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DISCUSSION PAPER SERIES

IZA DP No. 12056

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

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ABSTRACT

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

Crime perception has increased in Peru in recent years, as in other developing and developed countries, in spite of the reduction in crime victimization figures. Our hypothesis is that the news industry is in part responsible for such developments. Using a novel database of written news, we identify short-term deviations from the long-term trend in the coverage of crime news at the province level and estimate the effect of news media on crime perception. We measure coverage as a function of the area an article occupies in cm^2. Peruvians are great consumers of written news. For instance, *Trome*, a Peruvian gazette, is the most read Spanish-language newspaper in the world. We find that a spike of negative crime news increases people's perception about the probability of being a crime victim. We find the opposite for positive crime news. However, the effect per cm^2 of negative news is more than three times larger than the effect of positive news in absolute value, signaling a potential asymmetry in the revision of people's expectations. We show that these changes in perception are smaller for recent crime victims than for non-victims and that women's perception is less sensitive to positive crime news. We also explore how these perception changes are transmitted to the political landscape and how individuals distribute accountability and reward between different political institutions.

JEL Classification: D83, D84, L82

Keywords: expectation, crime, newspaper, information

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1 Introduction

Several countries in the world face persistent differences between actual criminality rates and individuals' crime perception. This problem has been particularly acute in Latin America in the XXI-st century, as people have consistently perceived their countries to be growing in insecurity each day, even though crime has followed an overall negative trend (see Figure 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, the Bureau of Justice Statistics and the Office for National Statistics.

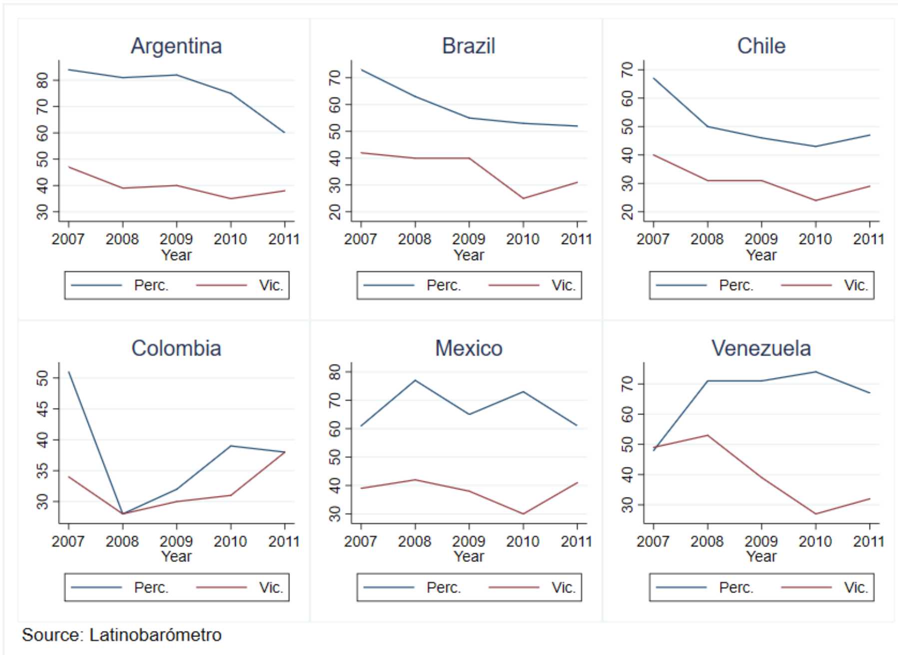
This so-called *perception gap*[1] is a topic worth studying not only due to its global presence, but also due to its potential economic implications regarding welfare and efficiency. One can easily think of four ways that this perception gap can be welfare-reducing. First, an overestimation of actual criminality rates may be associated with a higher and unjustified *fear of crime*,[2] which in turn can have negative consequences on health by increasing mental distresses (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 report to have avoided or have stopped to go out at night due to their fear of crime in 2017. A similar percentage report to have stopped using their cellphones on the street for the same reasons. 21% have stopped taking taxis and even 15% have avoided walking on the streets at all. These important changes in habits 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, misguided by short-term deviations in crime perceptions, can commit into irreversible investments. For example, about 10% of the population has installed bars in their windows and 15% has placed a bar-door to avoid house theft. Moreover, about 18% has added locks and latches to their houses for the same reason and has even bought watchdogs. All this entails significant initial and permanent expenditures. 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

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

[2] 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*". In any case, for the purposes of this research, we will simply define fear of crime as the consequence of an aggregate excess expected victimization (i.e. $E(victimization) > victimization$).

Figure 1: Percentage of people who think crime has increased and actual percentage of victims of crime in Latin American countries (2007-2011)



reputation of governmental institutions and to a misinformed voting behavior. For instance, Corbacho et al. (2015) find that crime reduces trust in the police, in local leadership and harms the overall social capital. They argue that this is not only detrimental for development (Tavits (2006); Horváth (2013)), but also costly by itself, because it makes the government spend their 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 Peru for the period 2013-2017. Perhaps contrary to what common sense might suggest in a digitalized world, 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[3] is about 78% of the total population (of almost 12 million individuals). Furthermore, Peruvians are the most avid newspaper readers in the region.[4] 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).

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

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

[4] As stated by the Regional Center for Book Promotion in Latin America and the Caribbean in 2012.

their position towards the crime situations being reported. Second, we tailor each news to a geographical location using other text mining techniques. Specifically, we apply the techniques of "Sentiment Analysis" and "Name Entity Recognition", respectively, which we describe with further detail below. Our main attention is then centered on the *area* in cm^2 that each piece of crime news occupies in the newspapers. For each province (there are 196 provinces in Peru), we construct a monthly time-series of the average area occupied by crime news. Then, we show that spikes (i.e. short-term deviations) in the average area devoted to negative crime news considerably increase crime perception. We find the opposite result for positive crime news. We argue that these *area shocks*, after controlling for the actual number of crime news and other critical controls, are more likely to exhibit a plausibly *exogenous* behavior, as they would be tracking short-term deviations in the occurrence of violent and morbid crimes, whose impact in crime perception is almost exclusively mediated by the press.[5] Thus, we do not identify the effect of increasing the number of crime news, but the effect of *employing larger newspaper space* to report them.

Coupled with several robustness checks, we find that negative crime news tend to have a larger effect per cm^2 on crime perception than 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.

