I Read the News Today, oh Boy: The Effect of Crime News Coverage on Crime Perception and Trust*

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December 10, 2019

Abstract

Crime perception has increased in Peru, as in other developing and developed countries, in spite of the reduction in crime victimization figures. Our hypothesis is that the news industry is partially responsible for such opposing trends, as Peruvians are great consumers of written news. Using a unique database of most news from the Peruvian written press, we georeference the location of each reported crime to identify short-term deviations from trend in the coverage of crime news at the province level and estimate their effect on crime perception. We measure coverage as the area an article occupies in cm^2. We find that a spike of negative crime news increases people's perception about the probability of being a crime victim. The effect of positive news is opposite. However, the effect per cm^2 of negative news is around three times larger than the effect of positive news in absolute value, signaling a potential asymmetry in the revision of people's expectations. These perception changes are smaller for recent crime victims than for non-victims. Moreover, perception changes are mostly driven by increases in the fear of house and car theft and common street crime, rather than more violent crimes like kidnapping or sexual abuse. We also explore how media coverage impacts institutional trust and show that individuals distribute accountability and reward unevenly between the main justice and security institutions.

JEL classification: D83, D84, L82

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1 Introduction

Several countries in the world face large and persistent differences between actual criminality rates and individuals' crime perception. This problem has been particularly acute in Latin America and Peru in the XXI-st century, as a large share of the population consistently perceives their countries to be growing in insecurity each year, regardless of the real change in victimization. As can be seen in Figure 1 for the case of six Latinamerican nations, the annual change in victimization can be negative, stable or slightly positive, but a typically large fraction of people will always consider that insecurity has increased in the country.[1] This prominent mismatch, however, is not a particular feature of developing countries. People in the USA and the UK also tend to state that they perceive crime to be higher each year, in spite of decreasing criminality, according to data from Gallup (2019), Bureau of Justice Statistics (2016) and the Office for National Statistics (2011).

This so-called *perception gap*[2] is a topic worth studying not only due to its global presence, but also due to its potential economic implications regarding welfare and efficiency. There are four ways how this perception gap could be welfare-reducing: increases in fear and corresponding health problems, habit changes, irreversible investments, and deterioration of institutions' reputation.

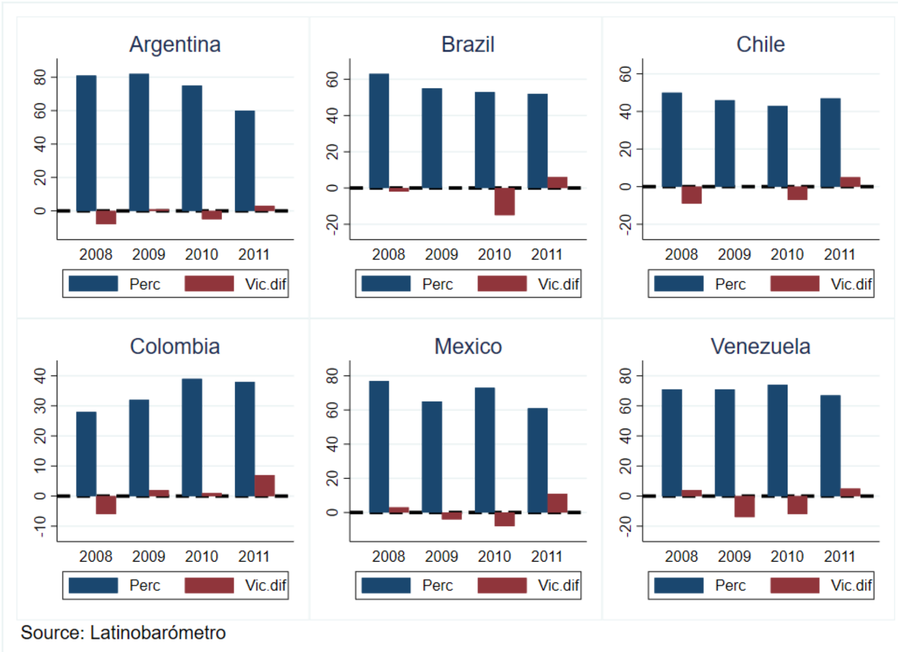
First, an overestimation of actual criminality rates may be associated with a higher and unjustified *fear of crime*,[3] which in turn can have negative consequences on health by increasing mental distress (Dustmann and Fasani, 2016) and the frequency of sleep deprivation (Braakmann, 2012). Second, individuals may also react to a higher crime perception by changing their habits inefficiently. These reactions can be divided into five categories: avoidance, protective behavior, insurance behavior, communicative behavior and participation behavior (DuBow et al., 1979), all of which can affect both time and money allocations. As a matter of fact, about 30% of Peruvians living in urban areas report to have avoided or have stopped

[1] The figure shows the evolution of crime perception and victimization for the 2008-2011 period only, as the years 2007-2011 were the last ones where these two questions were asked simultaneously and without interruption in the Latinobarómetro survey.

[2] Throughout this paper, we will refer to the perception gap as the systematic misperception of either the level or change of actual criminality rates.

[3] According to Fattah and Sacco (2012), questions on the assessment of the likelihood of being a crime victim are a cognitive measure of fear of crime. However, as it is explained in Hale (1996, p. 89), these measures of crime risk "*are distinct from and causally prior to fear of crime*". For our purposes, we will simply define fear of crime as the consequence of an aggregate excess of expected victimization (i.e. when expected victimization is higher than actual average victimization).

Figure 1: Percentage of people who perceive that living in their country is more insecure each day and actual change in the victimization rate in Latin American countries (2008-2011)



to go out at night due to their fear of crime in 2017. A similar percentage report having stopped using their cellphones on the street for the same reasons, around 20% have stopped taking taxis and even 15% have avoided walking on the streets at all (INEI, 2018). These important changes in habits may impose relevant restrictions on mobility, on labor decisions (Hamermesh, 1999) and even on housing choices (Ellen and O'Regan, 2010).

Third, fear of crime can also lead to economically inefficient investments as individuals can commit into irreversible investments, misguided by short-term deviations in crime perception. For that reason, about 10% of the population in urban Peru has installed bars in their windows, 15% has placed a bar-door to avoid house theft, and almost 20% has added locks and latches to their houses and has even bought watchdogs (INEI, 2018). All this entails significant initial expenditures and maintenance costs. Finally, fear of crime can also have politically relevant implications regarding who the public holds accountable for the increase in crime they perceive. If these perceptions are misguided, it could lead to an undeserved deterioration of the reputation of governmental institutions and to misinformed voting behavior. Corbacho et al. (2015) find that crime reduces trust in police and local leadership and harms overall social capital. They argue that this is not only detrimental for development (as do Tavits (2006) and Horváth (2013)), but also costly because it makes the government spend its resources to recover the lost trust.

The main objective of this study is to estimate the effect of crime news coverage on crime perception in urban Peru for the period 2013-2017. Evidence from developed countries suggests that fear of crime is associated with news media. Based on survey-data from the UK, Duffy et al. (2008) find that 57% and 48% of respondents mentioned the TV and newspapers as making them think that crime was higher than two years ago. These seem to be, by a wide margin, the most relevant sources of information for building crime perceptions. The third most common answer, experiences of people known by the interviewee, was only mentioned by 24% of the sample. [4] We use written crime news for our research, as this media outlet is particularly relevant in a country like Peru. As a matter of fact, weekly newspapers' readership rate in Lima metropolitan area[5] is around 78%, of a total population of almost 12 million individuals (CPI, 2017). Furthermore, Peruvians are the most avid newspaper readers in the region (CERLALC, 2012). This is reflected in the fact that the Peruvian newspaper, *Trome*, is the most read Spanish-language newspaper in the world. By selling around 734,000 copies on a daily basis, it surpasses other well-known Spanish-speaking newspapers like *El País* (Spain), *Clarín* (Argentina), or *El Tiempo* (Colombia) (Mineo, 2014). We use a unique dataset that contains information about the daily content of the most relevant newspapers in Peru, including local newspapers. First, we exploit text mining techniques to filter out crime news and determine whether they were positively or negatively toned in their position towards the crime situations being reported. Second, we link each news to a geographical location (province) using other text mining techniques. Specifically, we apply sentiment analysis and name entity recognition, respectively, which we describe with further detail below. Our main attention is centered on the *area* in cm^2 that each piece of crime news occupies in the newspapers. For each of the 196 provinces in Peru, we construct a monthly time-series of the average area of crime news in the newspapers. Then, we show that spikes (i.e. short-term deviations) in the average area devoted to negative crime news considerably increase crime perception. The effect of positive news is opposite. We argue that these *area shocks*, after

[4] Another study by Romer et al. (2003) brings more evidence towards this relation. Using US survey-data, they find that viewing local television news is strongly and positively associated with fear of crime.

[5] A conurbation of Lima (the country's capital) and Callao

including province and year fixed effects and controlling for the actual number of crime news and complaints, are more likely to exhibit an *exogenous* behavior. Thus, we do not identify the effect of increasing the number of crime news, but the effect of *larger newspaper space* devoted to crime.

Coupled with several robustness checks, we find that the effect per cm^2 of negative news is about 3 times larger than the effect of positive crime news (in absolute value). This suggests that there is an important asymmetry in the way people revise their expectations: to offset an increase in crime perception generated by a certain amount of negative information spilled by the media, it is required to triple such amount of information but in positively toned news. This sheds light on some of the reasons why the perception gap exists and, most importantly, persists. These features are consistent with two well-document types of cognitive biases: confirmatory bias (Lord et al., 1979) (Rabin and Schrag, 1999) and negativity bias (Rozin and Royzman, 2001).

In an attempt to answer some of the theoretical questions posed by fear of crime and the media literature, we then explore heterogeneity and find that (i) the size of negative crime news increases crime perception mostly on non-victims, which is consistent with the substitution thesis (Weitzer and Kubrin, 2004) and, less clearly, (ii) the size of positive crime news tends to have a smaller relieving effect on women than on men. Similarly, we observe that people who live in geographical regions where newspapers are less read are also less affected by newspapers' area shocks than their counterparts. Also, we find that negative crime news increase perception of domestic burglary and of common street robbery more relative to other crimes such as sexual abuse or kidnapping.

Last but not least, we delve into one of the four possible consequences of increasing aggregate fear of crime. We explore which political institutions are held accountable by the population, that is how people distribute guilt but also reward. We find that negative crime news does not affect overall trust in the police. However, its reputation regarding specific duties, such as attending promptly to crimes or maintaining public tranquility, is hurt. However, both negative and positive crime news affect the Judiciary's and the Attorney's reputation. Also, negative crime news tend to hamper the trust individuals deposit on municipal governments.

Our most direct contribution is to the literature on the relation between media and information and crime perceptions (Ardanaz et al. (2014), Ramírez-Álvarez (2017)). As far as we know, our paper is most closely related to the recent work by Mastrorocco and Minale (2018). They exploit the staggered introduction of digital TV in Italy to explore how it affected crime perceptions on people aged 50 and over. Ramírez-Álvarez (2017) performs a similar study to the previous one, but leverages an industry agreement to reduce coverage of violence, in Mexico.

Regarding our contributions, we expand upon previous research by using richer data and leveraging information engineering techniques for classification and creation of variables, which can vastly increase the scope of analysis. More specifically, a first important difference of our study is that we analyze shocks of both positive and negative news. This introduces a second dimension that allows us to study asymmetries and dig deeper into the subject, as opposed to the analysis of a natural experiment which only provides evidence on the impact of media in one direction. Second, we georeference each news according to the location of the reported crime to exploit cross-sectional variability at the geographical level and to identify the effect of news from crimes near to where people live, in contrast to country-wide crime. Third, we use an *absolute* measure of crime perception as our dependent variable, unlike past studies on the subject.[6] Thus, our coefficients have a very clear interpretation: how the share of the population who thinks they can become a crime victim is affected. This is not only more policy-relevant, but also more closely related to the impact of news on people's welfare and thoughts. Finally, we focus on *size* deviations of the news, not on its number. As far as we know, we are the first to take this approach. We argue that news size deviations are a better reflection of a conscious decision of media outlets, which reveals the relative importance given to crime coverage. Thus, it is a better representation of the actual *role* of media in shaping crime perceptions.

We also contribute to other fields of research. First, we provide new insights to a more general literature documenting the persuasive effects of media content, by showing that crime news can affect crime perceptions and other outcomes such as trust deposited in governmental institutions.[7] We also contribute to the literature about the determinants of trust and social

[6] Mastrorocco and Minale (2018) resort to relative measures of crime perception, like the position of "crime" in a ranking of country's problems. We posit that such a measure of crime perception is subject to more noise, as relative crime concern can fall due to other confounding unobserved factors related to any other problem to society. Ramírez-Álvarez (2017) uses a variable that depends upon past personal estimates of criminality.

