019***	0.010**
	(0.003)	(0.003)
Observations	63,599	64,077
R-squared	0.159	0.203
Homicide Control	Yes	Yes
Municipality Dummies	Yes	Yes
Municipality Time Varying Controls	Yes	Yes
Year Dummies	Yes	Yes
Individual Controls	Yes	Yes
Victimization Risks	Yes	Yes
Mean Dependent	0.667	0.523
Mean Treatment Intensity	24.61	24.61

Notes. This table tests the parallel trends assumption in the annual dataset. All regressions are estimated using the years 2009 and 2010 and define 2010 as the "placebo" post-policy period. All regressions include the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 in 2010; individual controls that include dummies for type of occupation, number of individuals living in the household, and number of cars owned; victimization risk controls that include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality and year dummies.

Table 9: Testing for the Parallel Trends Assumption, Crime Perceptions-Bi-annual data

Variables	(1) Crime Concern	(2) Crime Concern	(3) Crime Concern
post×treatment_intensity	-0.010	-0.011	-0.012
	(0.008)	(0.008)	(0.008)
Observations	3,112	3,112	3,112
R-squared	0.096	0.095	0.095
Homicide control	hom_lag1	hom_lag12	hom_lag36
Municipality Time-Varying Controls	Yes	Yes	Yes
Individual Controls & Victimization Risks	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes

Notes. This table tests the parallel trends assumption in the bi-annual dataset. All regressions are estimated using the years 2008 and 2010 and define 2010 as the "placebo" post-policy period. All regressions include a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; individual controls that include the number of vehicles per household, dummies for the availability of durable goods (i.e., television, refrigerator, phone, cellphone, washing machine, etc.), and a dummy equal to one if the individual has been a victim of crime; taxes collected at the municipality level and year dummies. hom_lag1, hom_lag12, and hom_lag36 are the average monthly number of homicides in the municipality one, twelve, and three years before the survey date. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 10: Robustness: The Impact of the Agreement with group-specific time trends. Crime Perceptions-Annual data

	(1)	(2)	(3)	(4)
Variables	State Crime Perception		Municipality Crime Perception	
post×treatment_intensity	-0.016***	-0.036***	-0.022***	-0.034***
	(0.002)	(0.005)	(0.002)	(0.005)
Observations	200,084	200,084	201,467	201,467
R-squared	0.136	0.137	0.158	0.158
Homicide Control	Yes	Yes	Yes	Yes
Municipality Dummies	Yes	Yes	Yes	Yes
Municipality Time Varying Controls	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes
Victimization Risks	Yes	Yes	Yes	Yes
Flexible Time Trend	Yes	Yes	Yes	Yes
Flexible Time Trend per Treatment	No	Yes	No	Yes
Mean Dependent	0.703	0.703	0.590	0.590
Mean Treatment Intensity	24.56	24.56	24.56	24.56

Notes. This table shows the reduced form effect of the Agreement on crime perceptions in the ENSI and ENVIPE datasets using group-specific time trends. Crime Perception State (Municipality) is dummy equal to 1 if the answer to the question: "Do you think living in your State (Municipality) ...?" is "Insecure" and equal to 0 if the answer is "Secure". All regressions include the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for survey years equal or after the announcement date (i.e. 2011-2013); individual controls that include dummies for type of occupation, number of individuals living in the household and number of cars owned; victimization risk controls that include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality fixed effects and a cubic time trend. Columns (2) and (4) include a group-specific cubic time trend. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 11: The Impact of the Agreement on the Coverage of Violence (ACIV) on Behavior, Annual data

Variables	(1) No longer going out at night
post×treatment_intensity	0.004
	(0.002)
Observations	193,349
R-squared	0.118
Homicide Control	Yes
Municipality Dummies	Yes
Municipality Time Varying Controls	Yes
Individual Controls	Yes
Year Dummies	Yes
Victimization Risks	Yes
Mean Dependent	0.511
Mean Treatment Intensity	24.56

Notes. This table shows the reduced form effect of the Agreement on the variable no longer going out at night in the annual dataset. No longer going out at night is a dummy equal to 1 if the answer to the question "For fear of being victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" is "Yes" and 0 if the answer is "No". The regression includes the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for survey years equal or after the announcement date (i.e. 2011-2013); individual controls that include dummies for type of occupation, number of individuals living in the household, and number of cars owned; victimization risk controls include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality and year dummies. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table 12: The Impact of the Agreement on the Coverage of Violence (ACIV) on Behavior with Alternative cut-offs

Variables	(1) No longer going out at night
post×treatment_intensity	0.002
(post=1 if t>=2012)	(0.002)
Observations	193,349
R-squared	0.118
Homicide Control	Yes
Municipality Dummies	Yes
Municipality Time Varying Controls	Yes
Individual Controls	Yes
Year Dummies	Yes
Victimization Risks	Yes
Mean Dependent	0.511
Mean Treatment Intensity	24.56

Notes. This table shows the reduced form effect of the Agreement on behavior in the annual dataset. The regression includes the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal for survey years 2012 and 2013; individual controls that include dummies for type of occupation, number of individuals living in the household, and number of cars owned; victimization risk controls include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality and year dummies.

Table 13: Testing for the Parallel Trends Assumption, Behavior

Variables	(1) No longer going out at night
post×treatment_intensity	0.008**
	(0.003)
Observations	61,964
R-squared	0.122
Homicide Control	Yes
Municipality Dummies	Yes
Municipality Time Varying Controls	Yes
Year Dummies	Yes
Individual Controls	Yes
Victimization Risks	Yes
Mean Dependent	0.465
Mean Treatment Intensity	24.61

Notes. This table tests the parallel trends assumption in the annual dataset. The regression is estimated using the years 2009 and 2010 and define 2010 as the "placebo" post-policy period. The regression includes the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 in 2010; individual controls that include dummies for type of occupation, number of individuals living in the household, and number of cars owned; victimization risk controls that include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality and year dummies.

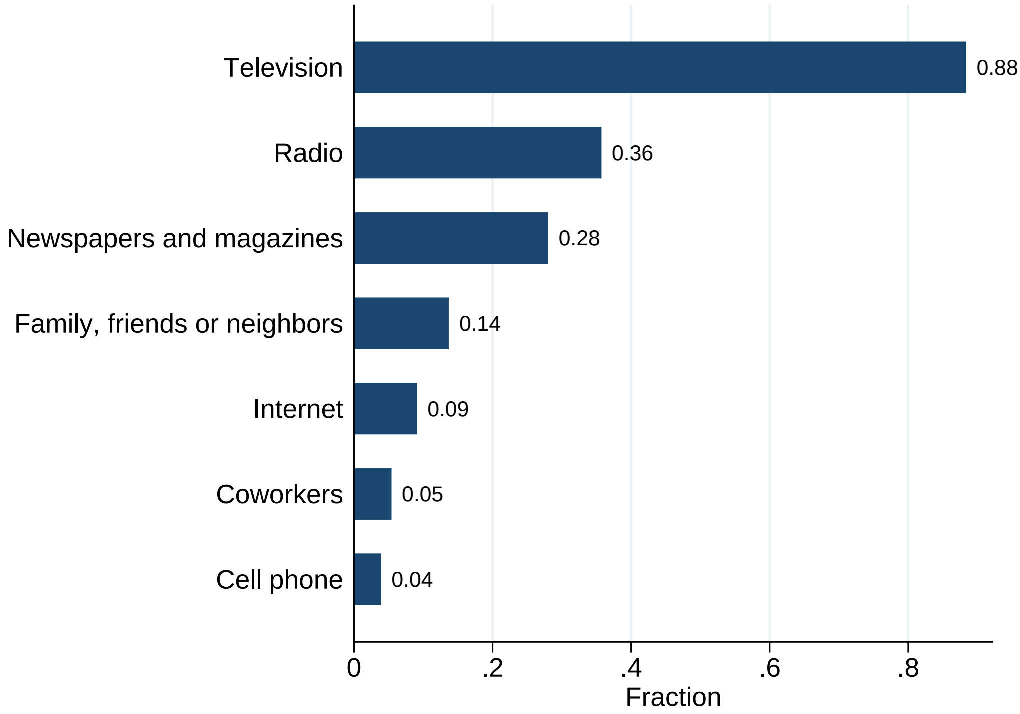
Table 14: Robustness: The Impact of the Agreement with group-specific time trends. Behavior

Variables	(1)	(2)
	No longer going out at night	
post×treatment_intensity	0.004	-0.001
	(0.002)	(0.005)
Observations	193,349	193,349
R-squared	0.118	0.118
Homicide Control	Yes	Yes
Municipality Dummies	Yes	Yes
Municipality Time Varying Controls	Yes	Yes
Individual Controls	Yes	Yes
Victimization Risks	Yes	Yes
Flexible Time Trend	Yes	Yes
Flexible Time Trend per Treatment	No	Yes
Mean Dependent	0.511	0.511
Mean Treatment Intensity	24.56	24.56

Notes. This table shows the reduced form effect of the Agreement on behavior in the ENSI and ENVIPE datasets using group-specific time trends. No longer going out at night is a dummy equal to 1 if the answer to the question "For fear of being victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" is "Yes" and 0 if the answer is "No". All regressions include the lagged number of homicides in the municipality; a $treatment\_intensity_{icy}$ variable defined in equation 6 of the main text; a *post* dummy equal to 1 for survey years equal or after the announcement date (i.e. 2011-2013); individual controls that include dummies for type of occupation, number of individuals living in the household and number of cars owned; victimization risk controls that include a full set of dummies for whether any individual in the household has been a victim of crime, if the individual has heard or knows if near his dwelling someone sells drugs, consumes drugs, or there have been frequent shootings; taxes collected at the municipality level are used as a proxy for municipality's income; municipality fixed effects and a cubic time trend. Column (2) includes a group-specific cubic time trend. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