In an attempt to answer some of the theoretical questions posed by fear of crime and the media literature, we then explore effect heterogeneity and find that (i) negative crime news increase crime perception mostly on non-victims and that (ii) positive crime news tend to have a smaller relieving effect on women than on men. Similarly, we observe that both self-declared TV-watchers and 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 the fear of domestic burglary and the fear of common street robbery more than the fear 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 both guilt, but also reward. We find that negative crime news do not affect the trust people deposit in the police; they only affect how people qualify their job. 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

[5] Some studies support the idea that the media tend to report and devote more space to shocking criminal events, especially if they are violent and sensational. These stories tend to be a regular feature of newspapers (Ditton and Duffy, 1983) (Weitzer and Kubrin, 2004) (Surette, 2014).

governments.

Our most direct contribution is to the literature on the relation between media and information and crime perceptions (Ardanaz et al. (2014), Ramirez-Alvarez (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. Ramirez-Alvarez (2017) performs a similar study to the previous one, but leverages an industry agreement to reduce coverage of violence, in Mexico.

A first important difference of our study relative to the previously mentioned efforts is that the analysis of a natural experiment only provides evidence on the impact of media in one direction: less exposure reduces crime perception. In our case, we analyze shocks of both positive and negative news which introduces a second dimension that allows us to study asymmetries and dig deeper into the subject. Second, we georeference each news according to the location of the reported crime to exploit cross-sectional variability among provinces. Third, we use an *absolute* measure of crime perception as our dependent variable, whereas Mastrorocco and Minale (2018) resort to relative measures of crime perception, like the position of "crime" in a ranking of country's problems. 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 almost any other problem to society. Ramirez-Alvarez (2017) uses a variable that depends upon past personal estimates of criminality. We, instead, use a dependent variable which leads to coefficients with a more direct interpretation: we explore how the share of the population who thinks they can become a crime victim in the next 12 months is affected. This is not only more policy-relevant but also more telling regarding the true impact of news on people's welfare and thoughts. Finally, there is an important conceptual difference in the way we identify the effect of crime news coverage: we focus on the *size* of the news, not on its sheer number.

We also make several other contributions to the literature. First, we contribute to a more general research documenting the persuasive effects of media content, by showing that crime news can affect crime perceptions and other outcomes such as the trust deposited in governmental institutions.[6] In line with this, we also contribute to the literature about the determinants of trust and social capital (e.g. Alesina and Ferrara (2000)). Furthermore, our results go in line with the discussion about the mode of delivery of information, since, as it is discussed later on, we provide evidence that increasing the area devoted to crime news in newspapers affects individuals' perceptions.[7] Finally, we contribute to a long tradition in the literature of criminology, psychology and sociology about the formation of specific beliefs.[8] In particular, about

[6] e.g. DellaVigna and Kaplan (2007); Ferraz and Finan (2008); Ladd and Lenz (2009); Snyder Jr and 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).

[7] e.g. Alt et al. (2016); Arias et al. (2018); Marshall (2018) and Chong et al. (ming).

[8] e.g. Tversky and Kahneman (1973); Schwarz et al. (1991); Kahneman (2002) and Schwarz and Bless (2007).

how individuals can mentally retrieve negative experiences and shape their concept of fear.[9]

Our contribution, thus, lies on expanding upon previous research by using a richer set of variables to further explore the relation between news media and crime perception, particularly asymmetries between positive and negative news and heterogeneities among different groups. Second, this paper utilizes a unique database and leverages information engineering techniques for classification and the creation of variables, which can vastly increase the scope of analysis. Third, the paper is also revealing on the mechanisms by which people update their expectations by highlighting the importance of news' size and how powerful these and images are for deviating people's beliefs.

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

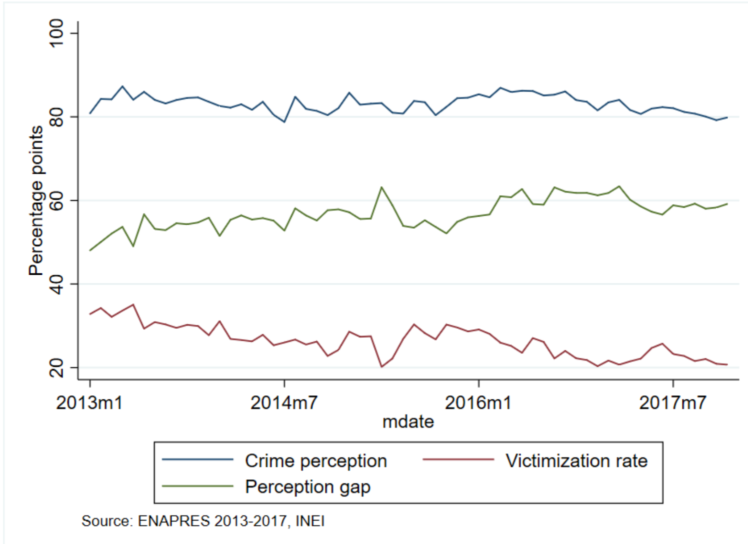
2.1 Crime in Peru

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 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. Nowadays, 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 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 "pessimists" (i.e. their expectation of their future state is worse 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 "optimists", as they believe they will improve on their "victim" situation. Finally, those who believe that their situation will remain the same, either as

[9] e.g. Tversky and Kahneman (1973); Gunter (1987); Hale (1996); Braakmann (2012) and Jackson and Gouseti (2014).

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

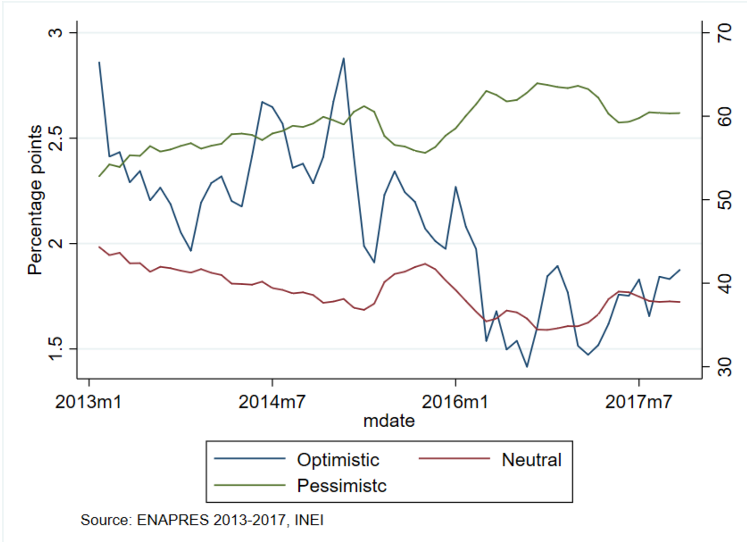


a victim or a non-victim, can be defined as "neutrals". The dynamics of the pessimists and the optimists are of our interest, as they should reflect the marginal individuals who are changing their beliefs towards crime in a positive or negative manner. As Figure 3 shows, there has been a rather steady 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. Optimism has been rather volatile, but has followed an overall negative trend.