[7] See DellaVigna and Kaplan (2007); Ferraz and Finan (2008); Ladd and Lenz (2009); Snyder Jr. and

capital (e.g. Alesina and La Ferrara (2000)) and to the discussion about the way how to deliver information.[8] Finally, we contribute to a long tradition in the literature of criminology, psychology and sociology about the formation of specific beliefs.[9] In particular, about how individuals can mentally retrieve negative experiences and shape their concept of fear.[10]

The rest of this paper is structured as follows: Section 2 briefly presents relevant background on criminality and newspapers in Peru. Section 3 then presents our data and describes the techniques used for the news database. In Section 4, we lay out our identification strategy and, in Section 5, we explain our baseline results, including robustness checks. Section 6 displays further consequences of crime news and, finally, Section 7 concludes.

2 Background

2.1 Crime in Peru

Crime has been one of Peru's most urgent problems in the eyes of its population over the last decade, particularly so in the last few years. Somewhat paradoxically, between the years 2013 and 2017, the real share of the urban population victim of a crime has exhibited a substantial decrease, whereas crime perception, as measured by the percentage of people who think that they can be a crime victim in the next year, has been mostly increasing (see Figure 2). In fact, crime perception followed a positive trend until 2016, whereas victimization decreased during the same time period. Perhaps more striking is the fact that the perception gap has steadily grown larger by around 10 pp in 5 years only. By 2017, crime perceptions sits at around 80% and victimization slightly above 20%.

To better understand the big picture here, it is useful to sort Peru's urban population on the basis of crime perception and crime victimization. We can divide the population into three groups under an adaptive expectations rationale, for illustrative purposes. We can label those who were not crime victims in the past year, but who think they can become one in the next year as "pessimistic" (i.e. their expectation of their future state is worse

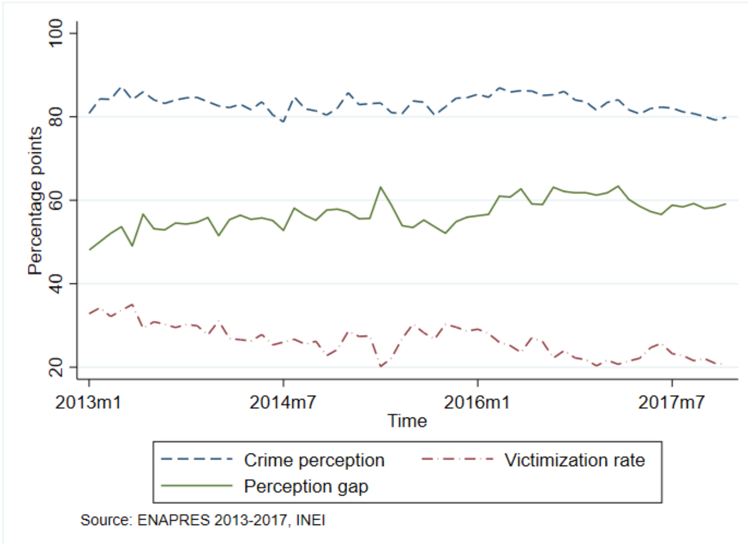
Strömberg (2010); Banerjee et al. (2011); Enikolopov et al. (2011); Humphreys and Weinstein (2012); de Figueiredo et al. (2014); Yanagizawa-Drott (2014); Adena et al. (2015); Chong et al. (2015); Spenkuch and Toniatti (2016); Martin and Yurukoglu (2017); Dunning et al. (2018) and Larreguy et al. (2018).

[8] See Alt et al. (2016); Arias et al. (2018); Marshall (2018) and Chong et al. (2018).

[9] See Tversky and Kahneman (1973); Schwarz et al. (1991); Kahneman (2002) and Schwarz and Bless (2007).

[10] See Tversky and Kahneman (1973); Gunter (1987); Hale (1996); Braakmann (2012) and Jackson and Gouseti (2014).

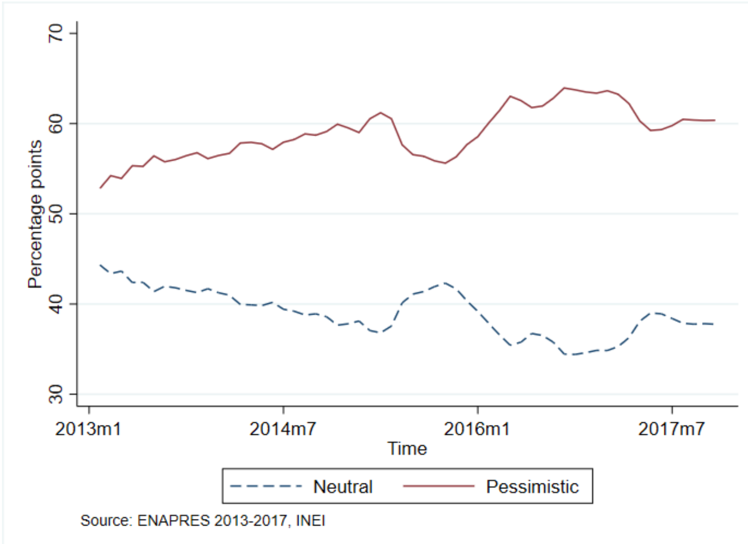
Figure 2: Evolution of crime perception and victimization: urban Peru, 2013-2017



than the current one). Conversely, those who were crime victims in the past year, but think they will not become one again in the coming one can be called "optimistic", as they believe they will improve on their "victim" situation. Finally, those who believe that their situation will remain the same, either as a victim or a non-victim, can be defined as "neutral". The dynamics of the pessimistic are of our interest, as they should reflect the marginal individuals who are changing their beliefs towards crime in a negative manner.[11] As Figure 3 shows, there has been a rather steady decrease of those with a neutral profile towards crime: less people believe that their current status (either as a regular crime victim or not) will remain the same. This is indicative of higher volatility in people's perception. These individuals could be migrating towards an optimistic or pessimistic viewpoint, but, as can be observed, most of the population has turned towards a pessimistic position. In fact, more than half of the urban population was not victim of a crime last year but thinks will become one in the next 12 months. On the other hand, the share of optimistics (not shown) has fluctuated around a very low 2% during the period of analysis.

[11]The dynamics of the optimistic are also interesting from a theoretical standpoint. However, they are only a small share of the population (2%), with high variability across time, but with a overall seemingly negative trend.

Figure 3: Evolution of population profiles regarding crime: urban Peru, 2013-2017 (3-month moving averages)



2.2 The newspapers market in Peru

As previously mentioned, newspapers are very popular in Peru. According to independent survey data from CPI (2017), a Peruvian consulting and market research firm, weekly readership in Lima metropolitan area stood in a high 78.0% by 2016. As Table 1 shows, daily readership is never lower than 23.8% and can be as large as 58.5% in the cities presented. This means that most of the city's population aged 15 or older is greatly exposed to news. This information is representative of the year 2016, right in the middle of the time period we are studying.[12] Survey data from Arellano Marketing (2017), another Peruvian research and consulting firm, also confirms most of these findings. Around 80% of the population in Lima reads newspapers weekly and does so on a basis of 1.1 hours per day. In provinces, the share of readers is lower (68%) yet the reading intensity is the same (1.1 hours per day). All this information suggests that, even though there are more media outlets than ever (e.g. TV and internet), the newspaper has not been replaced or crowded out in Peru. This fact is particularly important for our identification strategy.

[12]According to the same survey, on average men read more newspapers than women in Peru. Moreover, in most of the sampled cities, newspaper readership is slightly tilted towards those older than 38, although the percentage of readers aged 15-25 and 26-37 is not much smaller. Similarly, the share of readers is a bit higher in the socioeconomic status A/B than those in C/D/E. Most of the self-declared readers report to do so at home or at their workplace.

Table 1: Daily newspaper readership in Peru's main cities (2016)

City	Overall	Men	Women
Lima metropolitan area	46.4%	52.8%	40.5%
Arequipa	39.8%	44.0%	36.0%
Cajamarca	26.4%	31.7%	21.7%
Chiclayo	42.3%	49.1%	36.4%
Chimbote	34.7%	40.9%	28.4%
Cusco	24.1%	30.8%	17.9%
Huancayo	40.2%	49.4%	32.2%
Huaraz	23.8%	30.6%	17.3%
Ica	41.4%	50.7%	32.8%
Iquitos	45.3%	51.4%	39.1%
Juliaca-Puno	28.9%	32.7%	25.3%
Piura	58.3%	66.1%	51.2%
Pucallpa	30.8%	36.3%	24.8%
Tacna	34.1%	35.8%	32.4%
Tarapoto	29.6%	36.1%	22.5%
Trujillo	42.4%	53.1%	32.7%

Source: CPI, 2017

On the supply side, the newspaper industry in Peru is heavily concentrated, as in several countries in the world. Around 95% of market share is dominated by three media groups as of 2012: El Comercio (49%), Epensa (29%) and La República (17%). Conversely, smaller local newspapers have only a small fraction of total sales. They are most prevalent in the Northern region of Peru, but their aggregate market share is also rather small (6.61%) (Fernández-Baca, 2014). However, in mid-2013 El Comercio bought Epensa, configurating almost a duopoly in the market in terms of competing firms. Both El Comercio and La República have several newspapers to their name, as the aforementioned *Trome*, which belongs to El Comercio. Due to this media concentration and because we also have data on local newspapers, our newspapers' dataset is rather exhaustive in its scope of Peru's written press.

3 Data

3.1 Individual and household-level data

We use the National Survey of Strategic Programs (ENAPRES, for its Spanish acronym) for the years 2013-2017. The survey is conducted on a yearly basis by the National Institute of Statistics and Informatics (INEI), a Peruvian Government agency. It provides information on people's assessment and experience of criminality in urban areas (see Table 2). It is from this survey that we construct our crime perception variables. To create our measure of likelihood of victimization, we define, for each type of crime k, a dummy variable that takes the value of 1 if the surveyed individual answered positively to the following question: "*In the next 12 months, do you think you can be victim of crime k?*". This exercise is performed for the 14 crime categories included in the survey. Based on this, we measure *aggregate* crime perception (from here onwards simply *crime perception*) as the inclusive disjunction of the 14 crime perception categories. Thus, crime perception is equal to 1 if a person believes that he can a be victim of any of the 14 crimes in the next 12 months.

This way of measuring crime perception represents an improvement over a common problem found in other studies. Usually, there is a concern that the public may include into their definition of crime other factors like terrorism, "*litter on the streets, broken windows or a general lack of respect*" (Duffy et al., 2008, p. 28). Our measure of aggregate crime perception (and also of victimization) is based on 14 direct questions regarding different crimes. Compared to other studies that define crime perception as either (1) the placing of crime in a ranking of the country's problems (Mastrorocco and Minale, 2018)—which makes this particular measure quite noisy and dependent of variables affecting other elements of the ranking—or as (2) the answer to questions similar to "*how secure do you feel as compared to 12 months ago?*" (Ramírez-Álvarez, 2017) or "*do you think crime has increased?*"—which imply a comparison with a past personal estimates of crime perception—, we call our variable a more concrete and less noisier measure of absolute crime perception. In a regression setting, it can be modeled as the expected victimization rate, which leads to a quite natural interpretation of the parameters. The ENAPRES database also contains typical socioeconomic factors such as sex, civil status, age, etc. Most importantly, it has data regarding habits, such as watching TV, or possessions, like owning a cellphone with Internet or other electronic devices.

3.2 Province-level news data

To measure the coverage of crime news, we use a novel dataset compiled by "iMedia". "iMedia" is a Peruvian private firm specialized on tracking and monitoring news and performing data analysis. As part of their regular activities, they compile and store all types of news from national and local news suppliers, in different media formats such as newspapers and

Table 2: Crime categories surveyed by ENAPRES

#	Detailed crime description
1	House theft
2	Automotive vehicle (car, van, etc.) theft
3	Autoparts of automotive vehicle (headlights, tires, rims, etc.) theft
4	Motorcycle or motorcycle-taxi theft
5	Bicycle theft
6	Money, wallet or cellphone theft
7	Threat or intimidation
8	Physical or psychological abuse by household member
9	Sexual offenses (harassment, molestation, rape, etc.)
10	Kidnapping
11	Extortion
12	Fraud
13	Business theft
14	Other

Source: *ENAPRES*

TV. They own this information for the period 2013-2017. We requested them to compile all crime-related news using a list of validated keywords for the following crime categories, based on the crimes surveyed by INEI: theft, threat, fraud, extortion, abuse, sexual offense and kidnapping.[13] The resulting database contained all the registered crime news in the Peruvian written press tracked by iMedia, which includes not only daily newspapers, but also weeklies and magazines. The data contains several variables of interest such as the issuing newspaper, the type of crime, the text included in the news, the monetary cost, the area in cm^2 it occupied, and so on. These observations constitute most of the market share in Peru. A more extensive description of the variables is provided in Appendix Table 1. In what follows we explain how we classify news as positively or negatively-toned and how we georeference them.