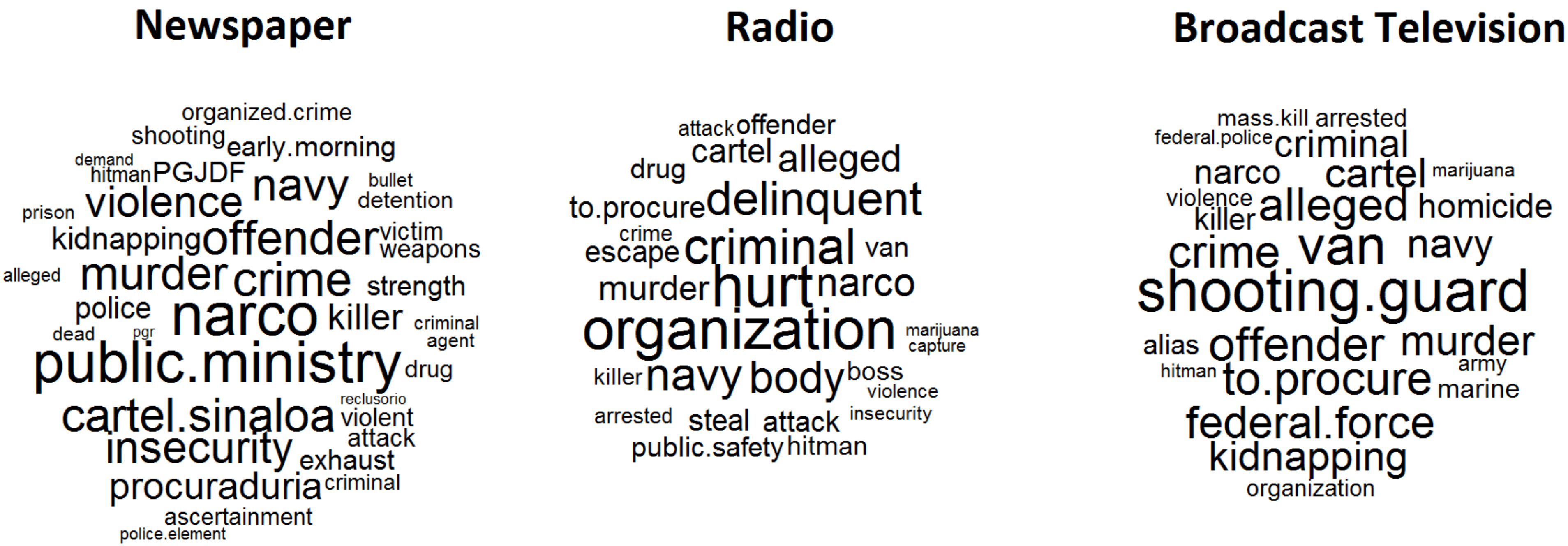
Figures

Figure 1: Fraction of people learning about public security in the country and in their state by type of media



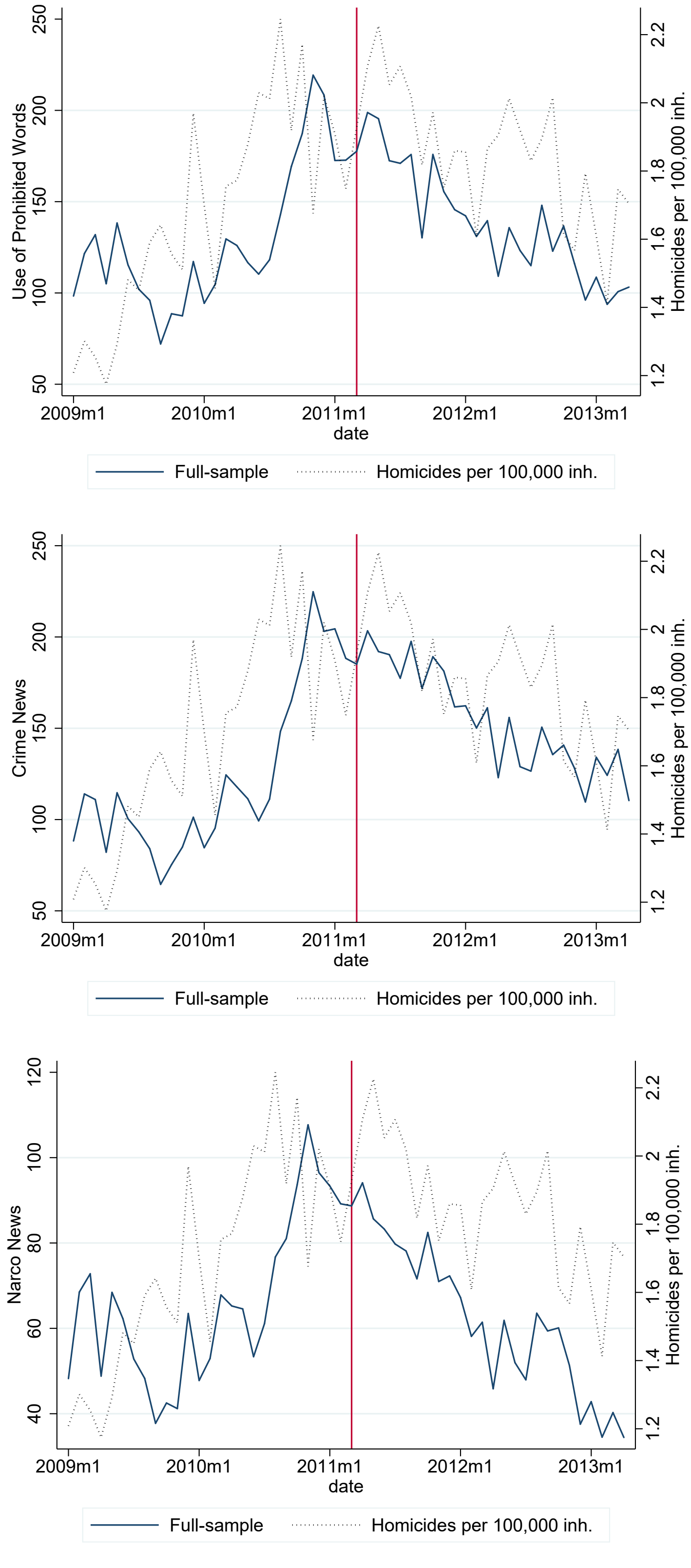
Notes. Author's calculations based on National Survey on Insecurity (ENSI), 2010

Figure 2: Positive Lasso Coefficients for the Crime Category



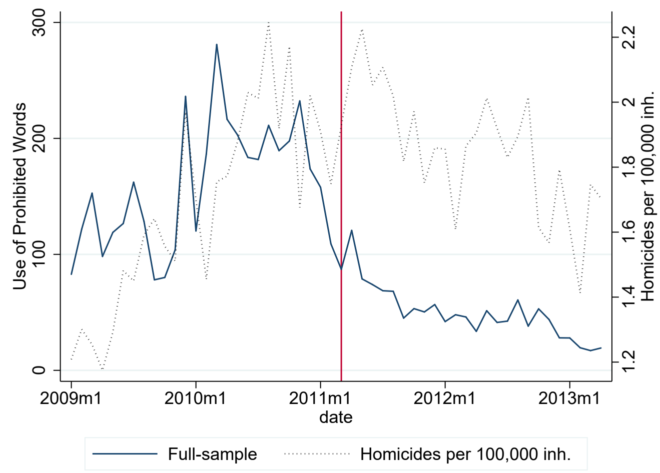
Notes This figure shows one-word and two-word phrases with positive lasso coefficients for the crime category. The content analysis is conducted in Spanish and translated to English for ease of exposition.The sample and model used are defined in section 4 of the main text.

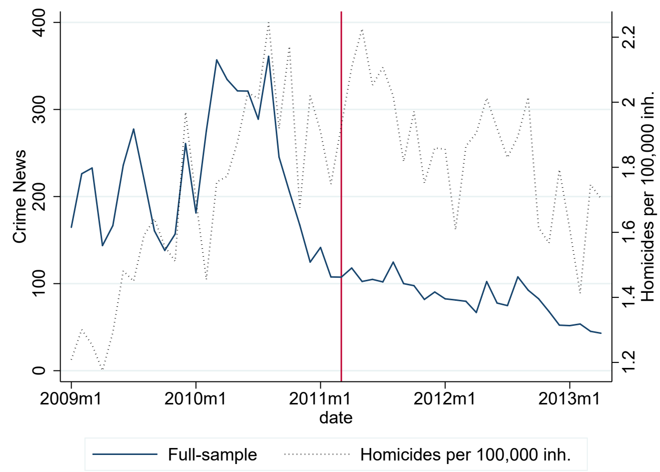
Figure 3: Crime News Coverage in Newspapers and National Homicide Rate

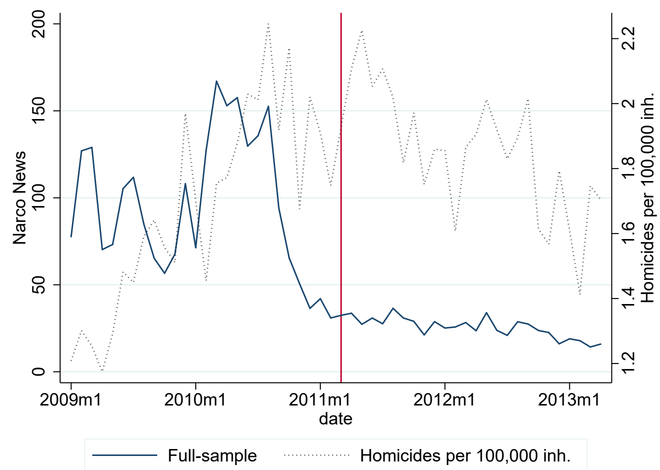


Notes. This figure shows the measures *Use of Prohibited Words, Crime News, and Narco News* in newspapers. Agreement newspapers include: El Economista, El Financiero, El Universal, Universal Gráfico, Excélsior, La Crónica de Hoy, La Razón de México, Milenio Diario and Publímetro. Non-Agreement newpapers include: El Sol de México, Impacto Diario, La Jornada, La Prensa, Ovaciones, Metro, Reforma, Uno más Uno. All measures are defined in section 4 of the main text and are normalized by the circulation of each newspaper. Circulation data is obtained from the Media Catalog 2014.