2.2 The newspapers market in Peru

As previously mentioned, newspapers are very popular in Peru. According to independent survey data from CPI in 2016, weekly readership in Lima metropolitan area stands in a high 78.0%, meaning that most of its population aged 15 or older are greatly exposed to our treatment. 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 information is representative of the year 2016). 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. Finally, according to Arellano Marketing in 2017, about 36% of newspapers readers in Lima metropolitan area stated that they read more than before, 45% read the same and only 19% less than before. This suggests that, even

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



though there are more media outlets than ever (e.g. internet), the newspaper has not been fully replaced, at least in Peru. This fact is particularly important for our identification strategy.

On the supply side, the newspaper industry in Peru, as in several countries in the world, is heavily concentrated with around 95% of market share dominated by three media groups as of 2012: El Comercio (49%), Epensa (29%) and La República (17%) (Fernández-Baca, 2013). However, in mid-2013 El Comercio bought Epensa, configurating almost a duopoly in the market in terms of competing firms. However, both El Comercio and La República have several newspapers to their name, as the aforementioned *Trome*, which belongs to the former group.

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 valuable information on people's assessment and experience of criminality (see Table 2). It is from this survey that we construct our crime perception variables. To create our measure of crime perception, we define, for each 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 and onward simply *crime perception*) as the inclusive disjunction of the 14 crime perceptions. Thus, crime perception is equal to 1 if

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, 2016*

a person believes that he can a be victim of any of these 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 is not simply irrational but that their definition of crime includes more 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?*" (Ramirez-Alvarez, 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 fact, one can easily interpret it as $E(victimization)$.[10]

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 type of news from

[10]This 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.

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*

national and local news suppliers, in different media formats such as newspapers and TV. They posses this information for the period 2013 to 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.[11] The resulting database contains several fields of interest such as a description of each news, the type of crime the news was about, the text included in the the news, the monetary cost, the area in cm^2 it occupied, and so on. Using these data, we carried out two text mining techniques that are described below.

A. Positive or negative crime news?: Sentiment Analysis

Acknowledging that crime-related news can also have a positive sentiment is critical for 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 can also inform about improvements in the security level (e.g. by informing the disbanding of a criminal gang, the conviction of a murderer or by factually describing decreasing criminality rates). 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 and policy-relevant question: do *positive* crime news actually *decrease* crime perception? This policy question is particularly relevant in our context: 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

[11] 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.

are over-provided.

Then, in order 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. In addition, we also include crime-specific keywords derived from the queries used to get the initial data set. 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 assign each news with a sentiment according to this word count. Appendix B describes and gives further detail of this algorithm.

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, when forming their expectation on the likelihood 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 this end, 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. For a better understanding of the data, the resulting descriptive statistics are displayed in Table 3.

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.

Table 3: Crime news dataset descriptive statistics

	2013	2014	2015	2016	2017
	Written Press	*Written Press*	*Written Press*	*Written Press*	*Written Press*
Number of news	24743	32073	49939	68762	64827
Number of newspapers	125	156	159	166	160
Crime mode	Theft	Theft	Theft	Theft	Theft
Average surface	332.59	267.16	345.42	624.0	884.41
Page mode	Second page	First page	First page	First page	First page
Average valuation	2593.22	2312.10	2003.77	4946	8370
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
Department mode	Lima	Lima	Lima	Lima	Lima
Province mode	Lima	Lima	Lima	Lima	Lima
District mode	San Juan de Lurigancho	San Juan de Lurigancho	San Juan de Lurigancho	Arequipa	Arequipa

4 Identification Strategy

4.1 Our variables of interest

We use the following simple definition (Marshall, 2018) as a first criteria to leverage *short-term deviations from trend* in the monthly average area (in cm^2) devoted to crime-related news for each province.[12] Peru is administratively divided into 25 regions and, in a second level, into 196 provinces. These constitute our first unit of analysis. A province p is defined as treated in the month t if it experiences a crime news coverage shock at such moment t. As we are using newspapers, a coverage shock, as it will be referred to, 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 news from that province happening on that four-month time span. Formally:

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

We apply this definition to all the provinces throughout the entire period of analysis in a continuous fashion so that all provinces are labeled either as treated or non-treated in each month, whenever there is at least one crime news. We compute separate measures of coverage shocks for both negative and positive news.

We define our *coverage shocks* based on the *average* area devoted to crime news each month,

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

not the *total* area nor the number of crime news. 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. Media resonance of crimes can be attributed to particularly violent or sadistic events, which are arguably more random in their occurrence (conditioning on several covariates). We expect these highly covered crimes to have a great impact on crime perception that is almost exclusively channeled by the media towards crime perception. As a single, yet violent, crime does not materially increase the actual likelihood of being a crime victim, but does make people feel insecure due to the press' coverage, they constitute the perfect fit for identification of the effect of interest. These highly newsworthy crimes are more likely to create short-term deviations in the average area of crime-related news. Consistent with our claim that these 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 start from 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 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 instead. The coefficients associated to both coverage shocks (β_1 and β_2) are our parameters of interest. 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 and tranquility 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 month and province ($Crime\ news^{s}_{pt}$) 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 months (or places) where newspapers decided to assign a larger area to crime news, rather than comparing more dangerous months (or places) 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 month-province-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. Note that including these fixed effects is not required for identification, nonetheless including them and finding similar results is reassuring of our identification strategy. Ideally, controlling for the variables above described, as well as province and year fixed effects, should clean up most of the possible remaining endogeneity. Thus, after conditioning on these variables, the variability we are exploiting should reflect the news' size (i.e. area) selection criteria of news suppliers or the extremely violent nature of the crimes being reported. Ex-ante, the only intuitive transmission channels between these two variables (controlling for everything else) and crime perception is the size of the news itself.