A. Positive or negative crime news?: Sentiment Analysis

Not all crime-related news tell *bad* stories. Some news can be crime-related and still transmit a positive message, such as improvements in the security level, by informing the disbanding of a criminal gang, the conviction of a murderer or by factually describing decreasing criminality rates. We name this type of news as simply *positive* crime news, as opposed to typical *negative* crime news. Acknowledging that crime news can also have a positive sentiment is critical for

[13] We used a keyword-based selection algorithm. This algorithm used a list of keywords that are in Spanish and that are particular to each crime category. This information is available upon request.

a proper and cleaner decomposition of the effect of crime coverage. Although one is used to think about crime news as generally transmitting a negative message—with headlines mainly referring to thefts and particular murders coming up to mind—crime-related news could also introduce feelings of relief and security. These positively-toned news should not increase crime perception, at least. Thus, grouping all crime-related news and assuming they all increase crime perception would lead to an underestimation of the real effect of negative crime news. Moreover, one would not be able to respond to an empirically-relevant question: do *positive* crime news actually *decrease* crime perception? This question is also relevant from a policy point of view: the perception gap could be explained if the impact of negative news is larger than that of positive news, even more so if negative news are over-provided. Performing this key distinction between positively and negatively-toned news and separating their effects is, as far as we know, a novelty of this paper.

To determine the news' text polarity, we use a sentiment dictionary, which classifies words as being positively, neutrally or negatively toned. We generate it by compiling different dictionaries published in referenced works for text analysis in Spanish (Perez-Rosas et al. (2012), Molina-González et al. (2013), Sidorov et al. (2012) and Urizar and Roncal (2013)) and other sources. In addition, we also include crime-specific keywords derived from the queries used to get the initial data set.[14] The main idea of this algorithm is to count the total number of positively, negatively, and neutrally toned words. This counting does not include the stopwords in the text, as is usual in text analysis. Then, we classify each news to the sentiment with the maximal word count. For example, if a piece of news has 5 positively toned words, 18 negatively-toned ones and 2 neutral ones, it will be classified as negatively toned. Appendix B describes and gives further technical detail on this algorithm. As a visual example of the outputs of our algorithm, Appendix Figure 1 shows a piece of crime news that was classified as negative and Appendix Figure 2 exhibits a different one that was labeled as positive.

B. Local or Neighbouring News?: Spatial Entities Extraction

Similarly, one can think that people tend to give more weight to news from crimes occurring near to where they live, work or frequent, when forming their expectation on the likelihood

[14]The final aggregate list of keywords for both positive and negative sentiments are available upon request.

of being crime victims. This consideration draws upon the discussion on possible differential effects of local and non-local crime news found in the literature. Liska and Baccaglini (1990) find evidence that fear of crime is increased only by local homicide stories, as opposed to stories from other cities. Moreover, they find that the latter make people feel safer by comparison. To be consistent with these observations, we perform a spatial entities extraction procedure to identify the location of the crime reported in each news. Grouping them all could also bias our results. Performing this procedure to diminish potential bias has also been previously untried, as far as we know.

We employ another dataset that contained the ID for the different possible combinations of the three administrative spatial sub-divisions in Peru (region, province and district) and their names. Then, for every piece of news in the database, we verify whether its text contained any of the names of any region, province or district in the country. Afterwards, for every news, with at least one spatial entity identified, we choose the smallest geographical entity listed. This first filtering is then subject to an ambiguity calculation process and double verification to address issues such as confounding spatial entities' names with street addresses, people's names or other spatial entities' names. Appendix C gives further methodological detail on the spatial entities extraction procedure and steps. All this allows to add variables on the district, province and region of location of each crime news and the latitude and longitude of the event to the previous database.

For a better understanding of the data, the resulting descriptive statistics are displayed in Table 3. As can be observed, the number of yearly crime news has more than doubled since 2013. However, the number of newspapers tracked by iMedia changes each year and is mostly increasing in time. Thus, a better measure of the degree of media focus on crime is given by the average the number of crime news that each newspaper published each year. This number has gone from 198 crime news per newspaper up to 405: media coverage of crime in Peru seems to have increased over the course of 5 years. The most reported crime type each year has always been theft and the most common page to find a crime news have been the newspaper cover since 2014. Both average size and value of crime news has been rather heterogeneous through the period of analysis.[15] As imagined, the majority of crime news were negatively-toned and most of the reported crimes occurred in Peru's capital, Lima.

[15]The reported averages for area and value were calculated using only news whose size was less than 1800 cm^2. This was done to reduce measurement error in news size, as will be explained next.

Table 3: Crime news dataset descriptive statistics

	2013	2014	2015	2016	2017
Number of news	24743	32073	49939	68760	64827
Number of newspapers	125	156	159	166	160
News per newspapers	198	206	314	414	405
Crime mode	Theft	Theft	Theft	Theft	Theft
Page mode	Second page	First page	First page	First page	First page
Avg. area in cm²	330.31	266.81	282.26	208.0	287.28
Avg. value in S/	520	1706	1285	1009	2048
Media source mode	El Comercio	El Comercio	El Popular	El Popular	Ojo
Date mode	2013-03-26	2014-09-03	2015-09-03	2016-06-01	2017-10-26
Sentiment mode	Negative	Negative	Negative	Negative	Negative
Region mode	Lima	Lima	Lima	Lima	Lima
Province mode	Lima	Lima	Lima	Lima	Lima
District mode	Constitución	San Juan de Lurigancho	San Juan de Lurigancho	Arequipa	Constitución

3.3 Other data

We also use the National Register of Crime and Misconduct Complaints, which contains information regarding the number of yearly complaints at the province level. Its information comes from administrative data from the police agencies, gathered by the INEI. The main objectives of the survey are to determine the homicide rate per 100,000 inhabitants and to have the exact number of felony or offense complaints. This data will provide controls for our main specification.

4 Identification Strategy

4.1 Our variables of interest

We use the following simple definition (Marshall, 2018) as the criteria to leverage *short-term deviations from trend* in the monthly average area (in cm^2) devoted to crime-related news for each province.[16] Peru is administratively divided into 25 regions and, in a second level, into 196 provinces. The latter constitute our unit of analysis. A province p is defined as treated in month t if it experiences a crime news coverage shock at such moment t. As we are using newspapers, a coverage shock is said to happen on month t in province p if the sum of the average areas of crime news from crimes that happened in province p on the current and previous month is larger than that of the next two months, conditional on at least one crime

[16] Our definition for a coverage shock is based on the one used by Marshall (2018) to identify homicide shocks at the municipality level.

news from that province happening on that four-month time span. Formally:

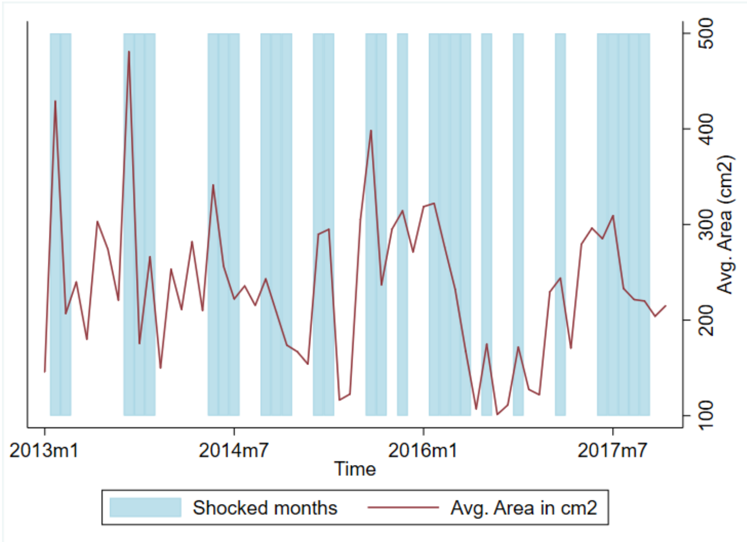
$$Coverage\ shock_{pt} = \begin{cases} 1 & \text{if } Avg.Area_{pt-1} + Avg.Area_{pt} > Avg.Area_{pt+1} \\ & +Avg.Area_{pt+2} \text{ and } \sum_{s=t-1}^{t+2} Avg.Area_{ps} > 0 \\ 0 & \text{if } Avg.Area_{pt-1} + Avg.Area_{pt} \leq Avg.Area_{pt+1} \\ & +Avg.Area_{pt+2} \text{ and } \sum_{s=t-1}^{t+2} Avg.Area_{ps} > 0 \\ \cdot & \text{if} \sum_{s=t-1}^{t+2} Avg.Area_{ps} = 0 \end{cases} \tag{1}$$

With this definition, we compare province-months experiencing a short-term spike in the average size of news during the two most recent months relative to the next two ones, with province-months that experience such spikes just after the month of analysis. These constitute our treatment and control groups, respectively. We apply this definition to the province-months throughout the entire period of analysis, so that all province-months are labeled either as treated or non-treated, whenever there is at least one crime news. We compute separate measures of coverage shocks for both negative and positive crime news. By way of example, consider Figure 4, which shows the monthly time series of the average area from negative crime news in the province of Cañete. As one can see, shocked months (shaded with light blue) are those where there's a relative spike in the series or are immediately preceded by one.[17] Thus, for the case of this province, the light blue months will conform the treatment group and the white months will constitute the control group. Note how this definition effectively retrieves peaks in the area size series.

Notice that, as we have data on all news from most Peruvian newspapers, we define our *coverage shocks* based on the *average* area devoted to tell crimes from each province in each month, not the *total* area nor the number of crime news. This has a series of advantages. First, we alleviate the problem of the changing composition of the newspapers database. We know that there is an increase in the number of tracked newspapers in the "iMedia" data, which could explain part of the increase in the number of crime news. Thus, by centering our attention in the average area of the news, we attempt to detach our treatment from the

[17] Applying other more traditional filters like detrending, for example, would not be feasible nor desirable. First, it could not be applied to all the provinces' time series, because not all provinces have at least one crime news reported each month. Second, the area series are highly irregular and variable across provinces, so choosing a single functional form for the trend might not be suitable for all cases.

Figure 4: Average area of negative crime news in Cañete 2013-2017



absolute number of crime news. Second, we know that some newspapers tend to report crime news more heavily due to editorial discretion. By focusing on average area *deviations*, our definition of coverage shock also seeks to address this possible source of concern. We aim to capture months in which crimes with particularly high media resonance happened, as these are expected to merit a larger area in the newspaper. We expect these highly covered crimes to have a great impact on crime perception that is almost exclusively channeled by the media, in a context where almost 80% of the population reads newspapers. Moreover, we argue that these salient crimes are more likely to create short-term deviations in the average area of crime-related news. Consistent with our claim that these type of news are arguably random in their occurrence, we find that within provinces the proportion of times the average area for negative crime news increased was fairly similar to the proportion of times it decreased (42.53% vs 40.63%). We find comparable results when assessing the likelihood that average area for positive crime-related news increases (32.50%) or decreases (30.15%).

4.2 Empirical Specification

We propose the following baseline linear probability model:

$$
\begin{aligned}
Crime\ perception_{ipt} &= \beta_0 + \beta_1 Coverage\ shock^{neg}_{pt} + \beta_2 Coverage\ shock^{pos}_{pt} \\
&+ \beta_3 Crime\ news^{neg}_{pt} + \beta_4 Crime\ news^{pos}_{pt} + \beta_5 Crime\ complaints_{py} \\
&+ \gamma_y + \gamma_p + \varepsilon_{ipt}
\end{aligned}
\tag{2}
$$

where i indexes individuals, p provinces, t months and y years. $Crime\ perception_{ipt}$ measures aggregate crime perception, as previously defined. It is an indicator that takes the value of 1 if individuals think that they will become a crime victim in the following 12 months. Next, $Coverage\ shock^{neg}_{pt}$ is defined as explained above and, broadly speaking, distinguishes between province-months where negative crime news had a short-term spike in their area. An equivalent definition applies for $Coverage\ shock^{pos}_{pt}$, but using positive crime news time series instead. On average, individuals in shocked province-months, experience negative crime news that are 55 cm^2 larger and positive crime news about 98 cm^2 larger than in their respective control groups. The coefficients associated to both coverage shocks (β_1 and β_2) are our parameters of interest and may be interpreted as the casual effect of experiencing a spike in the size of negative or positive crime news on the perceived probability of becoming a crime victim. We would expect that $\beta_1 > 0$, as larger negative news from crimes in one's province are theorized to increase crime perception. More uncertainty remains on the sign of coefficient β_2. However, one can expect that positive crime news could, at least temporarily, induce a sense of peace on newspapers' readers, thus reducing aggregate crime perception ($\beta_2 < 0$).

To identify our parameters of interests it is key to: (1) control for the total number of positive and negative crime news occurring in a certain province-month ($Crime\ news^{s}_{pt}$) and (2) control for the number of yearly crime complaints in each province ($Crime\ complaints_{py}$), as these should serve as proxies for local crime rates. By including them, we compare province-months where newspapers assigned a larger area to crime news, rather than comparing factually more dangerous province-months with less dangerous ones. This is possible because both the number of crime news and crime complaints are much more likely to track the actual number of crimes and other province-month-specific unobservable factors that are likely to covary with crime perception.

We also include year and province fixed effects (γ_y and γ_p, respectively) to control for unobserved time-invariant factors at the province level and cross-sectional-invariant factors at the year level affecting crime perceptions. Hence, we exploit within-province variation in coverage shocks to identify our parameters of interest. Ideally, controlling for the variables above described as well as province and year fixed effects may clean up most of the possible remaining endogeneity.