Figure 4: Crime News Coverage in Radio Channels and National Homicide Rate

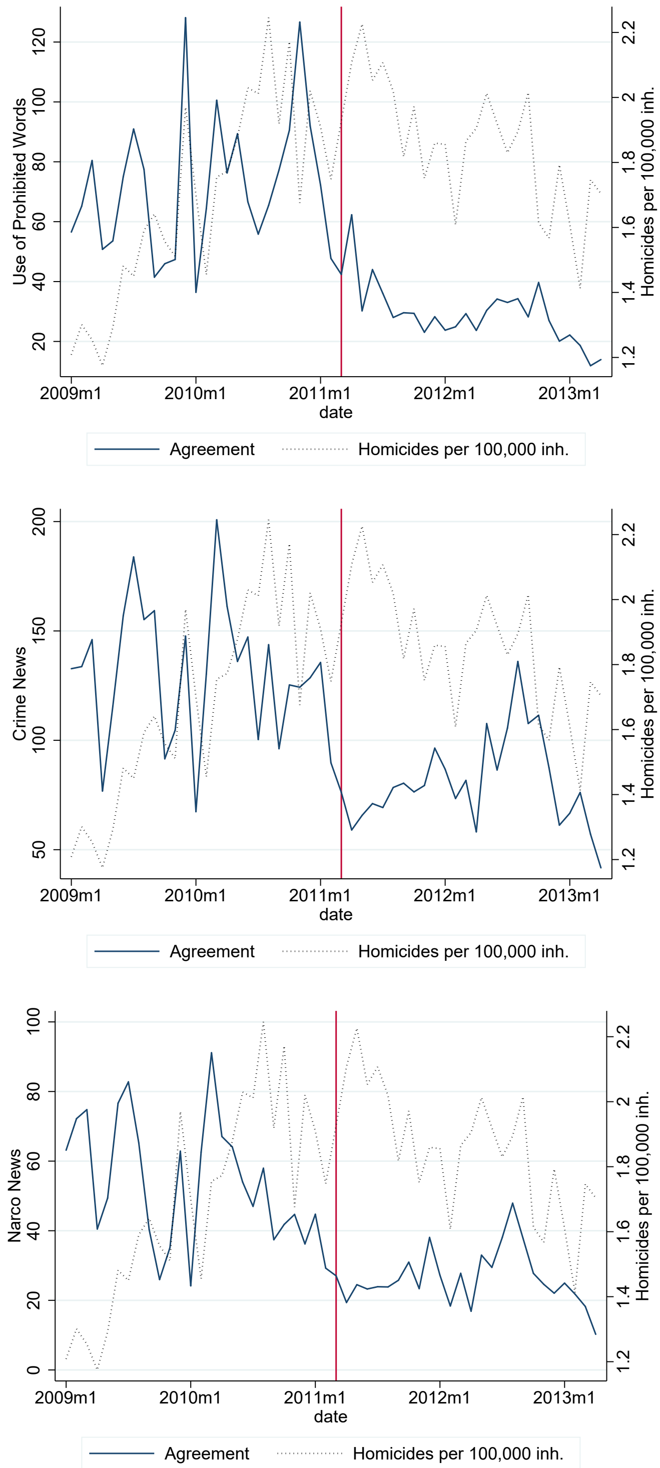






Notes. This figure shows the measures *Use of Prohibited Words, Crime News, and Narco News* in radio channels. Agreement radio channels include: 100.1 Stereo Cien, 103.3 Radio Fórmula, 104.1 Radio Fórmula, 107.9 Horizonte, 1290 Radio 13, 1470 Radio Fórmula, 690 La 69, 760 ABC Radio, 790 Formato 21, 88.1 Red FM, 88.9 Noticias, 90.5 Imagen, 96.9 WFM and 98.5 Reporte. Non-Agreement radio channels include: 102.5 Noticias MVS and 1060 Radio Educación. All measures are defined in section 4 of the main text and are normalized by the size (coverage) of each channel. Coverage data is obtained from Eficiencia Informativa. The following Agreement radio channels aren't included in the graphs because coverage data isn't available: 100.1 Stereo Cien, 1000 Radio Mil, 1030 Radio Centro, 1440 Cambio, 620 Radio, and 830 Radio Capital.

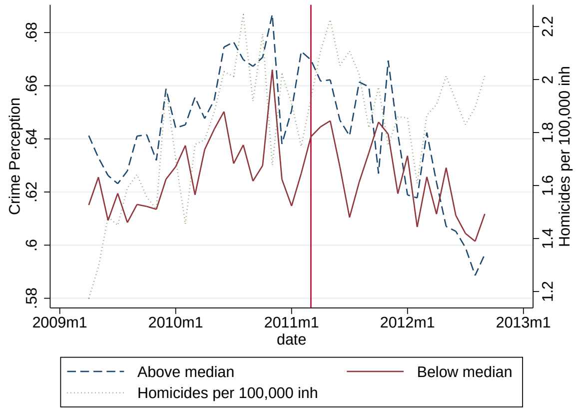
Figure 5: Crime News Coverage in Broadcast TV and National Homicide Rate



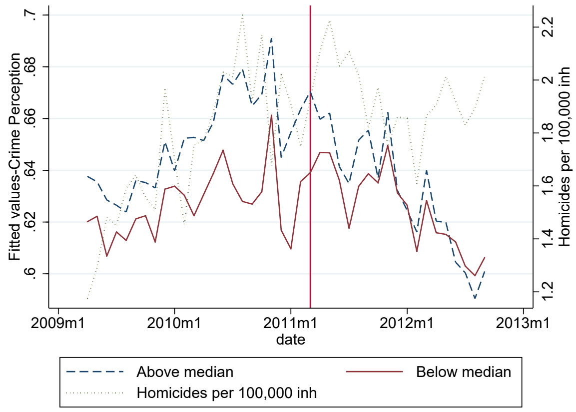
Notes. This figure shows the measures *Use of Prohibited Words, Crime News, and Narco News* in broadcast TV channels. All of them are Agreement channels and include Channel 2, Foro TV, Channel 7, Channel 9, Once TV, Channel 13, Channel 40, Channel 22, Cadena Tres, and Channel 34. All measures are defined in section 4 of the main text and are normalized by the size (share) of each channel. Data on shares by channel are from Nielsen-IBOPE's report on the evolution of Mexican Media market (2008-2009).

Figure 6: Personal Crime Perceptions by Treatment Intensity

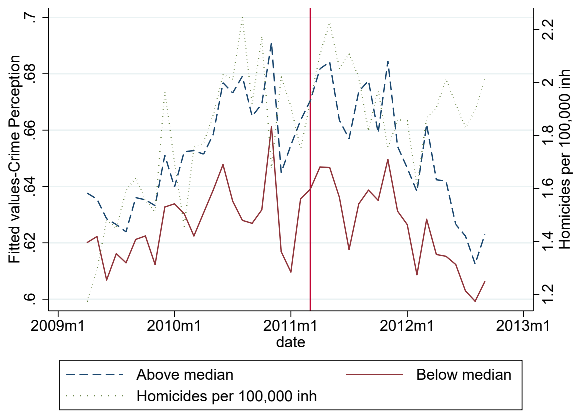
(a) Raw data



(b) Fitted values



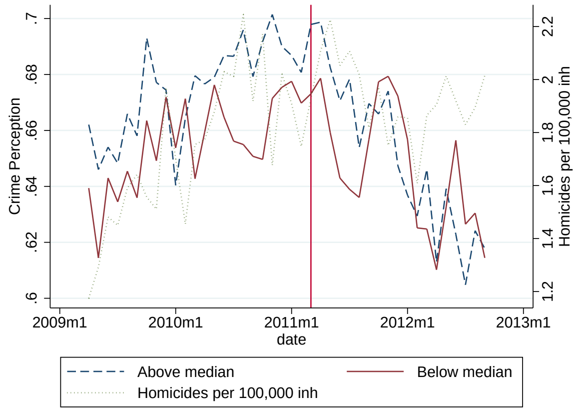
(c) Fitted values with $\beta = 0$



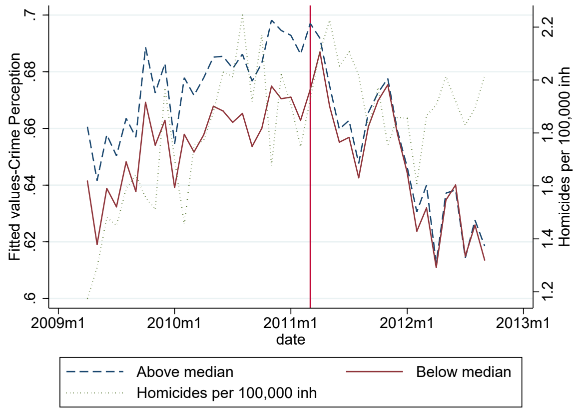
Notes. This figure shows personal crime perceptions in the monthly dataset, broken down by individuals that are above and below median treatment intensity. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". The figure in the middle plots the fitted values of the model defined by equation 7 of the main text but with the $treatment\_intensity_{ism}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity. The figure at the bottom plots the former fitted values but setting $\beta = 0$. The vertical line corresponds to the announcement of the Agreement (2011m3).

Figure 7: Country Crime Perceptions by Treatment Intensity

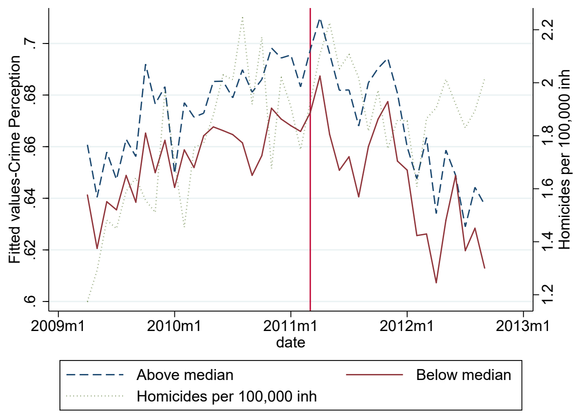
(a) Raw data



(b) Fitted values



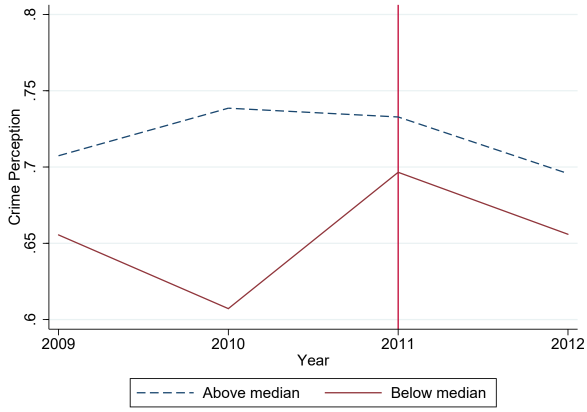
(c) Fitted values with $\beta = 0$



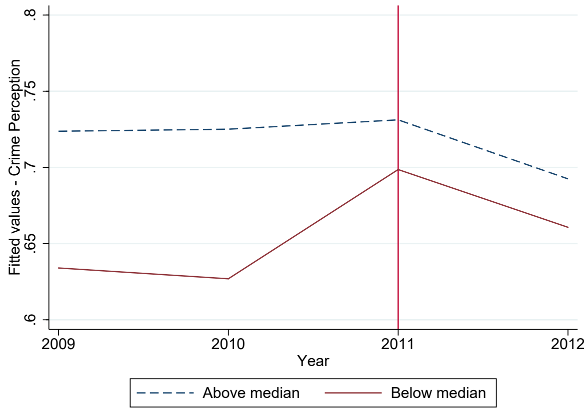
Notes. This figure shows country crime perceptions in the monthly dataset, broken down by individuals that are above and below median treatment intensity. Country Crime Perception is an index constructed from the answers to the question: "How do you consider security in the country today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". The figure in the middle plots the fitted values of the model defined by equation 7 of the main text but with the $treatment\_intensity_{ism}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity. The figure at the bottom plots the former fitted values but setting $\beta = 0$. The vertical line corresponds to the announcement of the Agreement (2011m3).