4.3 Potential issues with identification

4.3.1 Self-selection of readers

Concerning other 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 average treatment effect (i.e. ATE), which should include both the effect on 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 and are, in fact, part of the effect of interest.[13]

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

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 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.[14] This giver further strength to the argument that this there is no feedback relationship between the two variables.

4.3.3 Attenuation bias

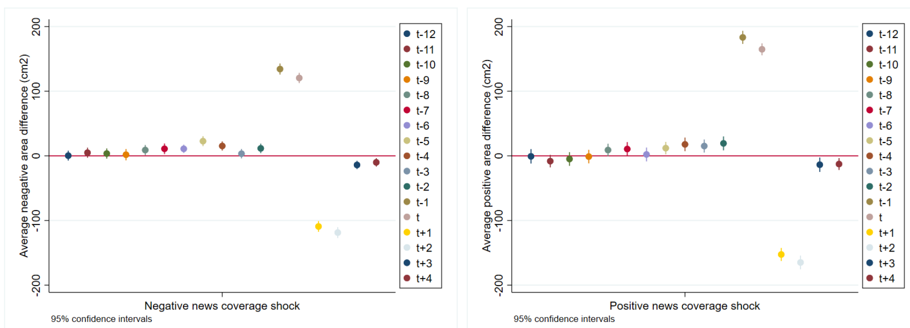
The use of our data on crime news is not without caveats. Recall that to define whether a province was shocked or not, we use the news' size in square centimeters as our main input. However, some of the areas reported on our data were wrongly measured due to human error. For instance, some news feature impossibly high areas (around 764,000 cm^2). To alleviate this concern we dropped from the computation of our coverage shocks any news featuring an area higher than 1,800 cm^2, which is the size of the largest Peruvian newspaper. 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.

[14]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.

4.3.4 Balance checks

We claim that our measures of coverage shocks are exogenous, conditional on several 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 provinces. 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 4, 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 pre-trend imbalances but these are small.

Figure 4: Pre-trend stability for unconstrained coverage shocks (t-12 - t+4)

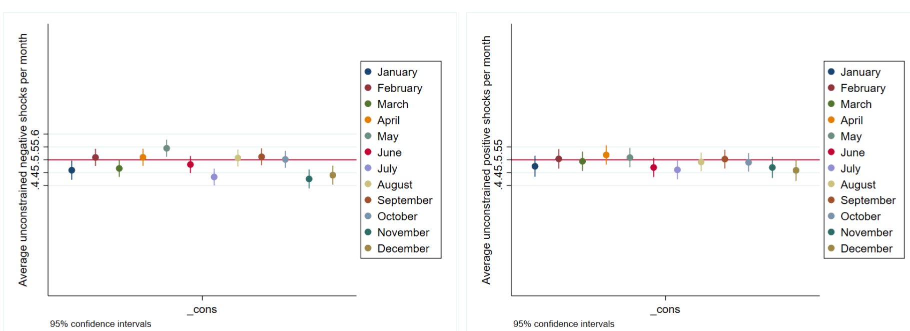


Although these small pre-trend imbalances should not bias our estimations by much, to address this concern, we create up to five different constrained versions of our measures of coverage shocks, each one with a more stringent pre-trend balance requirement. We constrain our measures of coverage shocks 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).

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. Appendix Figures 1-5 show the resulting pre-trend balance graphs for up to 5-month balance requirements and for both sentiment types.

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 5, 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 (see Appendix Figures 6-10), but any important systematic monthly deviation could be controlled for in the final specification.

Figure 5: 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.[15] In the case of the unconstrained positive crime news coverage shock, the treatment probability is statistically different from 0.5 for 5 provinces only.[16] Thus, for the large majority of provinces

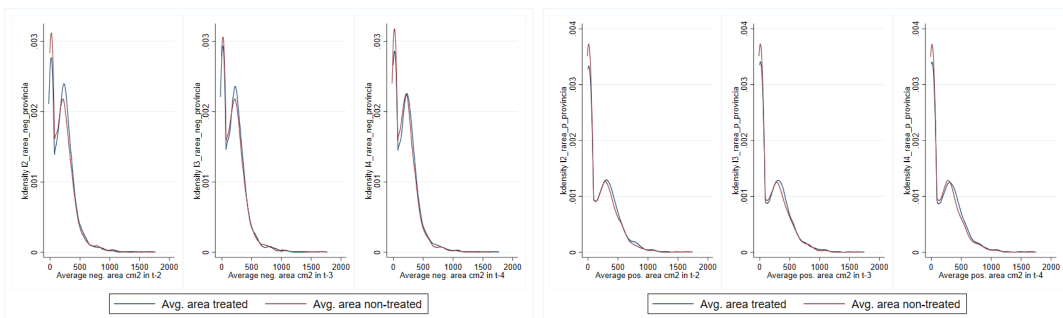
[15] The first one is the province Carlos Fermín Fitzcarrald in Áncash, where treatment never occurred due to absence of negative crime news over the entire sampling period, and the province La Unión in Arequipa, where treatment frequency was statistically different from 0.5.

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

in our sample, one cannot reject the proposition 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 (see Appendix Table 3 for further detail).

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 6). The same holds for all the constrained versions of the treatment (see Appendix Figures 11-15).

Figure 6: 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 some sort of direct robustness check, but also to observe how does 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 coefficient of these shocks, but when we require a 1-month pre-balance, and so on.

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 increase of crime perception of 1.5 percentage points. This coverage shock represents an average increase of around 45 cm^2 on the area devoted to every negative crime news per month, during a two-month time span. To put this effect in perspective, an increase of 45 cm^2 on the area devoted to every crime

Table 4: Effect of news coverage shocks on crime perception

	(1)	(2)	(3)	(4)	(5)	(6)
Negative area shock$_t$	0.0053*	0.015***	0.023***	0.024***	0.022**	0.023***
	(0.0029)	(0.0037)	(0.0048)	(0.0054)	(0.0086)	(0.0080)
Positive area shock$_t$	-0.0060**	-0.010**	-0.0043	-0.0023	-0.00032	-0.0027
	(0.0030)	(0.0043)	(0.0038)	(0.0038)	(0.0052)	(0.0054)
Months-balance	0	1	2	3	4	5
Observations	310913	165156	92775	87534	60006	54686

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

news during two months is associated with around 450,000 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.