4.3 Potential issues with identification

4.3.1 Self-selection of readers

Concerning some possible identification issues, the self-selection of newspapers readers should not be a problem, as our treatment variable is defined at the province-level. Thus, we are estimating an intention-to-treat effect (ITT), which should include the average effect between newspapers readers and non-readers. Although one might think that changes in readers' perception make up all of the observed effect, one cannot discard the possibility that the treatment is affecting non-readers. This could happen by up to two channels. First, newspaper readers can tell their acquaintances what they have read, particularly if their perception of crime changed as a result of reading such newspapers. Second, as in several places in the world, newspapers in Peru are sold in newsstands that hold newspapers' covers at sight of the pedestrians. Photos and large headlines (both more area-increasing relative to text) are more likely to be spotted by people walking by, intentionally or not, regardless if they end up buying the newspapers. These transmission channels, including news readership itself, would be captured by our estimation. As we are interested in the overall impact of crime news coverage on the population this does not represent a problem for the consistency of our estimates.[18]

4.3.2 Crime perception leading crime coverage

There could be a potential problem if there is a simultaneous relationship between the coverage of crime news and crime perception at the province-level. Given the controls we are already including in our main specification, this would imply that newspapers strategically manipulate

[18] The share of readers could also change as a result of area shocks. However, underpinning this mechanism is not our objective.

the *size* of their crime-related news according to changes in crime perception *in each province*. For example, newspapers could supply larger crime news when people are getting increasingly fearful. We argue this is unlikely for several reasons. First of all, news area devoted to crime depends on several other factors that are not related to crime perception and that might reduce the flexibility to continually manipulate news size to track crime perception. For example, other daily relevant news related to politics, the economy, or even sports might demand area changes that restrict the newspapers ability to permanently make a strategical assessment of news size. Second, it is also unlikely that this type of behavior can be sustained for 196 provinces and that the newspapers possess exact information on monthly changes in fear of crime. These ideas are also sustained empirically. For example, evidence from the UK reveals that stories about crime are usually leading—not following—changes in feelings of insecurity (Duffy et al., 2008). To give further confidence on the validity of these dynamics for the case of Peru, we performed a Granger causality test (Granger, 1969) exploiting within provinces variation in crime perception and news area. In general, we fail to reject the null hypothesis that lagged values of crime perception have zero explanatory power on the average area of crime news, after controlling for past realizations of such variable.[19] This giver further strength to the argument that there is no feedback relationship between the two variables.

4.3.3 Attenuation bias

To define whether a province was shocked or not, we use the news' size in square centimeters as our main input. However, some of the areas reported on our data were measured with error. Some news feature impossibly high areas (around 764,000 cm^2). To alleviate this concern we dropped from the computation of our coverage shocks news featuring an area higher than 1,800 cm^2, which is the size of the largest Peruvian newspaper.[20] Even though this should greatly reduce attenuation bias, some wrongly measured areas below the 1,800 cm^2 threshold still remain. Thus, our results represent lower-bound estimates of the true population parameters.

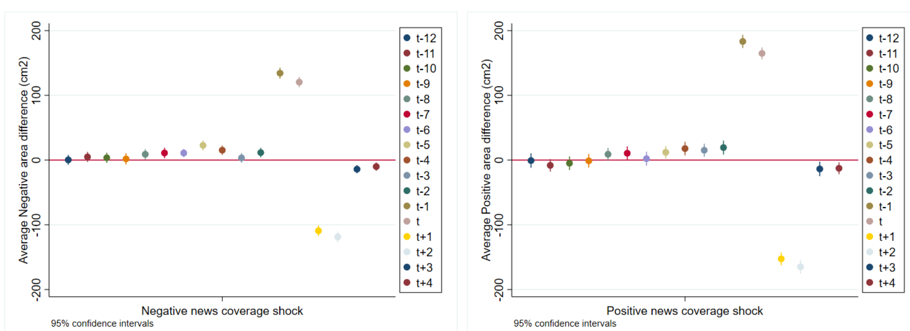
[19] We perform a Granger (1969) causality test with province fixed effect for both positive and negative crime news area. We use crime perception as the explanatory variable. We regress 3 specifications for each news sentiment: with only one lag, with two, and three. We fail to reject the null hypothesis for all three specifications of the negative area. For the equation with positive area, we only reject the null hypothesis in the specification with two lags. However, with three lags, the null hypothesis was not rejected again.

[20] We drop those news from any further calculations or descriptive statistics regarding area in cm^2.

4.3.4 Balance checks

We claim that our measures of coverage shocks are exogenous, conditional on covariates. To further validate our claim, we verify whether there were systematic differences in the pre-trends (i.e. before the occurrence of a coverage shock) of average areas between treated and non-treated province-months. As stated, the treatment group is composed by all province-months that were subject to a coverage shock. Provinces that were not shocked belong to the control group. Given that our definition of shock is a simple inequality that compares two two-month time spans, if crime news average areas were to follow a cyclical pattern lasting beyond two months, we could be confounding a coverage shock with the decreasing segment of a news area "cycle". Inspecting Figure 5, which displays the average area difference between treated and non-treated provinces across each month before and after the shock, one can see that treated and non-treated provinces are similar in terms of news coverage before the occurrence of the coverage shock. There are some area imbalances before the shock, but these are small in absolute terms and also small relative to the size of the upcoming area jump.

Figure 5: Difference in news' average area between treatment and control groups around the treatment month (unconstrained coverage shock)

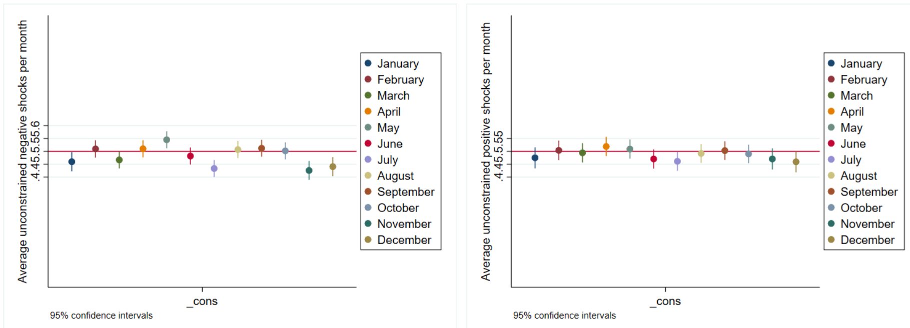


Although these small pre-trend imbalances should not bias our estimations by much, to address this concern, we create up to five different constrained versions of our measures of coverage shocks, each one with a more stringent pre-trend balance requirement. We constrain our measures of coverage shocks by dropping all observations coming from a month that i) was previous to a shock period and ii) showed any unbalance between treated and non-treated provinces. To exemplify how this procedure works, lets pick a month, say January 2015. For January 2015 (t), we can compare treated and non-treated provinces in terms of their average area (recall that we know which provinces were treated in January 2015, and which were not). This difference should be positive and large. The mean difference for December 2014 ($t-1$) should also be significant. Then, we can compare the average area in November 2014 ($t-2$) between those provinces that were treated and not treated in January 2015 (t). If treated and non-treated provinces are not equal (i.e. we reject the null hypothesis that the difference is 0), we drop all observations coming from January 2015, since we 'erroneously' assigned them as treated (i.e. shocked) and non-treated. Recall that what we are trying to do is to capture short-term deviations from the general trend (or cycle) of crime coverage in terms of area. If we find that there is an unbalance in a month previous to a "shock" period, then we are not capturing such short-term deviations. We repeat this process for every month in the period of analysis (not only January 2015, of course).

To be able to perform robustness checks and avoid an arbitrary cut in the number of months in which pre-trends balance was required, we evaluate up to six different measures: the first without any constraint, the second one requiring only 1-month of pre-trend balance (the penultimate month before the area shock), the third one requiring 2-months of pre-trend balance (months t-2 and t-3 without statistically significant differences in crime news area) and so on. We apply this procedure to our two measures of positive and negative coverage shocks. Although this should lead to a possible bias reduction, imposing these constraints entails a sometimes large sample size reduction.

We can further validate our empirical strategy by analyzing how coverage shocks are distributed among months. Ideally, we would want to observe a seemingly random assignment of the number of shocks, so as to avoid confounding possibly month-specific effects on crime perception with treatment effect. As can be observed in Figure 6, both the averages of positive and negative shocks are fairly centered around 0.5 with seemingly random deviations around it. Regarding constrained shocks, they are not as evenly distributed as their unconstrained counterparts. However, this potential problem is addressed in the Robustness subsection, with the inclusion of month-year fixed effects to the final specification.

Figure 6: Shocks' distribution among months



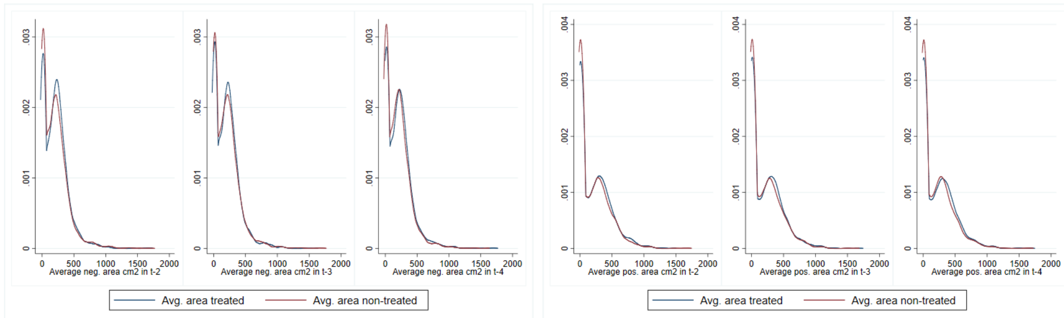
A similar analysis can be performed for the distribution of area across provinces. Although the sample size is very small for each province individually ($n < 60$), the null hypothesis of a 50% chance of negative coverage treatment cannot be rejected for all but 2 provinces in our sample.[21] In the case of the unconstrained positive crime news coverage shock, the treatment probability is statistically different from 0.5 for 5 provinces only.[22] Thus, for the large majority of provinces in our sample, one cannot reject the hypothesis that the unconditional probability of being subject to a news coverage shock is 0.5: as good as a coin toss. Regarding the constrained versions of the shock a few more provinces get a significantly different from 0.5 probability of receiving treatment, as some province-month combinations were eliminated due to pre-trend imbalance.

A last concern is that maybe shocked provinces, even though similar to non-shocked provinces in terms of average news' area, could be different in terms of other statistics. The following graphs show that this is not the case, since the distributions of the average crime news area are similar across several months before the treatment. (see Figure 7). The same holds for all the constrained versions of the treatment (see Appendix Figures **??**-**??**).

[21]The first one is the province Carlos Fermín Fitzcarrald in Áncash, where treatment never occurred due to absence of negative crime news over the entire sampling period, and the province La Unión in Arequipa, where treatment frequency was statistically different from 0.5.

[22]These correspond to: Antonio Raymondi, Carlos Fermín Fitzcarrald, Pomabamba, Purús (no positive crime news) and Moho (only one positive crime news).

Figure 7: Distribution of news' average areas (treated vs non-treated)



5 Baseline Results

5.1 Average Effects

In this section, we present the average effect of crime news shocks on crime perception. For all specifications, we show the results using all treatment variables: the unconstrained and constrained coverage shocks. We do this as a direct robustness check (as the sample size changes across columns), but also to observe how the effect of something progressively more akin to a short-term shock evolves. The first column of Table 4 shows the coefficients for unconstrained negative and positive shocks. The second column shows the coefficients of these shocks, but when we require a 1-month pre-balance. The third column requires two months of pre-balance, the fourth column three, the fifth one four, and the sixth one five. All the regressions were estimated using the individual weights (expansion factors) provided by the ENAPRES survey. These are designed so as to have a representative sample of Peru's urban population. Standard errors are clustered at the province level to account for within-province error correlation. This is necessary because (i) our treatment variables (coverage shocks) are defined at the province-level and the observations are individuals and (ii) because we are estimating a fixed-effects model with fixed effects at the level of the relevant clusters (Abadie et al., 2017).