Figure 8: State Crime Perceptions by Treatment Intensity

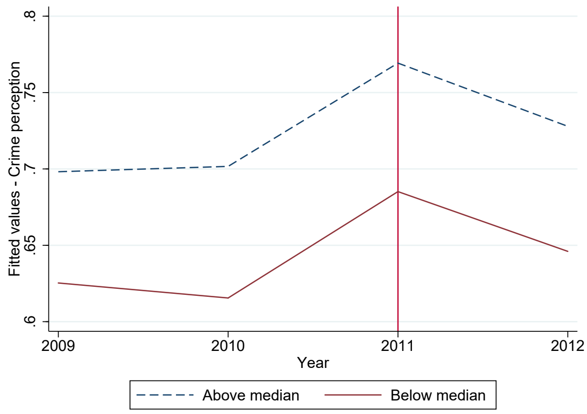
(a) Raw data



(b) Fitted values



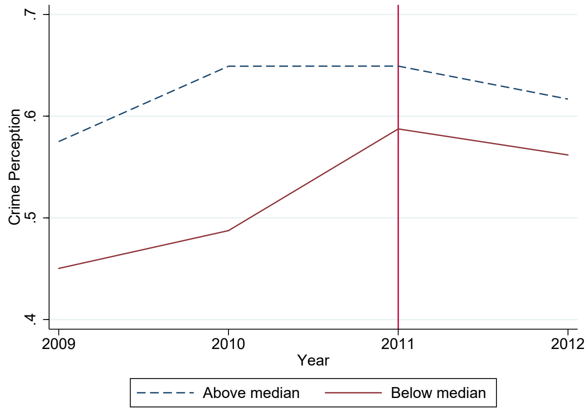
(c) Fitted values with $\beta = 0$



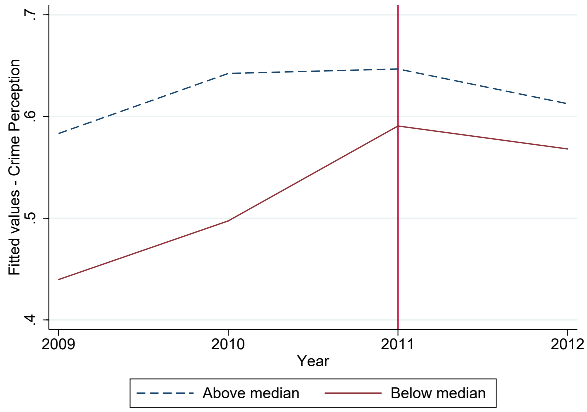
Notes. This figure shows state crime perceptions in the annual dataset, broken down by individuals that are above and below median treatment intensity. Crime Perception State is dummy equal to 1 if the answer to the question: "Do you think living in your State ...?" is "Insecure" and equal to 0 if the answer is "Secure". Treatment Intensity is defined in equation 6 of the main text. The figure in the middle plots the fitted values of the model defined by equation 8 of the main text but with the $treatment\_intensity_{icy}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity. The figure at the bottom plots the former fitted values but setting $\beta = 0$. The vertical line corresponds to the year the Agreement was announced (2011). The horizontal axis refers to the survey year.

Figure 9: Municipality Crime Perceptions by Treatment Intensity

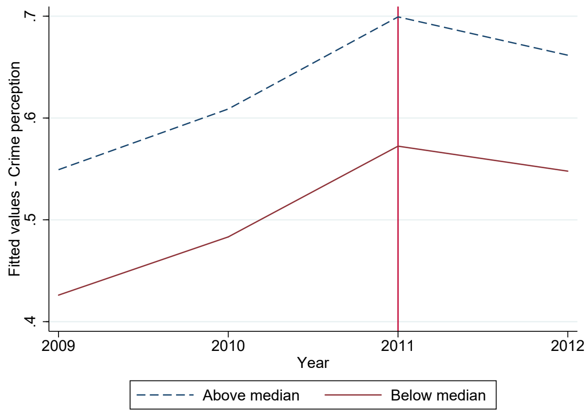
(a) Raw data



(b) Fitted values



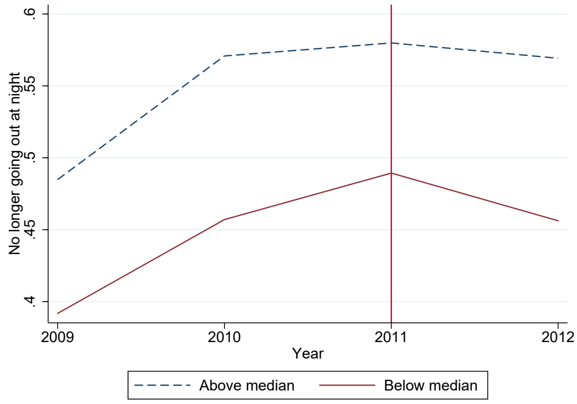
(c) Fitted values with $\beta = 0$



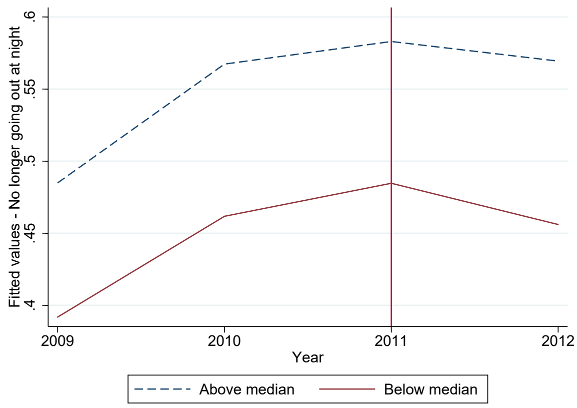
Notes. This figure shows municipality crime perceptions in the annual dataset, broken down by individuals that are above and below median treatment intensity. Crime Perception Municipality is dummy equal to 1 if the answer to the question: "Do you think living in your Municipality ...?" is "Insecure" and equal to 0 if the answer is "Secure". Treatment Intensity is defined in equation 6 of the main text. The figure in the middle plots the fitted values of the model defined by equation 8 of the main text but with the $treatment\_intensity_{icy}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity. The figure at the bottom plots the former fitted values but setting $\beta = 0$. The vertical line corresponds to the year the Agreement was announced (2011). The horizontal axis refers to the survey year.

Figure 10: No longer going out at night by Treatment Intensity

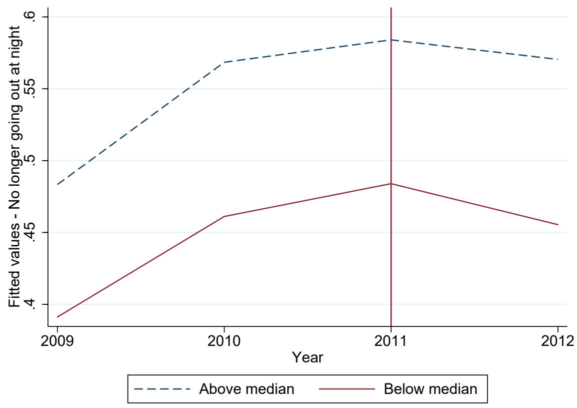
(a) Raw data



(b) Fitted values



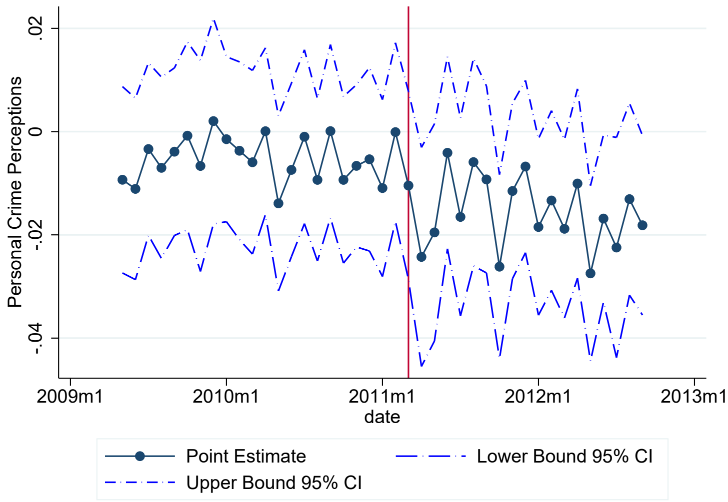
(c) Fitted values with $\beta = 0$



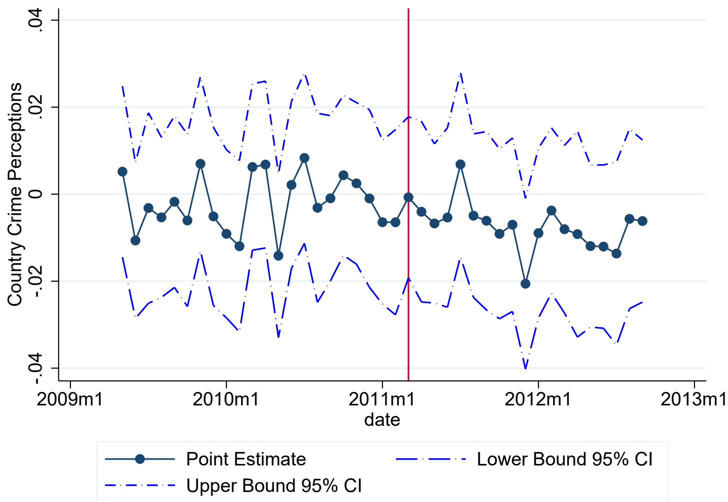
Notes. This figure shows the variable no longer going out at night in the annual dataset, broken down by individuals that are above and below median treatment intensity. No longer going out at night is a dummy equal to 1 if the answer to the question: "For fear of being a victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" is "Yes" and 0 if the answer is "No". Treatment Intensity is defined in equation 6 of the main text. The figure in the middle plots the fitted values of the model defined by equation 8 of the main text but with the $treatment\_intensity_{icy}$ variable replaced by a dummy variable equal to 1 for individuals above median treatment intensity. The figure at the bottom plots the former fitted values but setting $\beta = 0$. The vertical line corresponds to the year the Agreement was announced (2011). The horizontal axis refers to one year before the survey year to make it consistent with the survey question.