On the other hand, 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 significant reductions in sample size and the fact that the effect is relatively small. 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. Our benchmark specification implies that an average increase of 108 cm^2 on the average area devoted to positive crime news is associated with about 300,000 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 3.6 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 3.6 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. Be it because the images or words used are more impacting or because people tend to remember this type of news more (or both), this result brings evidence for the presence of a *negativity bias* while forming crime perceptions.

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 0.15 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 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 nonetheless. 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.

To avoid confounding the treatment with periods of overall increasing crime perception, we include an overall linear time trend to our specification in Column 4, and province-specific linear trends 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, but now are both significant at the 1%, reflecting possible collinearity between news size and number, albeit no relevant effect of the number of news itself. In Columns 8, 9 and 10 we remove province, year and both province and year fixed effects, respectively. Now, 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, Columns 11-12 include socioeconomic control variables at the individual 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. Column 12 uses a larger set of control variables, that are separated because they entail sample size reduction. Appendix Table 4 lists the entirety of covariates used.

Thus far, we have only considered the effect of newspapers on crime perception without

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Neg. area shock$_t$	0.015***	0.018***	0.015***	0.015***	0.014***	0.014***	0.013***
	(0.0037)	(0.0057)	(0.0039)	(0.0037)	(0.0038)	(0.0035)	(0.0033)
Pos. area shock$_t$	-0.010**	-0.019	-0.010**	-0.011**	-0.0073*	-0.012**	-0.011***
	(0.0043)	(0.011)	(0.0040)	(0.0042)	(0.0043)	(0.0047)	(0.0043)
Neg. area shock$_{t-1}$		-0.00053					
		(0.0050)					
Pos. area shock$_{t-1}$		-0.000034					
		(0.0067)					
Months-balance	1	1	1	1	1	1	1
Observations	165156	99113	165156	165156	165156	165156	165156
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	Yes
Linear time trend				Yes			
Province time trend					Yes		
Control Set #1							
Control Set #2							

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Neg. area shock$_t$	0.017***	0.020***	0.024***	0.015***	0.014***	0.014***	0.014***
	(0.0037)	(0.0057)	(0.0054)	(0.0041)	(0.0039)	(0.0036)	(0.0035)
Pos. area shock$_t$	-0.0033	-0.0086**	-0.0010	-0.0083**	-0.0088***	-0.010**	-0.0096**
	(0.0049)	(0.0034)	(0.0045)	(0.0038)	(0.0034)	(0.0042)	(0.0038)
Months-balance	1	1	1	1	1	1	1
Observations	165156	165156	165156	165147	116932	165156	165156
Control: #news$_t$				Yes	Yes	Yes	Yes
Control: #news$_{t-1}$							
Control: complaints$_t$				Yes	Yes	Yes	Yes
Province fixed effects		Yes		Yes	Yes	Yes	Yes
Year fixed effects	Yes			Yes	Yes	Yes	Yes
Linear time trend							
Province time trend							
Control Set #1				Yes			
Control Set #2				Yes	Yes		
Control: TV$_t$						Yes	
Control: TV$_{t-1}$						Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 the media. To address the possibility of this omitted variable bias, we control for the number of both positive and negative crime-related aired news in each province, as well as for their average duration in seconds. As can be seen in Columns (13) and (14), our estimates remain almost 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).

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 Table 6). 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 (Column 2). In fact, the interaction's coefficient is almost always significant at the 5% level 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 of crime. This would happen because crime reported on the media becomes a substitute for direct real-world experience (Gunter, 1987).

Additionally, being a crime victim is associated with a 12 pp increase in average crime perception. Thus, one can think of a relation akin to the one presented on the accompanying Figure 7, where victims tend to be on average more fearful of being a victim again in the near

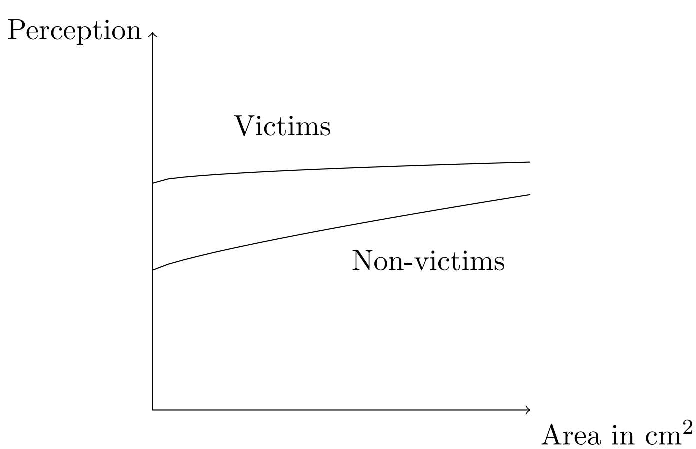
Table 6: Effect of news coverage shocks on crime perception (victim heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Victim any crime	0.11***	0.12***	0.13***	0.13***	0.13***	0.13***
	(0.0054)	(0.0066)	(0.0057)	(0.0054)	(0.0064)	(0.0062)
Victim × neg. shock	-0.0053	-0.011***	-0.017*	-0.021**	-0.025*	-0.020**
	(0.0038)	(0.0041)	(0.0091)	(0.0085)	(0.013)	(0.0081)
Victim × pos. shock	0.0019	0.0023	-0.0025	-0.0016	0.0024	0.0094
	(0.0033)	(0.0061)	(0.0050)	(0.0042)	(0.0061)	(0.0091)
Negative area shock$_t$	0.0067*	0.017***	0.027***	0.028***	0.028**	0.027***
	(0.0039)	(0.0045)	(0.0065)	(0.0072)	(0.012)	(0.010)
Positive area shock$_t$	-0.0057*	-0.010*	-0.0036	-0.0018	-0.0014	-0.0056
	(0.0034)	(0.0055)	(0.0043)	(0.0043)	(0.0068)	(0.0077)
Months-balance	0	1	2	3	4	5
Observations	310910	165154	92774	87533	60005	54685

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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.