Regarding the effect of a negative news coverage shock, we find robust evidence for a statistically significant positive effect on crime perception, mostly at the 1% level, for all six versions of treatment (see Table 4). Using the 1 month-balance coverage shock as our benchmark specification (see column 2), increasing the size of reported news leads to an

Table 4: Effect of news coverage shocks on crime perception

	(1)	(2)	(3)	(4)	(5)	(6)
Negative area shock$_t$	0.0053*	0.014***	0.022***	0.022***	0.022**	0.023***
	(0.0029)	(0.0034)	(0.0043)	(0.0044)	(0.0086)	(0.0080)
Positive area shock$_t$	-0.0060**	-0.010**	-0.0051	-0.0035	-0.00032	-0.0027
	(0.0030)	(0.0044)	(0.0032)	(0.0032)	(0.0052)	(0.0054)
Observations	310913	177479	98964	93723	60006	54686
Months balance	0	1	2	3	4	5

Standard errors clustered at the province-level are in parentheses. Significance stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

increase of crime perception of 1.4 percentage points. Although the average rate of crime perception in Peru is around 80% in our sample, the estimated effect is far from negligible. On average, negative crime news are about 54 cm^2 larger during two months in shocked province-months. This represents a 27% increase in negative news size relative to non-shocked province-months. To put this effect in perspective with a simple back-of-the-envelope calculation, an increase of 54 cm^2 on the area devoted to every crime news during two months is associated with around 336,000 Peruvians changing their minds on them being potential crime victims in the following year. This is a seemingly large and relevant impact, considering that it is only the size of the news that is changing and not its number nor the underlying criminality rates or trends.

The assessment of the positive news coverage shock is less clear, as no significant effects are found beyond the first month pre-trend balance requirement. However, this could be due to the smaller magnitude of the parameter. If anything, positive area shocks are linked with a decrease in crime perception. Once again, using column 2 as our benchmark, larger newspapers' area devoted to crime news leads to a reduction in crime perception of 1 pp. This result serves as a validation of our sentiment analysis procedure, but, most importantly, proves that the media can also play a key role on the never-convergent perception gap. In our sample, province-months that experience a positive news shock have 113 cm^2 larger positive crime news. This is a 46% size increase relative to non-shocked province-months. It implies that an increase of 113 cm^2 on the average area devoted to positive crime news is associated with about 240,000 Peruvians changing their minds and declaring to feel safe for the year.

How do these two effects stand in relation to each other? The difference of the effect per cm^2 of negative and positive coverage shocks is significant at the 1% level. In fact, the calculated average effect per cm^2 of negative news would be around 3 times larger than the calculated effect of positive news, signaling a potential and important asymmetry on the revision of people's expectations depending on the nature of the news received. This implies that it takes about 3 times more newspaper space of positive crime news to undo the increased crime perception of a given negative coverage shock. This finding is also relevant in the sense that it could explain how, even under "accurate" (using the term somewhat loosely) crime coverage by the press, people's perception can go astray, as negative news are weighted more heavily in the construction of one's beliefs. Thus, it is not only that negative crime news might be over reported (in number and size), but that their effect is also larger.

This result is consistent with individuals exhibiting *confirmatory bias* (Lord et al., 1979) (Rabin and Schrag, 1999). Under this framework, agents disregard or misinterpret new information that does not support their previous beliefs. Thus, if a majority of the population has a high subjective probability of becoming a crime victim, confirmatory bias will reinforce the impact of negative news, as they confirm one's previous position. Nonetheless, the bias will also reduce the effect of positive crime news, due to the the opposite reason. Persistence of false beliefs, even after receiving an infinite amount of information, is another important consequence of confirmatory bias (Rabin and Schrag, 1999), which could also help explain the documented growth of the perception gap. Finally, this impact asymmetry is also consistent with some form of *negativity bias*, operating through simple negative potency (Rozin and Royzman, 2001). This happens when a negative event (crime news) is more salient and potent than a positive event with the same objective magnitude (area in cm^2).

5.2 Robustness

Table 5 shows robustness checks for our results and, as can be generally seen, our main point estimates for the effect of both negative and positive crime news coverage tend to perform well in varying specifications. Their sign and, most notably magnitude remains rather unchanged. Column 1 shows the baseline specification with the initial 1.4 pp positive effect of negative news coverage on crime perception and the corresponding relieving effect of 10 pp of positive crime news coverage. Column 2 includes the lagged values of both coverage shocks, to address the possibility of omitted variable bias, as our definition of coverage shock could lead to treatment autocorrelation. Then, a current-period treatment effect could be

Table 5: Effect of news coverage shocks on crime perception (Robustness) with 1-month balance shock

	Baseline (1)	(1) + Shocks$_{t-1}$ (2)	(1) + News$_{t-1}$ (3)	(1) + Province time-trends (4)	(1) + Month-Year FE (5)	(1) − Complaints$_t$ (6)	(6) − News$_t$ (7)
Negative area shock$_t$	0.014***	0.018***	0.014***	0.013***	0.015***	0.013***	0.012***
	(0.0034)	(0.0057)	(0.0036)	(0.0035)	(0.0051)	(0.0032)	(0.0031)
Positive area shock$_t$	-0.010**	-0.019	-0.0100**	-0.0080*	-0.013***	-0.011**	-0.011**
	(0.0044)	(0.011)	(0.0043)	(0.0044)	(0.0049)	(0.0049)	(0.0044)
Negative area shock$_{t-1}$		-0.00053					
		(0.0050)					
Positive area shock$_{t-1}$		-0.000034					
		(0.0067)					
Observations	177479	99113	177479	177479	177479	177479	177479
Months balance	1	1	1	1	1	1	1
Control: #news$_t$	Yes	Yes	Yes	Yes	Yes	Yes	
Control: #news$_{t-1}$			Yes				
Control: complaints$_t$	Yes	Yes	Yes	Yes	Yes		
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes		Yes	Yes
Month-Year fixed effects					Yes		
Province time-trend				Yes			

	Only Year-FE (8)	Only Province-FE (9)	Treatment Only (10)	Socio-economic Controls (11)	News Content Controls (12)	News Value Controls (13)	TV-related Controls (14)
Negative area shock$_t$	0.016***	0.019***	0.022***	0.014***	0.014***	0.014***	0.013***
	(0.0034)	(0.0055)	(0.0053)	(0.0038)	(0.0039)	(0.0032)	(0.0033)
Positive area shock$_t$	-0.0032	-0.0088**	-0.0013	-0.0080**	-0.011**	-0.0096**	-0.0095**
	(0.0051)	(0.0037)	(0.0046)	(0.0038)	(0.0043)	(0.0043)	(0.0038)
Observations	177479	177479	177479	177465	170094	177479	177479
Months balance	1	1	1	1	1	1	1
Control: #news$_t$				Yes	Yes	Yes	Yes
Control: complaints$_t$				Yes	Yes	Yes	Yes
Province fixed effects		Yes		Yes	Yes	Yes	Yes
Year fixed effects	Yes			Yes	Yes	Yes	Yes
Control: Socioeconomic variables				Yes			
Control: Content shares$_{t,t-1}$					Yes		
Control: News value$_{t,t-1}$						Yes	
Control: TV$_{t,t-1}$							Yes

Standard errors clustered at the province-level are in parentheses. Significance stars: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

partially reflecting a persistent effect from a past shock. In this case, the inclusion of past shocks as controls should, if anything, reduce the absolute value of our estimates. However, as can be seen in Column 2, our coefficient for the negative coverage shock is robust to this inclusion and the effect of the positive area shock increases in absolute value, although it loses significance, barely. Perhaps most importantly, the lagged values of the coverage shocks have a very close to zero effect on the next period's crime perception. These two results reflect a very short-lived effect of news coverage, conditional on the contemporaneous one, although relevant in size. Similarly, in Column 3, we control for the lagged number of crime news, whose areas are also part of the definition of a contemporaneous coverage shock. Results remain unchanged.

To avoid confounding the treatment with periods of overall increasing crime perception, we include province-specific linear time trends in Column 4. Perhaps more strongly, we include month-year fixed effects in Column 5. Results remain unchanged: crime news coverage can drive perception both up and down. In Columns 6-10, we begin to remove covariates from our main equation. In Column 6, we do not control for the number of crime complaints; in Column 7, we additionally stop controlling for the number of crime news. After this, point estimates for both coverage shocks remain almost the same, although the effect of negative news is slightly smaller. In Columns 8, 9 and 10 we remove province, year and both province and year fixed effects, respectively. In the three specifications, the effect of negative news coverage is larger, signaling potential correlation between permanently more dangerous provinces or years and the likelihood of a negative crime coverage shock. On the other hand, the effect of positive news coverage loses significance when province fixed effects are removed. Finally, Column 11 includes socioeconomic control variables at the individual and household level and at the time of the treatment. These include the traditional socioeconomic variables, such as sex, age and living conditions, but also other topic-specific variables such as being a crime victim, owning a TV or having access to internet. Appendix Table 2 lists the entirety of covariates used.

One possible concern regarding our identification strategy, is that our definition of coverage shock might confound content-neutral size changes with content-varying ones. What do we mean by this? As one can imagine, pieces of news from some types of crime like life threats or abuses, usually merit a larger size per article than regular theft. In fact, average area is mostly heterogeneous among the 7 different crime types in our news data. To exemplify, the average difference in size between theft news and threat ones is of around 88 cm^2. If such content changes where actually driving the coverage shocks, our estimates' interpretation would not be, strictly speaking, reflecting the effect of changes in *news size* only, but would also compound the effect of changes in the *reported content or type of crimes*. Although we would still be capturing the influence of media (as news' composition is also part of a news' supplier decision spectrum) this is not our main interest. In order to test the validity of our interpretation, we compute measures of the shares of each type of crime news from the total number of crime news at the province-month level and include them in the main specification. As can be seen in Column 12, our main point estimates remain almost unchanged, signifying no previous omitted variable bias.

On a similar note, the news value might also be a relevant covariate. For example, one could argue that area shocks are not only reflecting regular changes in the size of the news, but also changes in the placement of the news in the newspaper, which would be reflected in the value of the news For example, an area shock could happen because news became larger and also occupied more front pages. Thus, one would likely observe an upward bias in the estimates, as news in the front covers or main pages of a newspaper are usually the most impactful ones. To solve this potential issue, we utilized the "value" variable in our dataset, which tells us the monetary value in Peruvian soles, of each piece of news. News value is computed as the product of the area of the news and the price per cm^2 of the page of the newspaper where it was published. Thus, we compute a variable that measures the value per cm^2 of each piece of news, by dividing value over area, and averaged it at the province-month level. This should only reflect the contributions of the newspaper and the saliency of its pages to the value of the news. We include these measures to the model, for both positive and negative crime news in t and $t-1$. Their associated coefficients are not significant individually, but have the expected signs: a higher average value of negative crime news is associated with increased crime perception and the opposite holds true for positive crime news. As can be seen in Column 13, their inclusion induces no important change into the original estimates.

Thus far, we have only considered the effect of newspapers on crime perception without including other important sources of mass communication like TV, for example. It could be argued that highly covered crimes are likely to receive widespread attention by not only the newspapers but also TV. Thus, we would be overestimating the effect of newspapers by actually estimating the effect of an overall increase of crime news coverage by different media. To address the possibility of this omitted variable bias, we control for the number of both positive and negative crime-related aired news from each province, as well as for their average duration in seconds. As can be seen in Column 14, our estimates remain practically unchanged to the inclusion of a second measure of total criminality (number of TV news) and to another coverage decision and relevance assessment (seconds on air), both in t and $t-1$.

5.3 Heterogeneous Effects

5.3.1 Victims and non-victims

Although we find significant and robust overall effects, it is likely that great heterogeneity on people's conditions, habits and exposure to crime news clouds some effects that are both more significant and of a higher magnitude than the ones already presented. On this line, we find evidence for heterogeneous effects among people who had been victim of a crime in the last 12 months and those who had not. Testing this can be particularly insightful as ex-ante it is unclear whether previous victims are more or less sensitive to crime news. It might be the case that a past crime victim is, as a consequence of the crime, more perceptive of crime overall and thus also more sensitive or alert to crime news. However, it is also plausible to assume that non-crime victims are more unaware of crime and, when first exposed to information about it, a disproportionate reaction follows, possibly because a greater revision of crime expectations is deemed necessary by the uninformed individuals. Our findings support the second hypothesis (see Column 1 in Table 6). For our preferred specification, the previously observed effect of negative coverage is now split in two groups and seems to be in the region of 1.7 pp for non-victims and around 0.6 pp for crime victims.[23] In fact, the interaction coefficient is significant and offsets most of the effect of crime news on non-victims. On the other hand, although the interaction coefficient for the positive coverage shock is non-significant, the net effect of positive news on crime victims is also negative and significant at the 5% level. These findings support the substitution thesis from fear of crime literature, which predicts that exposure to media representations of crime has a stronger effect on those without direct experience

[23]The victim-heterogeneity regressions, for all versions of the treatment, are robust and can be found in Appendix Table 3.

Table 6: Heterogeneous effect of news coverage shocks on crime perception

	(1)	(2)	(3)
Negative area shock$_t$	0.017***	0.019***	0.018***
	(0.0045)	(0.0073)	(0.0034)
Positive area shock$_t$	-0.0097*	-0.011**	-0.011**
	(0.0053)	(0.0048)	(0.0049)
Victim any crime	0.12***		
	(0.0064)		
Victim × neg. shock	-0.011***		
	(0.0043)		
Victim × pos. shock	0.0026		
	(0.0055)		
Woman		-0.010	
		(0.0070)	
Woman × neg. shock		-0.011	
		(0.010)	
Woman × pos. shock		0.00082	
		(0.0031)	
Mountains × neg. shock			-0.023***
			(0.0083)
Mountains × pos. shock			0.0055
			(0.0078)
Jungle × neg. shock			-0.011
			(0.013)
Jungle × pos. shock			0.0014
			(0.011)
Observations	177477	177479	177479
Months balance	1	1	1

Standard errors clustered at the province-level are in parentheses.
Significance stars: *** p <0.01, ** p <0.05, * p <0.1

of crime. This would happen because crime reported on the media becomes a substitute for direct real-world experience (Gunter, 1987) (Weitzer and Kubrin, 2004).