Figure 11: Treatment Intensity×Month Indicators

(a) Personal Crime Perceptions



(b) Country Crime Perceptions



Notes. This figure shows the point estimates and the bootstrapped 95% confidence intervals of the interaction of the treatment intensity variable and month dummies of equation 11 in the main text. These coefficients must be measured relative to the baseline time-period, or omitted month which I take to be April 2009.

A Appendix

A.1 Randomization process for manual classification of news

1. I start by selecting 7 random days (Monday to Friday) from the period January 2009 to December 2013.
2. For each day, I select a random channel/newspaper from the sample described in 4 for each type of media (i.e. one for broadcast television, one for radio, and one for newspapers).
3. I search in the Eficiencia Informativa database for all news available on this subsample of channel/newspaper-days. As a result of this process, I get the following channel/newspaper-days:

Day	Television	Radio	Newspaper
18-Dec-09	Foro TV	107.9 Horizonte	El Universal
3-Sep-10	Cadena Tres	620 Radio	Impacto Diario
22-Nov-10	Channel 11	88.1 Red FM	Milenio Diario
10-Oct-11	Foro TV	90.5 Imagen	La Crónica de Hoy
5-Mar-12	Channel 40	88.9 Noticias	El Economista
30-Oct-12	Channel13	100.1 Stereo Cien	Excélsior
6-Aug-13	Channel 13	88.9 Noticias	El Economista
Total number of news	580	459	930

   This gives a total of 580 news for broadcast television channels, 459 news for radio channels and 930 news for newspapers.

4. I randomly oversample a subset of possible crime related news for each type of media of 15% of each sample size: 87, 69, and 140 news for broadcast television, radio, and newspaper, respectively. This random selection of news is from a previously downloaded dataset with news with any of the words used by the Council of the Agreement to follow reports on crime news from the period January 2009 to December 2013 of the channels/newspapers described in section 4. These set of words include murder/ murders, homicide/homicides, organized crime, cartel, violence, and the group *prohibited words* as defined in section 2 of the main text.
5. The total number of manually classified news is 667 for broadcast television, 528 for radio, and 1070 news for newspapers.

A.2 Note on the Lasso-Logistic model for the automated classification of news

Assume that a news item i can either be crime-related ($g_i = 1$) or not ($g_i = 0$). Denote $y_i = I(g_i = 1)$ the indicator function that news item i belongs to the crime category. Let x_i denote the vector of transformed one-word or two-word phrases, that is $x_i = c_i/m_i$, where $c_i = [c_{i1}, ..., c_{ip}]$ is a sparse vector of counts of one or two-word phrases in the vocabulary (with size p) and $m_i = \sum_{j=1}^{p} x_{ij}$. The goal is to predict the category of news item i from x_i. Denote the random variable G as the crime class of a news item, I model

$$\Pr(G = 1|X = x) = \frac{e^{\beta_0+\beta^T x}}{1 + e^{\beta_0+\beta^T x}}$$

The lasso logistic regression minimizes the negative binomial log-likelihood plus a cost on the size of coefficients, solving the following program:

$$\min_{(\beta_0,\beta)\in\mathbb{R}^{p+1}} -\left[\frac{1}{N}\sum_{i=1}^{N} y_i \cdot (\beta_0 + x_i^T\beta) - \log(1 + e^{(\beta_0+x_i^T\beta)})\right] + \lambda||\beta||_1 \tag{13}$$

where N is the number of documents in the training set of my manually classified subset of news items. I fit the above model separately for each type of media to allow for possible different logistic distributions in the use of words. I clean the text for each news item according to standard criteria.[24] First, I remove stopwords, punctuation, convert to lowercase, and strip suffixes from roots according to the Porter's stemmer algorithm. Additionally, I reduce all the words that begin with narco to the root narco.[25] Second, I group words into one and two-word phrases. Third, I remove words and phrases that include the name of a person, place, or that consist of numbers, or a few other words with low semantic meaning. Fourth, I restrict attention to phrases used at least in 99% of the news items of my manually classified subsample.[26]

To construct the second measure *Narco News*, I fit the model described in equation 13. But in this case $g_i = 1$ defines a news item that is narco-related. *Narco News* is the total number of monthly news items predicted by this model to be narco-related conditional on being classified as a crime-related news.

[24]See Jurafsky and Martin (2014) for an overview.

[25]For example, I transform the word narcoviolence to narco.

[26]I pre-process text using software provided in "tm" package for R [Feinerer and Hornik (2015); Feinerer, Hornik and Meyer (2008)].

A.3 Granger-Causality

The focus of this appendix is to test whether criminal behavior is reacting to crime news coverage or crime news coverage is reacting to criminal behavior (as the theoretical framework in the paper assumes). I follow Jaeger and Paserman (2008) in testing these claims by using the Granger (1969) causality test. In a vector autoregression, a variable X is said not to Granger-cause Y if, conditional on lagged values of Y, lagged values of X have no predictive power for the current value of Y.

The following table shows Granger causality tests for different lag structures (i.e., including one, two, or three lags of X and Y) using data from Apr-2009 to March-2011. In the second column, Y is equal to *Use of Prohibited Words* and the X variable is given by the log of the homicides rate; while in the third column Y is the log of the homicides rate and X is *Use of Prohibited Words*. The entries of the table show χ^2 statistics and their corresponding p-values are in parenthesis. The joint null hypothesis is that the coefficients on the lagged values of X are equal to zero, in a regression of Y on lagged values of Y and lagged values of X. As shown in column 3, there is no evidence that crime news coverage is Granger-causing the homicide rate. However, there is evidence that crime news coverage is reacting to criminal behavior.

Monthly lags	Use of Prohibited Words	ln (homicides rate)
1 Lag	0.38	0.37
	(0.5353)	(0.544)
2 Lags	4.49	1.22
	(0.106)	(0.543)
3 Lags	17.26	1.69
	(0.0006)	(0.6382)

A.4 Criteria and results of the manual classification of crime news into different tones

The criteria for the manual classification of crime-related news into different tones was the following:

Positive. News that inform about accomplishments on crime (i.e. fewer murders, police solve a crime, etc.). For example:

The US Government congratulates Mexico for its fight against drug trafficking organizations, and congratulated Mexico for the operation to capture Arturo Beltran Leyva

Mixed. News that inform about solving a crime and about crimes perpetrated by individuals. Example:

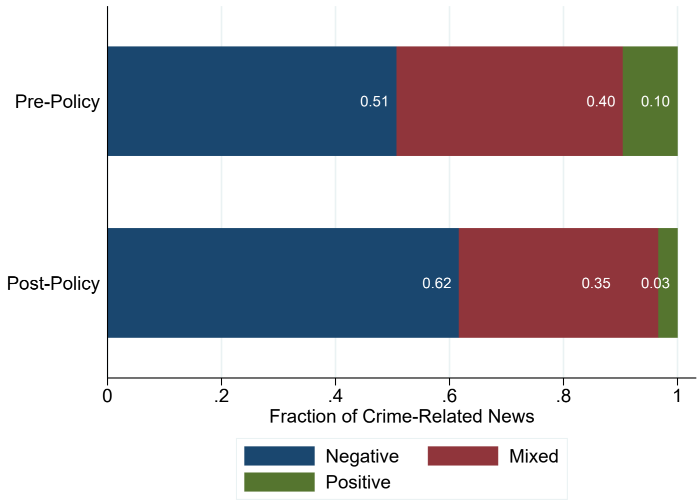
Clashes in Tamaulipas end with the $\underbrace{\textit{release of three hostages}}_{\textit{positive part}}$*, 25 dead and two soldiers wounded*

Negative. News that inform about a crime story.

The Jalisco Attorney General confirmed the discovery of several human remains last weekend in a garbage dump in Lagos de Moreno. The experts will determine their identity and whether or not they belong to some of the six young men disappeared last July.

Using the above criteria, I manually classify the crime-related items of the random manual sample described in subsection A.1 into positive, mixed, and negative tone. The distribution of the tone across the pre and post-policy period for each type of media including items for Agreement and non-Agreement media is the following:[27]

Tone in Crime News. Newspapers



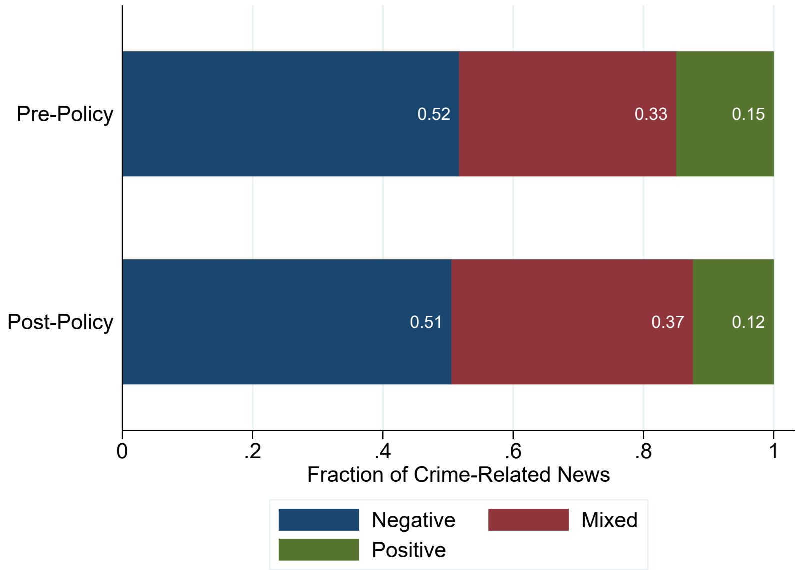
A.5 Trends in crime-related news and narco-related news using a manually classified random sample of news

I describe below the randomization process for selecting the manually classified subsample of news used in this subsection.