Figure 7: Victims and non-victims' crime perception



5.3.2 Men and women

The distinction between men and women in 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. We find heterogeneous effects depending on sex (see Table 7). Ex-ante it would be logical to think that women would be more sensitive to changes in crime news

Table 7: Effect of news coverage shocks on crime perception (sex heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Woman	-0.010**	-0.0088	-0.016***	-0.017***	-0.015*	-0.014
	(0.0047)	(0.0077)	(0.0060)	(0.0060)	(0.0086)	(0.0086)
Woman × neg. shock	-0.0060	-0.011	-0.0081	-0.0068	-0.016	-0.019
	(0.0066)	(0.011)	(0.0083)	(0.0084)	(0.015)	(0.015)
Woman × pos. shock	0.00059	0.00039	0.0093***	0.0099***	0.016***	0.015***
	(0.0019)	(0.0034)	(0.0034)	(0.0036)	(0.0044)	(0.0044)
Negative area shock$_t$	0.0084	0.020***	0.027***	0.027***	0.030*	0.032**
	(0.0058)	(0.0078)	(0.0080)	(0.0089)	(0.016)	(0.015)
Positive area shock$_t$	-0.0063*	-0.011**	-0.0092**	-0.0074*	-0.0089*	-0.011*
	(0.0033)	(0.0046)	(0.0038)	(0.0038)	(0.0053)	(0.0056)
Months-balance	0	1	2	3	4	5
Observations	310913	165156	92775	87534	60006	54686

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 crime news' coverage. However, we do find a statistically significant difference for positive crime news, as the interaction coefficient offsets almost the entirety of the treatment effect on males. In fact, previously non-significant coefficents 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. This results in a *second* type of asymmetry regarding the response of individuals to crime news.

5.3.3 Watching local TV

Regarding other sources of effect heterogeneity, watching local TV is also a likely important discriminator, as those who report to do so, present a marginally significant and smaller treatment effect than those who do not get their news from a local TV-channel (see Table 8). The reduced impact in absolute value of both positive and negative crime news coverage is consistent with the idea that the transmission channel is actually the newspaper and not other confounding variable, thus supporting our identification strategy. It is plausible to assume that people substitute between different communication media in order to consume locally-relevant news choosing between watching TV or reading the newspaper. Thus, observing a smaller treatment effect among local TV-viewers is coherent with them consuming little or less local news from the

Table 8: Effect of news coverage shocks on crime perception (local TV heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Watches local TV-channel	0.014**	0.0061	0.021	0.023	0.029**	0.021
	(0.0057)	(0.0091)	(0.013)	(0.015)	(0.014)	(0.015)
Local TV × neg. shock	-0.00030	0.00077	-0.026*	-0.031*	-0.038**	-0.030*
	(0.0048)	(0.0074)	(0.015)	(0.017)	(0.015)	(0.016)
Local TV × pos. shock	-0.0026	0.0084	0.013*	0.012*	-0.00057	0.0082
	(0.0041)	(0.0057)	(0.0076)	(0.0075)	(0.0090)	(0.010)
Negative area shock$_t$	0.0064**	0.014***	0.025***	0.027***	0.022**	0.022***
	(0.0030)	(0.0038)	(0.0054)	(0.0063)	(0.0089)	(0.0079)
Positive area shock$_t$	-0.0046*	-0.011***	-0.0064	-0.0048	-0.0003	-0.0053
	(0.0027)	(0.0041)	(0.0045)	(0.0049)	(0.0052)	(0.0049)
Months-balance	0	1	2	3	4	5
Observations	242135	127134	73887	68695	47609	42315

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

newspaper. On the other hand, among those who do not watch local TV the effect remains fairly similar to the ATE. This group can contain people who inform themselves with the newspaper and those who do not inform themselves at all, but the significance of the treatment remains. As stated before, this gives further evidence on the transmission channel actually being the newspaper and its reading.

5.3.4 Natural Regions

Somewhat curiously, we find that there is effect heterogeneity across the main natural regions of Peru, typically coast, mountains and jungle.[17] We observe that most of the overall effect of a negative news shock was in the coast, whereas in the case of the mountains and the jungle the interaction coefficient usually offsets most of or even the entire treatment effect (see Table 9). Focusing in our benchmark specification (Column 2), 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. This finding is consistent with the fact that people from coastal cities are more avid readers than their counterparts in other regions, as can be observed in Table 1. Once again, this is consistent with our identification strategy being the effect of newspapers.

5.3.5 Type of crimes

Finally, as has been documented, crime perception is in fact susceptible to crime news coverage, although 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

[17]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.

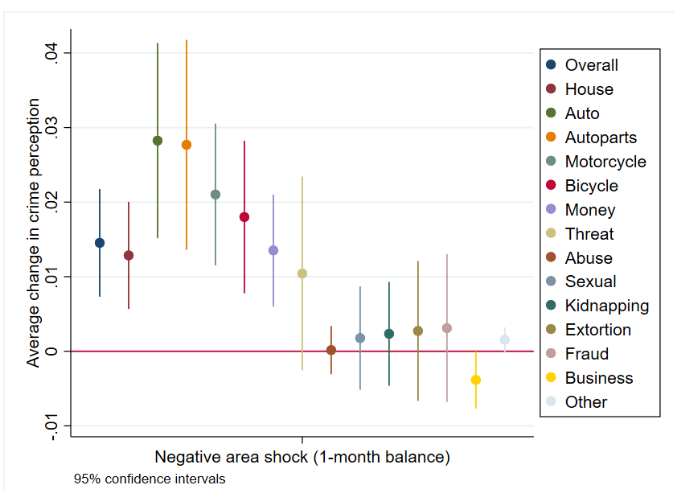
Table 9: Effect of news coverage shocks on crime perception (Natural region heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)
Mountains x neg.shock	-0.010*	-0.023***	-0.035***	-0.033***	-0.028	-0.020
	(0.0057)	(0.0088)	(0.011)	(0.012)	(0.017)	(0.020)
Mountains x pos.shock	0.000010	0.0048	-0.0081	-0.0058	0.0090	0.011
	(0.0071)	(0.0073)	(0.010)	(0.011)	(0.012)	(0.013)
Jungle x neg.shock	-0.015	-0.010	-0.0085	-0.0085	-0.035*	-0.035**
	(0.0095)	(0.014)	(0.014)	(0.015)	(0.018)	(0.017)
Jungle x pos.shock	-0.0083	0.0017	0.013	0.015	0.0072	0.0084
	(0.0083)	(0.012)	(0.011)	(0.013)	(0.018)	(0.017)
Negative area shock$_t$	0.0080***	0.019***	0.030***	0.030***	0.029***	0.028***
	(0.0027)	(0.0037)	(0.0048)	(0.0053)	(0.0081)	(0.0076)
Positive area shock$_t$	-0.0057	-0.011**	-0.0031	-0.0017	-0.0021	-0.0050
	(0.0037)	(0.0047)	(0.0046)	(0.0047)	(0.0053)	(0.0053)
Months-balance	0	1	2	3	4	5
Observations	310913	165156	92775	87534	60006	54686

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

identify the effect of the same coverage shocks on crime-specific perceptions. 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 of the 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 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 other edges by studying 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.[18] 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 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 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 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 the evaluated performance on 4 indicators: (i) attend promptly when a crime occurs, (ii) maintaining security and public tranquility, (iii)

[18] 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.