Additionally, being a crime victim is associated with a 12 pp increase in average crime perception. Thus, one can think of a situation where victims tend to be on average more fearful of being a victim again in the near future, but are simultaneously less sensitive to negative crime news coverage. On the other hand, those who have not been a crime victim in the last 12 months are those who are actually affected by crime news coverage. In the case of Peru, this second group is the majority of the population and is around 70% of it. This also has implications at the aggregate level, meaning that in countries where criminality rates are descending, people on average become more sensitive to news as, logically, the media becomes their primary source of information on the topic.

5.3.2 Men and women

The distinction between men and women in the literature of the consequences of crime perception is addressed by authors like Braakmann (2012) and Hale (1996), due to considerations on relative vulnerability and fear. Ex-ante it would be logical to think that women would be more sensitive to changes in crime news coverage, given the well-documented record of Peru as a country with very high femicide rates and overall higher female vulnerability. Thus, the female population could feel potentially more exposed to crime. However, women read the newspaper less than men in Peru, on average. As a consequence, the net effect could be either higher or lower on the female population. Introducing the sex heterogeneity does not result in significant differences in the treatment effect for negative and positive crime news' coverage in our preferred specification (see Column 2 in Table 6). Although less clearly, we do find suggestive evidence for a statistically significant difference in the effect of positive crime news for women, in some of our specifications (see Appendix Table 4). In such cases, the interaction coefficient offsets almost the entirety of the treatment effect on men. In fact, previously non-significant coefficients for positive crime news coverage now become statistically significant for the male population and are only non-significant for women. These results are consistent with the first hypothesis, in the sense that women would be less relieved than men with positive crime news, but almost equally affected by negative crime news.

5.3.3 Natural Regions

Third, we find that there is effect heterogeneity across the main natural regions of Peru, typically coast, mountains and jungle.[24] We observe that most of the overall effect of a negative news shock was in the coast, whereas in the case of the mountains the interaction coefficient offsets the entire treatment effect. Focusing in our benchmark specification (Column 3 in Table 6), the effect of both negative and positive crime news coverage is only statistically significant for the coast provinces, but not for the jungle nor the mountains. Similar conclusions can be drawn from the heterogeneity regressions with the different versions of treatment (Appendix Table 5). This finding is consistent with the fact that people from coastal cities

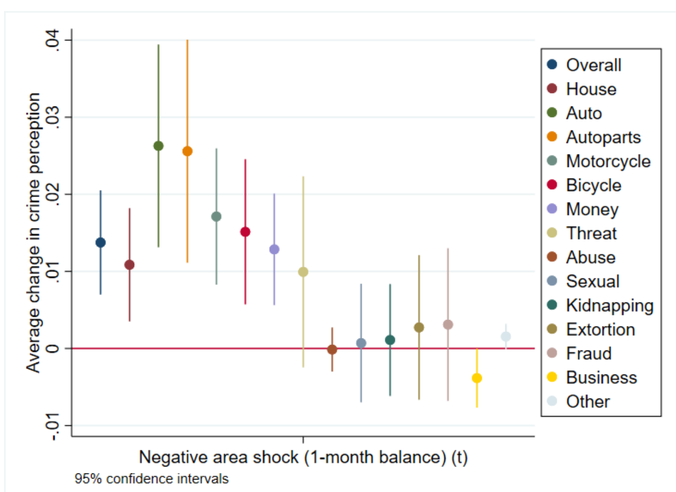
[24] Usually this division is done as follows: Tumbes, Piura, Lambayeque, La Libertad, Ánchash, Lima, Callao, Ica, Arequipa, Moquegua, Tacna belong to the coast, Cajamarca, Huánuco, Pasco, Junín, Ayacucho, Apurímac, Cusco and Puno belong to the mountains and Amazonas, San Martín, Loreto, Ucayali and Madre de Dios belong to the jungle.

are more avid readers than their counterparts in other regions, as can be observed in Table 1. It is thus consistent with our identification strategy being the effect of newspapers.

5.3.4 Type of crimes

As has been documented, crime perception is in fact susceptible to crime news coverage. However, one can ask: which crimes' perception? To answer that question, we exploit the variables used to build our aggregate measure of crime perception and use them separately to identify the effect of the same coverage shocks on crime-specific perceptions. These crime-specific perceptions were listed in Table 2. Figure 8 shows the results for the negative coverage shock and reveals that the overall increase in crime perception is mostly driven by three types of crimes. First, the fear of house theft; second the fear of burglary of other important properties (auto, autoparts, motorcycle and bicycle theft) and; third, the fear of money, wallet or cellphone theft, which is usually associated with the common violent street crime or pickpocketing. However, there is no significant evidence for crime news coverage to be increasing fear to other potentially more violent crimes like threats, abuse, sexual offenses, kidnapping, extortion and fraud. Somewhat strangely, we observe that negative crime news coverage has a negative effect on business theft crime perception.

Figure 8: Effect of negative crime news coverage shocks on different crime-specific perceptions



6 Consequences of Crime Perception

In this section of our study, we explore some of the consequences of changes in crime perception, as a result of crime news coverage.

6.1 Trust in Government Institutions

Given that we observe varying crime perception, it is worth asking: who do people hold accountable for these changes in perceived criminality? Which Government institution is more likely to receive blame for increased crime? Does any institution receive any credit at all when people feel safer? These questions draw upon the aforementioned relevance of crime perceptions on trust in institutions and overall social capital. To investigate how people distribute accountability after perceived increases in crime, we try our main specification but using four different dependent variables. These measure confidence in the police, the Judiciary Power, the municipality and the Attorney in a discrete scale from 1 to 3.[25] The survey question was: "*Regarding citizen security: How much trust does the j-th institution inspire you?*", so we are using a variable that is directly aimed at measuring the perceived ability of these institutions to fight crime.

Our results are less conclusive and robust than before, but are revealing nonetheless. For the case of the police, confidence in it remains generally almost unchanged after both negative and positive coverage shocks. Somewhat differently, both the Judiciary and the Attorney seem to be affected by both negative and positive crime news, meaning that people assign both guilt and reward to these two institutions. Finally, the local municipalities' reputation seems to be the most harmed by the press' crime news coverage, as confidence in it is reduced clearly by negative crime news, but is not conversely increased by positive crime news. These results are relevant for two reasons. First, because they suggest an asymmetric treatment from the public between institutions, as some are more susceptible than others to the the press, but also asymmetric within institutions, as some can only be negatively affected by news and other in both directions. Second, these results are important, as they represent a further dimension on the possible impact of crime news coverage: these do not only affect people's fear of crime, welfare and behavior, but also their trust on Government's institutions. This

[25] For the year 2013, the survey question was in a scale from 1-4. That year was adapted for comparability with the following 4 years.

has the potential to bring an entirely different set of politically relevant consequences into the table.

6.2 Police task-specific ratings

Finally, although we do not find robust significant effects of crime news coverage on the trust in the police, we do find other consequences on their evaluated performance on 4 indicators: (i) attend promptly when a crime occurs, (ii) maintaining security and public tranquility, (iii) informing the community on crime prevention and (iv) treating everyone without any distinction. The survey question was "*How do you qualify the performance of the National Police in relation to duty j?*" and the answer was in a scale from 1 to 4. Once again, we find asymmetry and negativity bias, as the decrease in the police qualification is always significant at the 1% level after negative news, but not significantly affected by positive news.

7 Concluding Remarks

We started by observing a seemingly conflicting result: decreasing criminality rates coupled with increasing crime perception in several countries across the globe. Our main hypothesis was that news media could be held in part accountable for the widening perception gap and resulting unwarranted fear of crime. We centered our attention on crime news coverage in Peruvian newspapers between 2013 and 2017, understanding coverage not as the number of news itself, but as the area in cm^2 each piece of news occupied. In order to establish a causal relation between these two variables, we identify province-level crime news coverage shocks, which represent short-term deviations from trend in the area devoted to tell crime news from each province. These are arguably exogenous after (i) controlling for relevant covariates on real criminality, (ii) discarding other potential issues, (iii) verifying balance between provinces and (iv) performing several robustness checks. Moreover, to identify a relevant population parameter, we split news according to their sentiment and to their geographical location.

Under this framework, we find that changes in the area size of negatively-toned crime news increase crime perception and that the converse is also true for positively-toned crime news. Thus, media is revealed to be very powerful as it can, for very little cost, shift crime perception in both directions, albeit with the caveat that negative crime news are a much more powerful

Table 7: Effect of news coverage shocks on confidence in different institutions (standardized)

	(1)	(2)	(3)	(4)	(5)	(6)
	Police	Police	Police	Police	Police	Police
Negative area shock$_t$	-0.00069	-0.021***	0.0025	-0.0036	-0.010	-0.011
	(0.0042)	(0.0054)	(0.0082)	(0.0086)	(0.012)	(0.012)
Positive area shock$_t$	-0.0072	-0.0013	-0.0021	-0.0052	0.0053	0.0043
	(0.0055)	(0.0061)	(0.0083)	(0.0089)	(0.015)	(0.016)
Observations	307531	175777	98131	92987	59608	54384
Months balance	0	1	2	3	4	5
	(7)	(8)	(9)	(10)	(11)	(12)
	Judic.	Judic.	Judic.	Judic.	Judic.	Judic.
Negative area shock$_t$	-0.0071	-0.023***	-0.013	-0.016	-0.029*	-0.028*
	(0.0063)	(0.0059)	(0.012)	(0.010)	(0.015)	(0.015)
Positive area shock$_t$	-0.0071	0.0054	0.026***	0.021***	0.029**	0.027*
	(0.0060)	(0.0052)	(0.0077)	(0.0078)	(0.014)	(0.015)
Observations	292457	167305	93367	88474	56697	51817
Months balance	0	1	2	3	4	5
	(13)	(14)	(15)	(16)	(17)	(18)
	Munic.	Munic.	Munic.	Munic.	Munic.	Munic.
Negative area shock$_t$	-0.011	-0.035***	-0.027***	-0.021**	-0.028*	-0.024
	(0.0080)	(0.0060)	(0.0085)	(0.0088)	(0.017)	(0.017)
Positive area shock$_t$	-0.0023	0.0020	-0.0082	-0.012	-0.0058	-0.0058
	(0.0046)	(0.0050)	(0.010)	(0.0087)	(0.010)	(0.011)
Observations	305664	174700	97508	92391	59245	54056
Months balance	0	1	2	3	4	5
	(19)	(20)	(21)	(22)	(23)	(24)
	Attor.	Attor.	Attor.	Attor.	Attor.	Attor.
Negative area shock$_t$	-0.0034	-0.015**	-0.0034	-0.0053	-0.025*	-0.022
	(0.0071)	(0.0066)	(0.015)	(0.013)	(0.015)	(0.014)
Positive area shock$_t$	-0.0070	0.0053	0.026**	0.022**	0.026*	0.025
	(0.0058)	(0.0049)	(0.010)	(0.011)	(0.015)	(0.015)
Observations	290885	166390	92856	87996	56452	51593
Months balance	0	1	2	3	4	5

Standard errors clustered at the province-level are in parentheses. Significance stars: *** p <0.01, ** p <0.05, * p <0.1

Table 8: Effect of news coverage shocks on police qualifications (standardized)

	Speed	Secur.	Info.	Equal.
	(1)	(2)	(3)	(4)
Negative area shock$_t$	-0.036***	-0.034***	-0.028***	-0.029***
	(0.0069)	(0.0069)	(0.0074)	(0.010)
Positive area shock$_t$	-0.0024	-0.0010	0.00020	-0.0028
	(0.0063)	(0.0065)	(0.0071)	(0.0094)
Observations	177926	177925	177924	177924
Months balance	1	1	1	1

Standard errors clustered at the province-level are in parentheses. Significance stars: *** p <0.01, ** p <0.05, * p <0.1

perception-deviator than positive ones. Altogether, the media exerts a stronger influence on non-crime victims and men, and mostly increases the perception of regular street-crime and property theft. Furthermore, such simple news' size changes have also an important effect on trust in governmental institutions like municipalities, the Attorney and the Judiciary.

Although telling, our results lead to some other important research questions and leave them open for further analysis. First, this papers does not shed light on whether is an *optimal* level of perception gap and what it would be. Clearly, some perception of criminality is needed, as it could lead to efficient crime avoidance behavior, but widening misperceptions are almost surely not positive. Optimal crime perception, as defined in this paper, most likely lies below current levels in Peru, but above the actual victimization rate. Second, one can speculate that the current crime-perception literature is finding a total impact of media, that accounts for both the number of news and its size, by not separating them as we do. An identification strategy with exogenous variability for *both* the number of news *and* their size would be required to disentangle such effects. Third, this paper brings evidence for the existence of the perception gap in Peru, as a case-study. However, studying such gap in other countries might be insightful, as not all are likely to present such misperceptions and crime news coverage style might also differ. A valid question would then be why are some citizens less affected to crime news coverage in some countries and not in others? Consumption patterns, preferences for different media outlets, lifestyle and education are some variables that could explain differing sensitivities to news media. Finally, further study could be done on why political institutions are affected differently by the media. Putting partisan media targeting aside, governmental institutions could use from more knowledge on the reasons for their relative vulnerability to both negative *and* positive crime news.