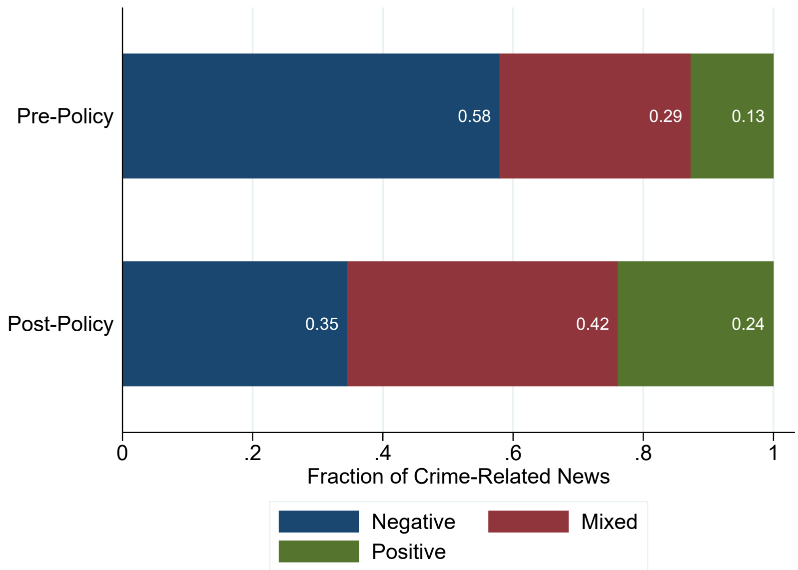
This random sample is slightly different from the random sample used in the main analysis of the text (Baseline sample from here onwards). This Alternative sample (from here onwards) eliminates the fraction of oversampled news used in the Baseline sample but adds another randomly selected subset of news. I use this Alternative sample instead of the baseline sample to eliminate concerns that the oversampled subset of news is

[27] The post-policy period are all days after the Agreement was announced (March 23th).

Tone in Crime News. Radio



Tone in Crime News. Broadcast Television



introducing noise into the estimation. I define the Alternative sample as the Monthly sample + Daily sample.

Daily sample. I start by selecting 6 random days (Monday to Friday) from the period January 2009 to April 2013. For each day, I select a random channel/newspaper from each type of media (i.e. one for television, one for radio, and one for newspapers). I search in the "Eficiencia Informativa" database for all news available on this subsample of channel/newspaper-days. As a result of this process, I get the following channel/newspaper-days:

Day	Television	Radio	Newspaper
18-Dec-09	Foro TV	107.9 Horizonte	El Universal
3-Sep-10	Cadena Tres	620 Radio	Impacto Diario
22-Nov-10	Channel 11	88.1 Red FM	Milenio Diario
10-Oct-11	Foro TV	90.5 Imagen	La Crónica de Hoy
5-Mar-12	Channel 40	88.9 Noticias	El Economista
30-Oct-12	Channel13	100.1 Stereo Cien	Excélsior
6-Aug-13	Channel 13	88.9 Noticias	El Economista
Total number of news	580	459	930

Monthly sample. I start by randomly selecting one month from the pre-period and other from the post-period. This process gives December 2010 (pre-period) and March 2013 (post-period). I choose the newspaper with the highest circulation ("Ovaciones"), the radio program with the highest rating ("En los tiempos de la Radio"), and the broadcast television program with the highest rating ("Noticiero Joaquín López Dóriga"). I download all the news available at the Eficiencia Informativa database and randomly select a subset of them (around 600 news items per media).

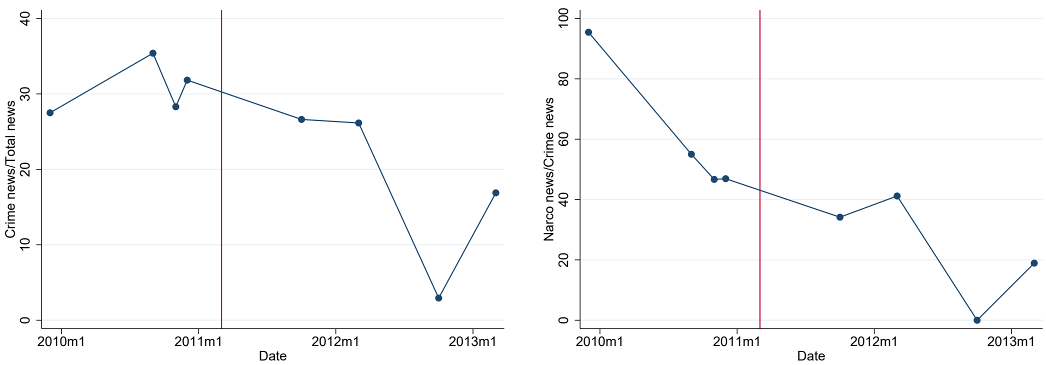
The total number of news in the Alternative sample are for newspapers, 1525; for radio, 1,099; and for television, 1227.

The basic patterns from the manually classified subset of news of this Alternative sample are the following:

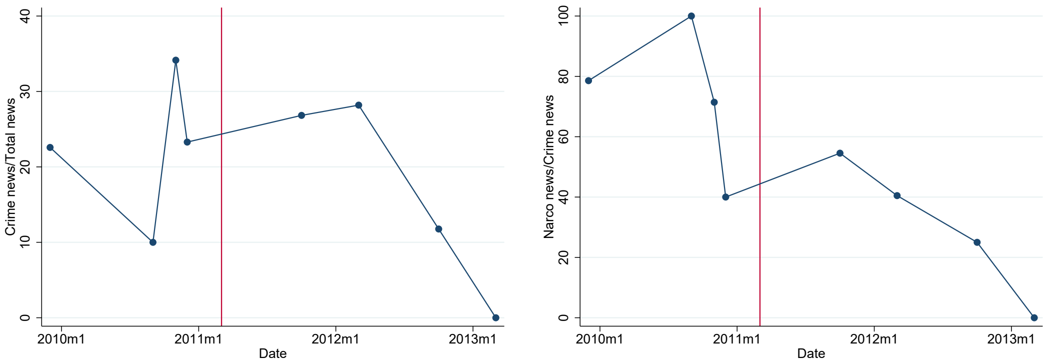
- Fraction of crime-related news as a proportion of total news is decreasing for all types of media. (T-test on the difference in means rejects the null that they are equal for TV and newspapers)
- Within crime news, the emphasis in narco-related news decreases for all types of media. (T-test on the difference in means rejects the null that they are equal for TV, radio, and marginally significant for newspapers (p-value=0.07)). (Graphs below)

Taken together these results suggest that the patterns documented in section 4 are not driven by media outlets using different words to refer to violent incidents but simply that media outlets are talking less about crime.

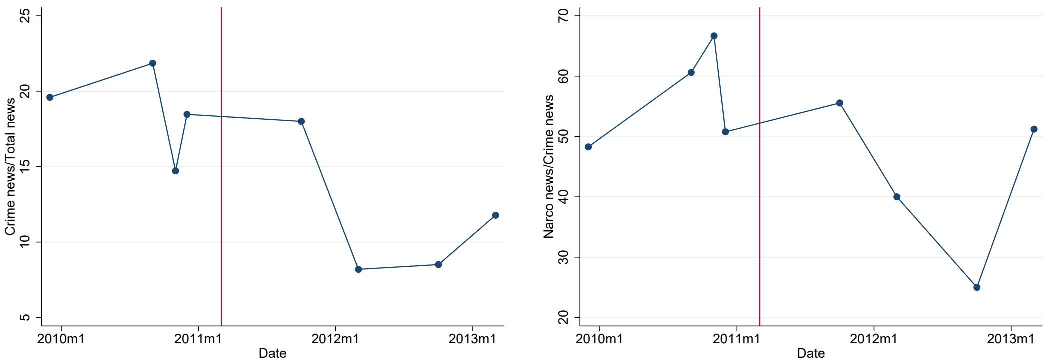
Crime-related news. Broadcast Television



Crime-related news. Radio



Crime-related news. Newspaper



B Appendix Tables

Table B.1: Agreement and Non-Agreement media

Type of media	Agreement	Non-Agreement
Broadcast Television	Channel 2 Foro TV Channel 7 Channel 9 Once TV Channel 13 Channel 40 Channel 22 Cadena Tres Channel 34	None
Radio	100.1 Stereo Cien 1000 Radio Mil 103.3 Radio Fórmula 1030 Radio Centro 104.1 Radio Fórmula 107.9 Horizonte 1290 Radio 13 1440 Cambio 1470 Radio Fórmula 620 Radio 690 La 69 760 ABC Radio 790 Formato 21 830 Radio Capital 88.1 Red FM 88.9 Noticias 90.5 Imagen 96.9 WFM 98.5 Reporte	102.5 Noticias MVS 1060 Radio Educación
Newspapers	El Economista El Financiero El Universal Universal Gráfico Excélsior La Crónica de Hoy La Razón de México Milenio Diario Publímetro	El Sol de México Impacto Diario La Jornada La Prensa Ovaciones Metro Reforma Uno más Uno

Notes. This table shows the media outlets included in the sample of Agreement and non-Agreement media used in the content analysis of section 4 of the main text.