Table 10: Effect of news coverage shocks on confidence in different institutions (standardized)

	(1) Police	(2) Police	(3) Police	(4) Police	(5) Police	(6) Police
Negative area shock$_t$	-0.00069	-0.020***	0.0069	0.00067	-0.010	-0.011
	(0.0042)	(0.0052)	(0.010)	(0.0095)	(0.012)	(0.012)
Positive area shock$_t$	-0.0072	0.0018	0.0038	-0.00026	0.0053	0.0043
	(0.0055)	(0.0064)	(0.0087)	(0.0089)	(0.015)	(0.016)
Months-balance	0	1	2	3	4	5
Observations	307531	163500	91960	86816	59608	54384
	7	(8)	(9)	(10)	(11)	(12)
	Judic.	Judic.	Judic.	Judic.	Judic.	Judic.
Negative area shock$_t$	-0.0071	-0.020***	-0.012	-0.014	-0.029*	-0.028*
	(0.0063)	(0.0064)	(0.015)	(0.013)	(0.015)	(0.015)
Positive area shock$_t$	-0.0071	0.0079	0.031***	0.026***	0.029**	0.027*
	(0.0060)	(0.0056)	(0.0091)	(0.0089)	(0.014)	(0.015)
Months-balance	0	1	2	3	4	5
Observations	292457	155606	87464	82571	56697	51817
	(13)	(14)	(15)	(16)	(17)	(18)
	Munic.	Munic.	Munic.	Munic.	Munic.	Munic.
Negative area shock$_t$	-0.011	-0.037***	-0.031***	-0.025***	-0.028*	-0.024
	(0.0080)	(0.0066)	(0.0093)	(0.0094)	(0.017)	(0.017)
Positive area shock$_t$	-0.0023	0.00021	-0.013	-0.016	-0.0058	-0.0058
	(0.0046)	(0.0064)	(0.013)	(0.011)	(0.010)	(0.011)
Months-balance	0	1	2	3	4	5
Observations	305664	162529	91391	86274	59245	54056
	(19)	(20)	(21)	(22)	(23)	(24)
	Attor.	Attor.	Attor.	Attor.	Attorn.	Attorn.
Negative area shock$_t$	-0.0034	-0.015**	-0.0061	-0.0091	-0.025*	-0.022
	(0.0071)	(0.0067)	(0.015)	(0.013)	(0.015)	(0.014)
Positive area shock$_t$	-0.0070	0.0043	0.026***	0.021**	0.026*	0.025
	(0.0058)	(0.0054)	(0.0098)	(0.0094)	(0.015)	(0.015)
Months-balance	0	1	2	3	4	5
Observations	290885	154793	87004	82144	56452	51593

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Effect of news coverage shocks on police qualifications (standardized)

	(1) Speed	(2) Secur.	(3) Info.	(4) Equal
Neg. area shock$_t$	-0.035***	-0.032***	-0.026***	-0.031***
	(0.0074)	(0.0079)	(0.0088)	(0.0099)
Pos. area shock$_t$	-0.0022	0.0011	0.0010	-0.0044
	(0.0063)	(0.0069)	(0.0070)	(0.011)
Months-balance	1	1	1	1
Observations	165546	165545	165544	165544

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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 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 crime news, and 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 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 simple 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.

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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
Duration	The amount of time (in seconds) taken to address the news on air. For radio and tv news format only.	Integer
Surface	The total surface the news occupies in the newspaper. For written press only.	Float
Page	The page number in which the news is located in the newspaper. For written press only.	String
Height	The height of the news article in the newspaper. For written press only.	Float
Width	The width of the news article in the newspaper. For written press only.	Float
Press section	The newspaper section in which the news is located. For written press only.	String
Title	The title of the news.	String
News format	The type of format in which the news is delivered. Namely written press, tv or radio	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: New crime dataset

Variable	**Description**	**Data type**
Crime	The type of crime the news talks about. Namely, theft, threats, abuse,sexual offense, kidnap, extortion or fraud.	String
Duration	The amount of time (in seconds) taken to address the news on air. For radio and tv news format only.	Integer
Surface	The total surface the news occupies in the newspaper. For written press only.	Float
Page	The page number in which the news is located in the newspaper. For written press only.	String
Height	The height of the news article in the newspaper. For written press only.	Float
Width	The width of the news article in the newspaper. For written press only.	Float
Press section	The newspaper section in which the news is located. For written press only.	String
Title	The title of the news.	String
News format	The type of format in which the news is delivered. Namely written press, tv or radio.	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
District	The district which the news references.	String
Province	The province which the news references.	String
Department	The department which the news references.	String
Ambiguity	Boolean variable that explains whether or not the entity extraction is ambiguous,given the criteria beforementioned.	Boolean
UBIGEO Id	The UBIGEO Id for the given spatial units.	String
Latitude	The latitude associated to the given spatial units.	Float
Longitude	The longitude associated to the given spatial units.	Float
Sentiment	The sentiment that the news text denotes. Namely, positive, negative or neutral.	String

Table 3: Number of provinces with a statistically different from 0.5 unconditional probability of treatment (out of 195 provinces)

Months-balance restriction	Negative coverage	Positive coverage
Unrestricted	2	5
1 month-balance	3	5
2 month-balance	5	7
3 month-balance	5	8
4 month-balance	8	10
5 month-balance	11	12

Table 4: Control Sets 1 and 2

	Variable name	Type	Description
1	*victim*	dummy	Victim of any crime in the last 12 months
2	*victim2*	dummy	Victim of any crime or attempt in the last 12 months
3	*woman*	dummy	Is a woman
4	*age*	cont.	Age
5	*reg_mountains*	dummy	Lives in the mountains region
6	*reg_jungle*	dummy	Lives in the jungle region
7	*num_hab*	cont.	Number of household inhabitants
8	*water*	dummy	Water supplied by truck, tank, well, river or canal
8	*ubi1*	dummy	Basic need #1 unsatisfied
9	*ubi2*	dummy	Basic need #2 unsatisfied
10	*ubi3*	dummy	Basic need #3 unsatisfied
11	*ubi3*	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
16	*watch_tv*	dummy	Watches one of the most-viewed TV-channels
17	*trust_jp*	cont.	Trust in the Judiciary Power
18	*trust_at*	cont.	Trust in the Attorney
19	*trust_pnp*	cont.	Trust in the Peruvian National Police
20	*trust_muni*	cont.	Trust in the Municipality

Variables numbered 1-15 belong to Control Set #1. All are present in Control Set #2.