As closing comments, even though all our conclusions are drawn from the study of newspapers in Peru, we believe that they serve as a general proof of the persuasive power of media, that is applicable to several countries in the world. The main transmission mechanism, news *size*, is also not limited to written press only and can be adapted to other media outlets like radio, TV and the internet, using other metrics like seconds on air, for example. This type of exercise, thus, can be replicated in several countries if the appropriate data is available.

The straightforward policy recommendation that arises from these findings is the need for a more responsible and conscious crime news reporting, that ponders over (i) the effects of editorial choices like size and the use of images, and (ii) the asymmetric impact of positive and negative crime news. Arguably, countries with a large perception gap could do with a better balance between positive and negative crime news. In a context of decreasing criminality, an accurate and objective representation of the country's crime situation might not lead to a justified decrease in crime perception if negative and positive news are not reported with an appropriate coverage balance.

References

Abadie, A., Athey, S., Imbens, G. W., and Wooldridge, J. (2017). When should you adjust standard errors for clustering? NBER Working Paper 24003, National Bureau of Economic Research.

Adena, M., Enikolopov, R., Petrova, M., Santarosa, V., and Zhuravskaya, E. (2015). Radio and the Rise of the Nazis in Prewar Germany. *The Quarterly Journal of Economics*, 130(4):1885–1939.

Alesina, A. and La Ferrara, E. (2000). The Determinants of Trust. NBER Working Paper 7621, National Bureau of Economic Research.

Alt, J. E., Marshall, J., and Lassen, D. D. (2016). Credible Sources and Sophisticated Voters: When Does New Information Induce Economic Voting? *The Journal of Politics*, 78(2):327–342.

Ardanaz, M., Corbacho, A., and Ruiz-Vega, M. (2014). Mind the Gap: Bridging the Perception and Reality of Crime Rates with Information. IDB Working Papers Series 6595, Inter-American Development Bank.

Arellano Marketing (2017). Estudio nacional del consumidor peruano: informe final.

Arias, E., Larreguy, H. A., Marshall, J., and Querubin, P. (2018). Does the Content and Mode of Delivery of Information Matter for Electoral Accountability? Evidence from a Field Experiment in Mexico. Working Paper.

Banerjee, A., Kumar, S., Pande, R., and Su, F. (2011). Do informed voters make better choices? Experimental evidence from urban India. Unpublished manuscript.

Braakmann, N. (2012). How do individuals deal with victimization and victimization risk? Longitudinal evidence from Mexico. *Journal of Economic Behavior & Organization*, 84(1):335–344.

Bureau of Justice Statistics (2016). Criminal Victimization, 2015. "`https://www.bjs.gov/content/pub/pdf/cv15.pdf`".

CERLALC (2012). Comportamiento lector y hábitos de lectura. "http://www.observatoriopoliticasculturales.cl/OPC/wp-content/uploads/2013/03/Comportamiento-Lector-y-H%C3%A1bitos-Lectores-%E2%80%93-CERLALC.pdf".

Chong, A., De La O, A. L., Karlan, D., and Wantchekon, L. (2015). Does Corruption Information Inspire the Fight or Quash the Hope? A Field Experiment in Mexico on Voter Turnout, Choice, and Party Identification. *The Journal of Politics*, 77(1):55–71.

Chong, A., León-Ciliotta, G., Roza, V., Valdivia, M., and Vega, G. (2018). Urbanization Patterns, Information Diffusion and Female Voting in Rural Paraguay. *American Journal of Political Science*, 63(2):323–341.

Corbacho, A., Philipp, J., and Ruiz-Vega, M. (2015). Crime and Erosion of Trust: Evidence for Latin America. *World Development*, 70(C):400–415.

CPI (2017). Estudio de lectoría de diarios en Lima y 15 principales ciudades - 2016. "https://cpi.pe/images/upload/paginaweb/archivo/23/LectoriaDiarios_2016.pdf".

de Figueiredo, M., Hidalgo, D., and Kasahara, Y. (2014). When do Voters Punish Corrupt Politicians? Experimental Evidence from Brazil. Working Paper.

DellaVigna, S. and Kaplan, E. (2007). The Fox News effect: Media bias and voting. *The Quarterly Journal of Economics*, 122(3):1187–1234.

DuBow, F., McCabe, E., and Kaplan, G. (1979). *Reactions to crime: a critical review of the literature: executive summary*. Department of Justice, Law Enforcement Assistance Administration, National Institute of Law Enforcement and Criminal Justice Washington, DC.

Duffy, B., Wake, R., Burrows, T., and Bremner, P. (2008). Closing the gaps – crime and public perceptions. *International Review of Law, Computers & Technology*, 22(1-2):17–44.

Dunning, T., Grossman, G., Humphreys, M., Hyde, S. D., McIntosh, C., and Nellis, G. (2018). Metaketa I: Information, accountability, and cumulative learning. Unpublished manuscript.

Dustmann, C. and Fasani, F. (2016). The Effect of Local Area Crime on Mental Health. *Economic Journal*, 126(593):978–1017.

Ellen, I. G. and O'Regan, K. (2010). Crime and urban flight revisited: The effect of the 1990s drop in crime on cities. *Journal of Urban Economics*, 68(3):247–259.

Enikolopov, R., Petrova, M., and Zhuravskaya, E. (2011). Media and political persuasion: Evidence from Russia. *American Economic Review*, 101(7):3253–85.

Fattah, E. A. and Sacco, V. F. (2012). *Crime and Victimization of the Elderly*. Springer Science & Business Media.

Fernández-Baca, J. (2014). Estudio de la estructura del mercado de la prensa escrita en el Perú. Documento de discusión. Universidad del Pacífico – Centro de Investigaciones.

Ferraz, C. and Finan, F. (2008). Exposing corrupt politicians: the effects of Brazil's publicly released audits on electoral outcomes. *The Quarterly Journal of Economics*, 123(2):703–745.

Gallup (2019). Crime. "`https://news.gallup.com/poll/1603/crime.aspx`".

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37(3):424–438.

Gunter, B. (1987). *Television and the Fear of Crime*. John Libbey.

Hale, C. (1996). Fear of crime: A review of the literature. *International review of Victimology*, 4(2):79–150.

Hamermesh, D. S. (1999). Crime and the Timing of Work. *Journal of Urban Economics*, 45(2):311–330.

Horváth, R. (2013). Does trust promote growth? *Journal of Comparative economics*, 41(3):777–788.

Humphreys, M. and Weinstein, J. (2012). Policing politicians: citizen empowerment and political accountability in Uganda preliminary analysis. Columbia Universities. Unpublished manuscript.

INEI (2018). Perú - Encuesta Nacional de Programas Presupuestales 2017.

Jackson, J. and Gouseti, I. (2014). Fear of Crime and the Psychology of Risk. In *Encyclopedia of criminology and criminal justice*, pages 1594–1603. Springer.

Kahneman, D. (2002). Maps of Bounded Rationality: A Perspective on Intuitive Judgment and Choice. *Nobel Prize Lecture*, 8:351–401.

Ladd, J. M. and Lenz, G. S. (2009). Exploiting a rare communication shift to document the persuasive power of the news media. *American Journal of Political Science*, 53(2):394–410.

Larreguy, H. A., Marshall, J., and Snyder Jr., J. M. (2018). Publicizing Malfeasance: How Local Media Facilitates Electoral Sanctioning of Mayors in Mexico. Working Paper.

Liska, A. E. and Baccaglini, W. (1990). Feeling safe by comparison: Crime in the newspapers. *Social problems*, 37(3):360–374.

Lord, C. G., Ross, L., and Lepper, M. R. (1979). Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of Personality and Social Psychology*, 37(11):2098–2109.

Marshall, J. (2018). Political information cycles: When do voters sanction incumbent parties for high homicide rates? Working paper.

Martin, G. J. and Yurukoglu, A. (2017). Bias in cable news: Persuasion and polarization. *American Economic Review*, 107(9):2565–99.

Mastrorocco, N. and Minale, L. (2018). News media and crime perceptions: Evidence from a natural experiment. *Journal of Public Economics*, 165(C):230–255.

Mineo, L. (2014). El Diario Más Vendido en el Mundo de Habla Hispana se Hace en Perú. *ReVista: Harvard Review of Latin America.*

Molina-González, M. D., Martínez-Cámara, E., Martín-Valdivia, M.-T., and Perea-Ortega, J. M. (2013). Semantic orientation for polarity classification in Spanish reviews. *Expert Systems with Applications*, 40(18):7250–7257.

Office for National Statistics (2011). Crime and Justice: Social Trends 41. "`https://webarchive.nationalarchives.gov.uk/20151014074225/http://www.ons.gov.uk/ons/rel/social-trends-rd/social-trends/social-trends-41/social-trends-41---crime-and-justice.pdf`".

Perez-Rosas, V., Banea, C., and Mihalcea, R. (2012). Learning Sentiment Lexicons in Spanish. In *LREC*, volume 12, page 73.

Rabin, M. and Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, 114(1):37–82.

Ramírez-Álvarez, A. A. (2017). Media and crime perceptions: Evidence from Mexico. Serie documentos de trabajo del Centro de Estudios Económicos 2017-06, El Colegio de México, Centro de Estudios Económicos.

Romer, D., Jamieson, K. H., and Aday, S. (2003). Television News and the Cultivation of Fear of Crime. *Journal of Communication*, 53(1):88–104.

Rozin, P. and Royzman, E. B. (2001). Negativity bias, negativity dominance, and contagion. *Personality and Social Psychology Review*, 5(4):296–320.

Schwarz, N. and Bless, H. (2007). Mental Construal Processes: The Inclusion/Exclusion Model. *Assimilation and contrast in social psychology*, pages 119–141.

Schwarz, N., Bless, H., Strack, F., Klumpp, G., Rittenauer-Schatka, H., and Simons, A. (1991). Ease of retrieval as information: Another look at the availability heuristic. *Journal of Personality and Social Psychology*, 61(2):195–202.

Sidorov, G., Miranda-Jiménez, S., Viveros-Jiménez, F., Gelbukh, A., Castro-Sánchez, N., Velásquez, F., Díaz-Rangel, I., Suárez-Guerra, S., Trevino, A., and Gordon, J. (2012). Empirical study of machine learning based approach for opinion mining in tweets. In *Mexican International Conference on Artificial Intelligence*, pages 1–14. Springer.

Snyder Jr., J. M. and Strömberg, D. (2010). Press coverage and political accountability. *Journal of Political Economy*, 118(2):355–408.

Spenkuch, J. L. and Toniatti, D. (2016). Political advertising and election outcomes. Working Paper.

Tavits, M. (2006). Making democracy work more? Exploring the linkage between social capital and government performance. *Political Research Quarterly*, 59(2):211–225.

Tversky, A. and Kahneman, D. (1973). Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology*, 5(2):207–232.

Urizar, X. S. and Roncal, I. S. V. (2013). Elhuyar at TASS 2013. In *Proceedings of the Workshop on Sentiment Analysis at SEPLN (TASS 2013)*, pages 143–150.

Weitzer, R. and Kubrin, C. E. (2004). Breaking news: How local TV news and real-world conditions affect fear of crime. *Justice Quarterly*, 21(3):497–520.

Yanagizawa-Drott, D. (2014). Propaganda and Conflict: Evidence from the Rwandan Genocide. *The Quarterly Journal of Economics*, 129(4):1947–1994.