Table B.2: Possitive Lasso Coefficients for the Crime Category. Newspapers

One-word or two-word phrase		**Coefficient**
English	**Spanish**	
narco	narc	260.64
public ministry	ministeri.pblic	257.65
crime	crim	201.94
offender	delincuent	201.77
murder	asesinat	192.45
cartel.sinaloa	crtel.sinalo	189.96
navy	armad	184.74
insecurity	insegur	177.86
violence	violenci	168.47
procuraduria	procuradur	134.73
killer	asesin	126.26
kidnapping	secuestr	103.85
police	polic	92.28
PGJDF	pgjdf	84.13
early morning	madrug	83.67
exhaust	escap	78.54
strength	fuerz	74.56
violent	violent	67.24
attack	ataqu	65.61
weapons	armas	62.69
victim	vctim	61.29
shooting	dispar	59.23
drug	drog	55.28
ascertainment	averiguacin	53.10
organized crime	crim.organiz	52.90
detention	deten	49.96
criminal	criminal	45.32
hitman	sicari	39.48
dead	muert	29.57
agent	agent	29.06
bullet	bal	28.05
criminal	delict	26.66
prison	prisin	24.64
alleged	presunt	23.73
demand	exig	12.70
police element	element.polic	11.03
reclusorio	reclusori	7.98
pgr	pgr	6.80
hurt	her	0.58
(Intercept)	(Intercept)	-2.09

Performance Measures	**Value**
Area under the ROC curve	0.79
Mean error	0.11

Confusion matrix (Test set)

	Assigned	
Observed	Non-Crime (0)	Crime (1)
Non-Crime (0)	238	5
Crime (1)	31	47

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the crime category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the "glmnet" package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.3: Possitive Lasso Coefficients for the Crime Category. Radio

One-word or two-word phrase		Coefficient
English	**Spanish**	
hurt	her	71.13
organization	organiz	69.68
criminal	criminal	55.74
delinquent	delict	54.01
navy	armad	51.06
body	cuerp	47.29
narco	narc	40.50
alleged	presunt	39.10
murder	asesinat	32.30
cartel	crtel	31.67
to procure	procur	26.99
escape	escap	25.65
Steal	rob	24.45
attack	atac	23.25
Van	camionet	22.59
offender	delincuent	21.84
public safety	segur.pblic	20.85
drug	drog	20.18
boss	jef	18.95
hitman	sicari	18.64
killer	asesin	13.07
crime	delit	11.36
arrested	deten	10.67
attack	ataqu	10.01
insecurity	insegur	7.08
violence	violenci	7.07
capture	captur	4.93
marijuana	marihuan	4.82
Mexican Army	ejrcit.mexican	1.17
seek justice	procur.justici	1.15
marine	marin	0.72
execute	ejecut	0.44
confrontation	enfrent	0.44
(Intercept)	(Intercept)	-1.29

Performance Measures	Value
Area under the ROC curve	0.70
Mean error	0.21

Confusion matrix (Test set)

	Assigned	
Observed	Non-Crime (0)	Crime (1)
Non-Crime (0)	103	0
Crime (1)	33	22

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the crime category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the "glmnet" package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.4: Possitive Lasso Coefficients for the Crime Category. Broadcast Television

One-word or two-word phrase		**Coefficient**
English	**Spanish**	
shooting guard	escolt	46.11
van	camionet	42.23
offender	delincuent	34.20
to procure	procur	33.40
alleged	presunt	32.30
crime	crim	32.25
federal force	fuerz.federal	31.68
murder	asesinat	28.37
navy	armad	28.28
cartel	crtel	27.89
kidnapping	secuestr	27.48
criminal	criminal	25.21
narco	narc	21.17
homicide	homicidi	20.18
killer	asesin	17.76
alias	ali	13.05
marine	marin	12.90
arrested	deten	10.52
violence	violenci	9.78
organization	organiz	9.60
mass kill	masacr	8.80
army	ejrcit	7.32
federal police	polic.federal	5.55
hitman	sicari	4.62
marijuana	marihuan	4.59
pgr	pgr	1.28
	(Intercept)	-0.95

Performance Measures	**Value**
Area under the ROC curve	0.71
Mean error	0.23

Confusion matrix (Test set)

	Assigned	
Observed	Non-Crime (0)	Crime (1)
Non-Crime (0)	123	2
Crime (1)	43	32

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the crime category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the "glmnet" package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.5: Possitive Lasso Coefficients for the Narco Category. Newspapers

One-word or two-word phrase		**Coefficient**
English	**Spanish**	
narco	narc	483.36
organized crime	delincuent.organiz	428.44
hitman	sicari	419.50
spread	difund	387.17
crime	crim	295.36
organized crime	crim.organiz	284.58
pgr	pgr	270.05
zetas	zet	231.32
ask	pregunt	211.42
drug	drog	208.99
antecedent	antecedent	193.37
family	familiar	188.80
navy	armad	182.39
cartel	crtel	126.33
fact	hech	95.91
science	cienci	82.27
announcement	convoc	81.27
leader	mandatari	75.65
capture	captur	73.71
agent	agent	71.99
head	cabez	63.84
police	polic	56.79
ministerial	ministerial	50.19
find	encontr	44.19
bullet	bal	29.91
victim	vctim	15.87
ascertainment	averiguacin	5.24
public safety	segur.pblic	5.22
public ministry	ministeri.pblic	2.08
(Intercept)	(Intercept)	-3.12

Performance Measures	**Value**
Area under the ROC curve	0.83
Mean error	0.07

Confusion matrix (Test set)

	Assigned	
Observed	Non-Narco (0)	Narco (1)
Non-Narco (0)	262	5
Narco (1)	17	37

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the narco category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the "glmnet" package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.6: Possitive Lasso Coefficients for the Narco Category. Radio

Radio

One-word or two-word phrase		**Coefficient**
English	**Spanish**	
organization	organiz	79.35
navy	armad	65.97
narco	narc	38.85
cartel	crtel	37.22
hitman	sicari	22.87
delinquent	delict	17.59
boss	jef	15.91
arrested	deten	15.80
drug	drog	11.15
Van	camionet	6.56
confrontation	enfrent	2.55
(Intercept)	(Intercept)	-1.74

Performance Measures	**Value**
Area under the ROC curve	0.61
Mean error	0.15

Confusion matrix (Test set)

	Assigned	
Observed	Non-Narco (0)	Narco (1)
Non-Narco (0)	127	0
Narco (1)	24	7

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the narco category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the "glmnet" package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.7: Possitive Lasso Coefficients for the Narco Category. Broadcast TV

One-word or two-word phrase		Coefficient
English	**Spanish**	
cartel	crtel	93.07
confiscate	decomis	62.54
execute	ejecut	61.17
navy	armad	59.22
narco	narc	51.54
criminal	criminal	47.06
marijuana	marihuan	44.29
crime	crim	43.62
shooting guard	escolt	37.51
alleged	presunt	36.73
to procure	procur	35.05
marine	marin	28.40
spokesman	vocer	28.39
drug	drog	27.71
organization	organiz	23.53
hitman	sicari	20.70
federal	federal	16.37
mass grave	fos	15.31
die	mur	15.20
hurt	her	4.82
kidnapping	secuestr	3.72
	(Intercept)	-1.94

Performance Measures	Value
Area under the ROC curve	0.68
Mean error	0.14

Confusion matrix (Test set)

	Assigned	
Observed	Non-Narco (0)	Narco (1)
Non-Narco (0)	158	2
Narco (1)	25	15

Notes. This table shows one-word and two-word phrases and the value of lasso coefficients for the narco category. The sample and model used are defined in section 4 of the main text. I use the software available in R as the “glmnet” package. The model is restricted to give only positive coefficients; sets lambda equal to 1.5; and uses 10-fold cross-validation.

Table B.8: Survey Period and Geographical Coverage of the Monthly and Annual Crime Perception Surveys

Survey's Name	**Survey Period**	**Geographical Area** Survey designed to be representative at the following levels of disaggregation:					**Metro area or mun id**
		National	Urban	Rural	State	Cities	
Annual Data							
ENSI 2009	March 9th to March 27th of 2009	Yes	Yes	Yes	Yes	16 metro areas individually	Yes/Yes
ENSI 2010	August 2th to September 3th of 2010	Yes	Yes	Yes	Yes	17 metro areas individually	Yes/Yes
ENVIPE 2011	March 14th to April 22nd of 2011	Yes	Yes	Yes	Yes	17 metro areas individually	Yes/Yes
ENVIPE 2012	March 5th to April 30th of 2012	Yes	Yes	Yes	Yes	No	No/Yes
ENVIPE 2013	March 4th to April 26th of 2013	Yes	Yes	Yes	Yes	No	No/Yes
Monthly Data							
ECOSEP	April 2009 to September 2012 the first 20 days of each month.	No	No	No	No	32 metro areas (in the aggregate)	Yes/No

Notes. Author's elaboration based on the Survey on the Perception of Public Security (ECOSEP), the National Survey on Insecurity (ENSI) and the National Survey of Victimization and Perception of Public Safety (ENVIPE). Urban localities are defined as localities with more than 2,500 inhabitants.

Table B.9: Probability of watching, listening, or reading news

Variables	(1)
Individual is a woman	-0.568***
	(0.145)
Age	0.165***
	(0.0178)
Age squared	-0.00140***
	(0.000179)
Individual has preschool	2.543**
	(0.997)
Individual has primary	3.326***
	(0.288)
Individual has secondary	4.819***
	(0.304)
Individual has high school	5.132***
	(0.328)
Individual has teacher's training	5.268***
	(0.632)
Individual has technical	5.456***
	(0.352)
Individual has bachelor degree	5.831***
	(0.314)
Individual has grad	6.006***
	(0.645)
Individual is working	-0.708***
	(0.177)
Individual is a student	-1.777***
	(0.372)
Individual does housekeeping	-0.315
	(0.217)
Urban	1.566***
	(0.134)
Observations	60,455
State Dummies	Yes

Notes. This table shows the coefficients obtained from a regression on the frequency at which an individual watches, listens, or reads news in the ENSI 2010 dataset. The dependent variable can take five possible values: daily (30), three times per week (12), once a week (4), once a month (1), or never (0). Robust standard errors in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table B.10: Probability of watching, listening, or reading news

Variables	(1)
Individual is a woman	-0.585***
	(0.144)
Age	0.170***
	(0.017)
Age squared	-0.001***
	(0.000)
Years of education	0.694***
	(0.049)
Squared of years of education	-0.022***
	(0.002)
Individual is retired	1.189***
	(0.266)
Individual is a student	-1.085***
	(0.338)
Individual does housekeeping	0.381**
	(0.171)
Urban	1.488***
	(0.134)
Observations	60,456
R-squared	0.058
State Dummies	Yes