Appendices

A Tables and Figures

Table 1: Crime Dataset Description

Variable	**Description**	**Data type**
Crime	The type of crime the news talks about. Namely, theft, threats, abuse, sexual offense, kidnap, extortion or fraud.	String
Surface	The total surface the news occupies in the newspaper.	Float
Page	The page number in which the news is located in the newspaper.	String
Height	The height of the news article in the newspaper.	Float
Width	The width of the news article in the newspaper.	Float
Press section	The newspaper section in which the news is located.	String
Title	The title of the news.	String
Valuation	The economic cost of publishing or delivering the news.	Float
Audience	The amount of people to who received the news.	Integer
Text	The textual description or transcription of the news.	String
Media source	The media source in which the news is published or delivered.	String
Date	The date in which the news was published or delivered.	Date

Table 2: Socioeconomic controls used for Column 11 in Table 5

	Variable name	**Type**	**Description**
1	*victim*	dummy	Victim of any crime in the last 12 months
2	*victim2*	dummy	Victim of any crime or crime attempt in the last 12 months
3	*woman*	dummy	Is a woman
4	*age*	continuous	Age in years
5	*reg_mountains*	dummy	Lives in the mountains regions
6	*reg_jungle*	dummy	Lives in the jungle regions
7	*num_hab*	continuous	Number of household inhabitants
8	*water*	dummy	Household has water supplied by truck, tank, well, river or canal
9	*nbi1*	dummy	Basic need #1 unsatisfied
10	*nbi2*	dummy	Basic need #2 unsatisfied
11	*nbi3*	dummy	Basic need #3 unsatisfied
12	*has_tv*	dummy	Household has color TV
13	*has_internet*	dummy	Household has internet
14	*has_cable_tv*	dummy	Household has cable-TV
15	*has_cell*	dummy	Household has cellphone with internet service

Table 3: Effect of news coverage shocks on crime perception (victim heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Victim any crime	0.11***	0.12***	0.13***	0.13***	0.13***	0.13***
	(0.0054)	(0.0064)	(0.0058)	(0.0056)	(0.0064)	(0.0062)
Victim × neg. shock	-0.0053	-0.011***	-0.015*	-0.019**	-0.025*	-0.020**
	(0.0038)	(0.0043)	(0.0089)	(0.0085)	(0.013)	(0.0081)
Victim × pos. shock	0.0019	0.0026	-0.0013	-0.00048	0.0024	0.0094
	(0.0033)	(0.0055)	(0.0054)	(0.0046)	(0.0061)	(0.0091)
Negative area shock$_t$	0.0067*	0.017***	0.025***	0.027***	0.028**	0.027***
	(0.0039)	(0.0045)	(0.0063)	(0.0067)	(0.012)	(0.010)
Positive area shock$_t$	-0.0057*	-0.0097*	-0.0039	-0.0024	-0.0014	-0.0056
	(0.0034)	(0.0053)	(0.0040)	(0.0039)	(0.0068)	(0.0077)
Observations	310910	177477	98963	93722	60005	54685
Months balance	0	1	2	3	4	5

Standard errors clustered at the province-level are in parentheses. Significance stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Effect of news coverage shocks on crime perception (sex heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Woman	-0.010**	-0.010	-0.017***	-0.018***	-0.015*	-0.014
	(0.0047)	(0.0070)	(0.0051)	(0.0050)	(0.0086)	(0.0086)
Woman × neg. shock	-0.0060	-0.011	-0.0080	-0.0069	-0.016	-0.019
	(0.0066)	(0.010)	(0.0075)	(0.0076)	(0.015)	(0.015)
Woman × pos. shock	0.00059	0.00082	0.0095***	0.0100***	0.016***	0.015***
	(0.0019)	(0.0031)	(0.0035)	(0.0036)	(0.0044)	(0.0044)
Negative area shock$_t$	0.0084	0.019***	0.026***	0.025***	0.030*	0.032**
	(0.0058)	(0.0073)	(0.0069)	(0.0074)	(0.016)	(0.015)
Positive area shock$_t$	-0.0063*	-0.011**	-0.010***	-0.0087**	-0.0089*	-0.011*
	(0.0033)	(0.0048)	(0.0034)	(0.0037)	(0.0053)	(0.0056)
Observations	310913	177479	98964	93723	60006	54686
Months balance	0	1	2	3	4	5

Standard errors clustered at the province-level are in parentheses. Significance stars: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Effect of news coverage shocks on crime perception (natural region heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Mountains × neg. shock	-0.010*	-0.023***	-0.035***	-0.032***	-0.028	-0.020
	(0.0057)	(0.0083)	(0.010)	(0.010)	(0.017)	(0.020)
Mountains × pos. shock	0.000010	0.0055	-0.0054	-0.0027	0.0090	0.011
	(0.0071)	(0.0078)	(0.010)	(0.010)	(0.012)	(0.013)
Jungle × neg. shock	-0.015	-0.011	-0.0063	-0.0055	-0.035*	-0.035**
	(0.0095)	(0.013)	(0.013)	(0.014)	(0.018)	(0.017)
Jungle × pos. shock	-0.0083	0.0014	0.015	0.018	0.0072	0.0084
	(0.0083)	(0.011)	(0.011)	(0.013)	(0.018)	(0.017)
Negative area shock$_t$	0.0080***	0.018***	0.028***	0.027***	0.029***	0.028***
	(0.0027)	(0.0034)	(0.0042)	(0.0040)	(0.0081)	(0.0076)
Positive area shock$_t$	-0.0057	-0.011**	-0.0049	-0.0040	-0.0021	-0.0050
	(0.0037)	(0.0049)	(0.0035)	(0.0033)	(0.0053)	(0.0053)
Observations	310913	177479	98964	93723	60006	54686
Months balance	0	1	2	3	4	5

Standard errors clustered at the province-level are in parentheses. Significance stars: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 1: Example of a negatively-toned crime news
The negatively-toned piece of news has the following headline: "*Land tenants from community report vandals' threats*". Its header says: "*Again, there would be problems because of land dispute*".
Source: Correo - Piura, 31st of December, 2017

Nuevamente habrían problemas por litigio de tierras.

Posesionarios de comunidad denuncian amenazas de vándalos

Tras el desalojo a varios posesionarios de terrenos de la Comunidad Campesina de Castilla, estos denunciaron ayer en la comisaría de El Indio las amenazas que vendrían recibiendo por parte de un grupo de delincuentes que se encuentran apostados en la zona.
Uno de los denunciantes en diálogo con Correo manifestó que tienen información que los vándalos "sembrarán" armas a los comuneros con la finalidad que la policía durante una intervención que realizarán en los predios judicializados los intervenga y detenga.
"Tenemos miedo, nos han dicho que la Policía coludida con estos delincuentes nos pondrán armas de fuego y droga para hacernos pasar como delincuentes cuando no lo somos. Eso es injusto fuimos a la comisaría y no nos querían aceptar la denuncia, nosotros no somos ningunos delincuentes", refirió el denunciante.

Figure 2: Example of a positively-toned crime news
The positively-toned piece of news has the following headline: "*They detain Ramón Linares after request due to embezzlement of public funds*".
Source: El Mercurio - Cajamarca, 1st of December, 2017

Detienen a Ramón Linares por requisitoria de peculado

En la víspera, luego de ser detenido por la Policía Nacional del Perú de Contumazá, Flavio Ramón Linares Verástegui, director de "El Centinela", fue conducido a Cajamarca y se encuentra en poder de la policía judicial, para luego ser llevado a Bagua.
"El Tonco", venía siendo requisitoriado a nivel nacional desde el 28 de agosto del presente año por la sala penal de Bagua (Amazonas) por el delito de Peculado, producto de actos de corrupción cometidos cuando era Subprefecto. En el momento de su detención se identificó con un documento que no le pertenecía (usurpación de identidad) pero luego en el local de la comisaría se identificó como tal.
Según se sabe, que Linares Verástegui es profesor de educación física en la I.E. San Isidro de Tembladera, había llegado a Contumazá para afrontar una denuncia ante la UGEL por parte de una docente del lugar y al promediar las seis de la tarde fue detenido.
Según el Código Penal en su Artículo 387: Peculado doloso y culposo. El funcionario o servidor público que se apropia o utiliza en cualquier forma, o consiente que un tercero se apropie o utilice caudales o efectos públicos, cuya percepción, administración o custodia le estén confiados por razón de su cargo, será reprimido con pena privativa de libertad no menor de cuatro ni mayor de ocho años. Cuando el valor de lo apropiado o utilizado sobrepase diez unidades impositivas tributarias, será reprimido con pena privativa de libertad no menor de ocho ni mayor de doce años. Si los caudales o efectos, independientemente de su valor, estuvieran destinados a fines asistenciales o a programas de apoyo social, la pena privativa de libertad será no menor de ocho ni mayor de doce años.

B Sentiment Analysis

This section defines the sentiment analysis procedure with detail. As explained, we use it to determine the polarity of each piece of news: negative, positive or neutral. First, we detail the data pre-processing that allows the analysis techniques to work optimally. For the news dataset, the process went as follows: (i) accents and special characters elimination through the appropriate encoding handling, (ii) line breaks removal, (iii) punctuation marks and extra spaces are removed, (iv) repeated letters are reduced and (v) stopwords are removed. The algorithm in Figure 3 depicts the repeated process used to evaluate all pieces of news in the database.

Figure 3: Algorithm for news sentiment analysis

```
news_dataset ←news texts from News dataset
keywords ←domain-specific keywords
positive ←list of positive words
negative ←list of negative words
positive_count ←0
negative_count ←0
neutral_count ←0
foreach news in news_dataset do
    tokens ←news white space split
    foreach token in tokens do
        if token is in positive then
            positive_count ←positive_count + 1 ;
        else if token in negative or keywords then
            negative_count ←negative_count + 1;
        else
            neutral_count ←neutral_count + 1 ;
        end
    end
    sentiment ←max(positive_count, negative_count, neutral_count) ;
    return sentiment
end
```

Furthermore, considering n as the list of news texts, p the list of positive sentiment keywords, neg the combination of negative sentiment keywords and domain-specific keywords, and neu all other words different from p and neg, the algorithm can be summarized with the equations below:

$$\begin{aligned} positive_{count}(n_i) = & \quad \textstyle\sum_0^j count(p_{ij}) \\ negative_{count}(n_i) = & \quad \textstyle\sum_0^j count(neg_{ij}) \\ neutral_{count}(n_i) = & \quad \textstyle\sum_0^j count(neu_{ij}) \end{aligned}$$

,where p_{ij} symbolizes the positive word j in news i, neg_{ij} symbolizes the negative word j in news i, and neu_{ij} symbolizes the neutral word j in news i. Each piece of news was classified to the sentiment for which it had the highest count. Crime news classified as neutral were not used for our analysis, as they were relatively scarce and of less interest than those classified as positive or negative.

C Spatial Entities Extraction

This section explains the extraction procedure with detail. As mentioned, it was used to determine the geographical location of each piece of news. First, the UBIGEO Id database for the different possible combinations of administrative spatial sub-divisions in Peru was used. The fields that compose it are explained in the Table 6. The importance of this dataset relies on the dictionaries constructed from it: a dictionary per spatial unit containing their unique elements (e.g all the unique regions, provinces or districts), and a homonyms dictionary (spatial entities with the same name, but referring to different places or locations). This dataset was also subject to a pre-processing, that basically consisted on accents and special characters removal, through the appropriate encoding handling.

Table 6: UBIGEO dataset description

Variable	**Description**
UBIGEO Id	Id corresponding to a combination of spatial administrative subdivisions, given by INEI.
District	Third-level spatial administrative subdivision in Peru.
Province	Second-level spatial administrative subdivision in Peru.
Region	First-level spatial administrative subdivision in Peru.

C.1 Initial Spatial Entities Extraction

In this stage, the initial extraction of spatial entities in the news is carried out. For each spatial entity in the regions' dictionary, we verify whether it appears in the news description or not. If the entity is found in a given description, it is added to a list of found regions. This process is then executed in the same way for provinces and districts. Then, empty lists are removed (regions, provinces or districts lists). Finally, the entity list of the smallest geographic unit is chosen.

C.2 Ambiguity Calculation

In this stage, the ambiguity (represented by a Boolean Value) of the spatial entities extraction is computed. First, we verify the entities list size. If it is greater than 1 (there is more than one district name in the text, for example), then it receives a Boolean value = 1, as it would be unclear which one was the actual crime location. Then, if the entities list size is not greater than 1, we check whether the spatial entity has a homonym or not. If it does have an homonym, it is given a Boolean value = 1. All other cases are assigned a Boolean value = 0.

C.3 Double Verification

The double verification process comprises four main activities:

- We verify that the entity do not refers to an address (*e.g.*, streets, avenues, boulevards, intersections). For this, we have a dictionary of the different types of addresses, as well as their variations and abbreviations. We verify 4 words before and forth from the spatial entity to see if any of the type of addresses appears. In case of encountering an address, it is georeferenced through the Google Maps API, from where the corresponding district can be obtained.

- We check if the spatial entity, in the context of the news, is not a surname nor a proper name. Towards this aim, we look if the word immediately before is capitalized or not. If so, it is considered to be a proper name.

- We analyze if the full name of the geographical entity is extracted. The search algorithm may extract only a part of the full name of the spatial entity, since that specific part matches the searched text. For example, let's compare the region or province San Martín vs. the district San Martín de Porres. The algorithm may have found and selected San Martín as the geographic entity (since this part satisfies the search), when in reality the text refers to San Martín de Porres. In that sense, it is necessary to do this verification step.

- The different variations of the spatial entity's name are standardized, compared and fixed.

C.4 Valid News Filtering

In this subsection we remove news which will not add valuable data for our analysis. Specifically, news without any spatial data (either district, provincial or regional) are filtered out as they are not analyzable.

C.5 Computation of Upper Spatial Granularity and Georeferentiation

In this subsection, we compute the upper spatial granularity and georeference the news. This is, from the smallest spatial unit available, the information for the larger units is completed through queries to the UBIGEO dataset. Example: Given the district data, reconstruct the data corresponding to its corresponding province and region. Then, spatial entities are georeferenced through the Google Maps API. In this way, we get the latitude and longitude associated with each news item.