Notes. This table shows the coefficients obtained from a regression on the frequency at which an individual watches, listens, or reads news in the ENSI 2010 dataset. The dependent variable can take five possible values: daily (30), three times per week (12), once a week (4), once a month (1), or never (0). This specification was used to predict the treatment intensity variable in the bi-annual dataset. Robust standard errors in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table B.11: The Impact of the Agreement on Crime Perceptions, Monthly data

Variables	(1) Personal Crime Perception	(2) Country Crime Perception
post×above	-0.022***	-0.019***
	(0.006)	(0.005)
Observations	51,280	51,231
R-squared	0.155	0.098
Household Fixed Effects	No	No
Metro Dummies	Yes	Yes
Individual Controls	Yes	Yes
Month*Year*Metro	Yes	Yes
Mean Dependent	0.643	0.663

Notes. This table shows the reduced form effect of the Agreement on personal and country crime perceptions in the monthly dataset. Personal Crime Perception is an index constructed from the answers to the question: "Speaking in terms of public safety, how secure do you feel today as compared to 12 months ago?" The index increases with the perceived level of crime. It is equal to 1, 0.75, 0.5, 0.25, and 0, if the answers are "Much more insecure", "More Insecure", "The same", "A little safer", and "Much safer". Similarly, Country Crime Perception is an index constructed from answers to the question: "How do you consider security in the country today as compared to 12 months ago?". The model estimated is similar to the model defined in equation 7 of the main text but replaces the $treatment\_intensity_{ism}$ variable by a dummy variable equal to 1 for individuals above median treatment intensity. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table B.12: The Impact of the Agreement on Crime Perceptions and Behavior, Annual data

Variables	(1) State Crime Perception	(2) Municipality Crime Perception	(3) No longer going out at night
post x above	-0.067***	-0.093***	0.002
	(0.011)	(0.012)	(0.011)
Observations	200,093	201,476	193,357
R-squared	0.136	0.158	0.117
Homicide Control	Yes	Yes	Yes
Municipality Dummies	Yes	Yes	Yes
Municipality Time Varying Controls	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Victimization Risks	Yes	Yes	Yes
Mean Dependent	0.703	0.590	0.511

Notes. This table shows the reduced form effect of the Agreement on crime perceptions and behavior in the ENSI and ENVIPE datasets. Crime Perception State (Municipality) is dummy equal to 1 if the answer to the question: "Do you think living in your State (Municipality) ...?" is "Insecure" and equal to 0 if the answer is "Secure". No longer going out at night is a dummy equal to 1 if the answer to the question: "For fear of being a victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" is Yes and 0 if the answer is No. The model estimated is similar to the model defined in equation 8 of the main text but replaces the $treatment\_intensity_{icy}$ variable by a dummy variable equal to 1 for individuals above median treatment intensity. Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

Table B.13: The Impact of the Agreement on Crime Perceptions and Behavior, Annual data

Variables	(1) State Crime Perception	(2) Municipality Crime Perception	(3) No longer going out at night
post×treatment_intensity	-0.010***	-0.014***	0.002
	(0.002)	(0.003)	(0.002)
Observations	214,212	215,864	206,974
R-squared	0.202	0.222	0.173
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Municipality*Year FE	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Victimization Risks	Yes	Yes	Yes
Mean Dependent	0.694	0.578	0.506
Mean Treatment Intensity	24.63	24.63	24.63

Notes. This table shows the reduced form effect of the Agreement on crime perceptions and behavior in the ENSI and ENVIPE datasets. Crime Perception State (Municipality) is dummy equal to 1 if the answer to the question: "Do you think living in your State (Municipality) ...?" is "Insecure" and equal to 0 if the answer is "Secure". No longer going out at night is a dummy equal to 1 if the answer to the question: "For fear of being a victim of crime (robbery, assault, kidnapping, etc.) in the previous year, did you stop going out at night?" is Yes and 0 if the answer is No. The model estimated is similar to the model defined in equation 8 of the main text but includes municipality-year fixed effects (i.e., thus municipality varying controls are subsumed). Bootstrapped standard errors are in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

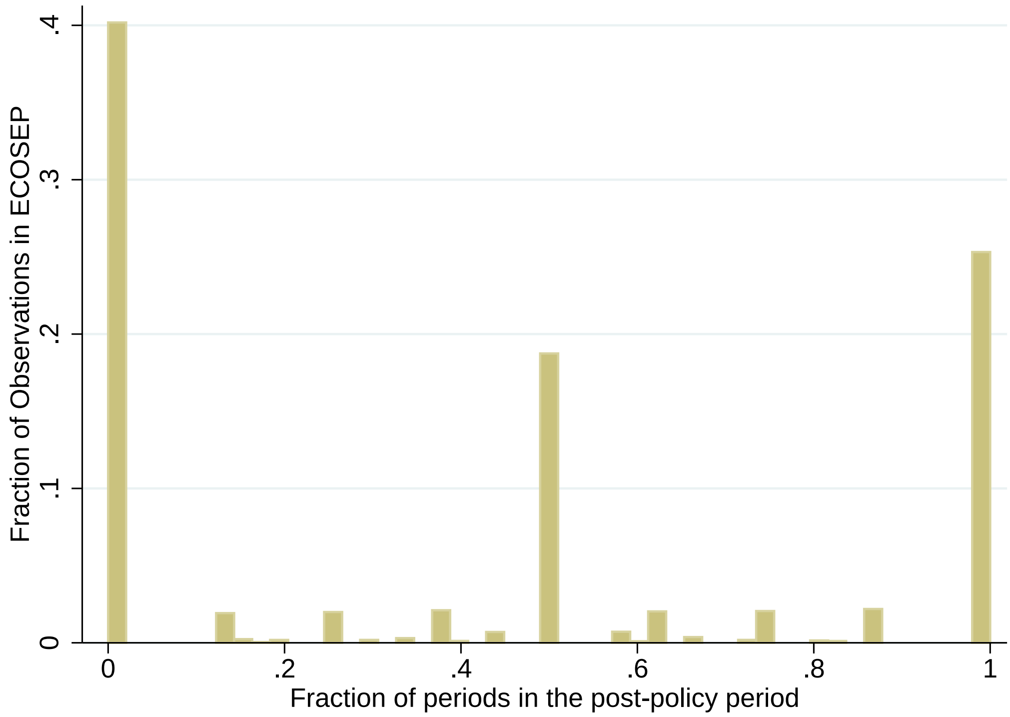
Table B.14: Testing for Structural Break in *Use of Prohibited Words*

Variables	(1) Use of Prohibited Words	(2) Use of Prohibited Words
	Agreement	Full Sample
post	-64.822***	-56.711***
	(0.002)	(0.002)
Observations	1,976	2,496
R-squared	0.752	0.782
Homicides Control	Yes	Yes
Channel Fixed Effects	Yes	Yes
Calendar Month Dummies	Yes	Yes
Time Varying Control	Yes	Yes

Notes. This table shows the coefficients that capture the size of the break in *Use of Prohibited Words*. The model estimated is defined by equation 10 in the main text. The variable post is a dummy equal to 1 for months equal or greater than the break date. For Agreement media the break date is February 2011 and for the full sample of media outlets May 2011. Wild bootstrapped p-values clustered at the channel/newspaper level are reported in parentheses. *** Significant at 1%. **Significant at 5%. * Significant at 10%

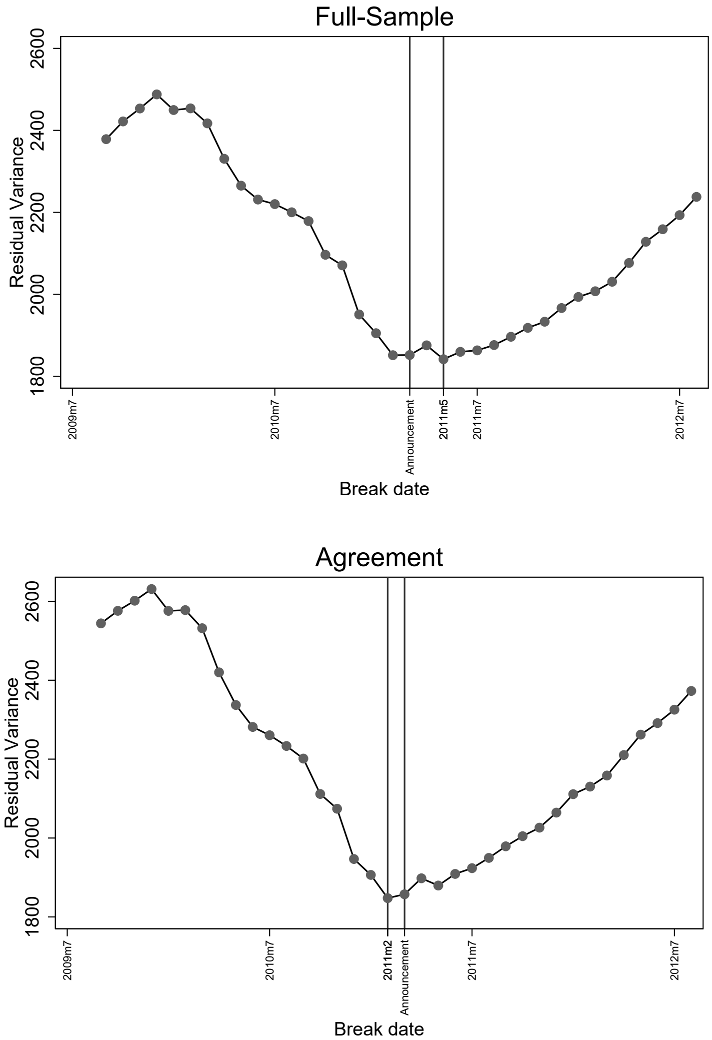
C Appendix Figures

Figure C.1: Fraction of periods in the post-policy period (t≥2011m3) in the monthly dataset



Notes. This figure shows the distribution of the fraction of periods in the post-policy period over the total number of periods that each observation is in the monthly data. For example, 40% of the individuals in the monthly data are only interviewed before 2011m3; while 25% are only interviewed after 2011m3.

Figure C.2: Testing for Structural Break in *Use of Prohibited Words*



Notes. This figure plots the sum of squared residuals as a proportion of the number of observations of the model defined by equation 10 in the main text. The figure at the top uses the full sample of media outlets defined in section4 of the main text, while the figure at the bottom only uses Agreement media outlets.