Figure 1: Pre-trend stability for 1-month balance coverage shocks (t-12 - t+4)

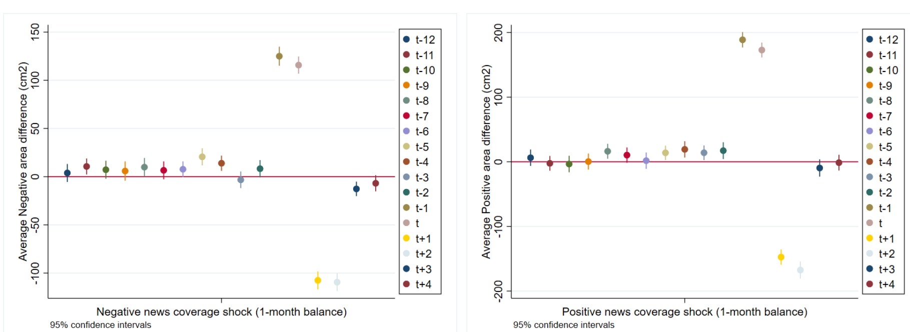


Figure 2: Pre-trend stability for 2-month balance coverage shocks (t-12 - t+4)

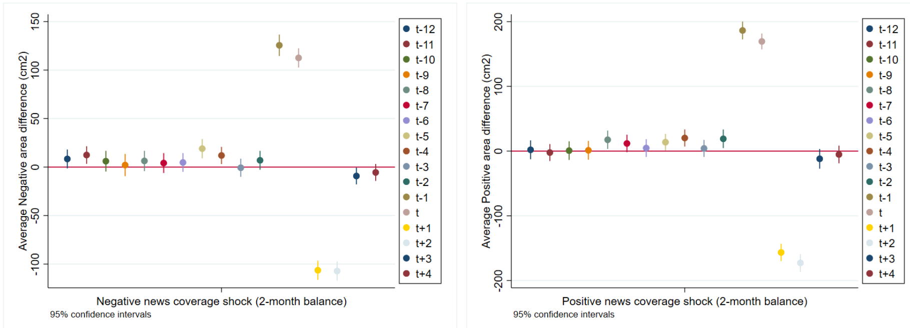


Figure 3: Pre-trend stability for 3-month balance coverage shocks (t-12 - t+4)

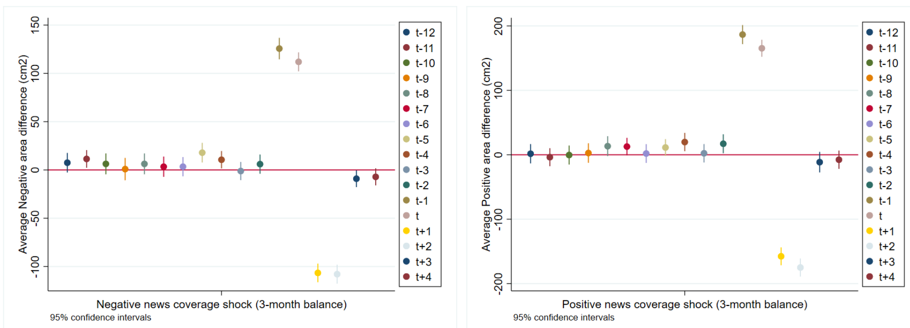


Figure 4: Pre-trend stability for 4-month balance coverage shocks (t-12 - t+4)

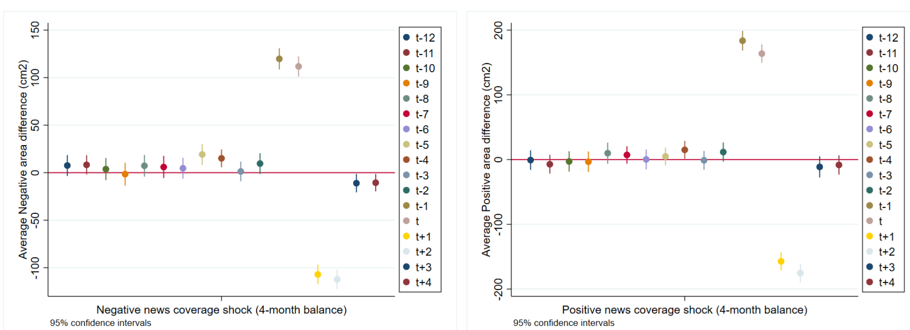


Figure 5: Pre-trend stability for 5-month balance coverage shocks (t-12 - t+4)

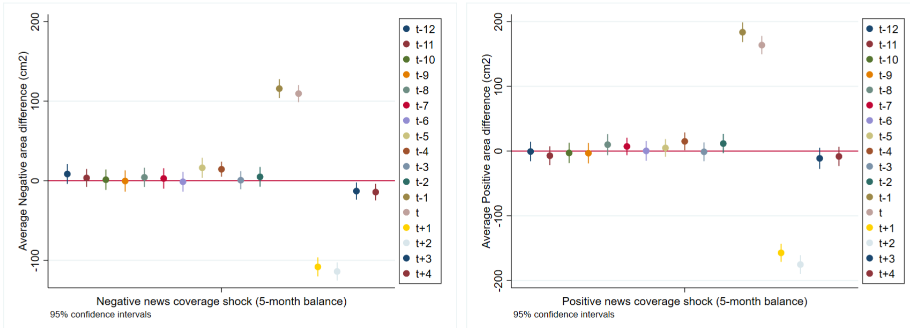


Figure 6: Shocks' distribution among months (1-month balance)

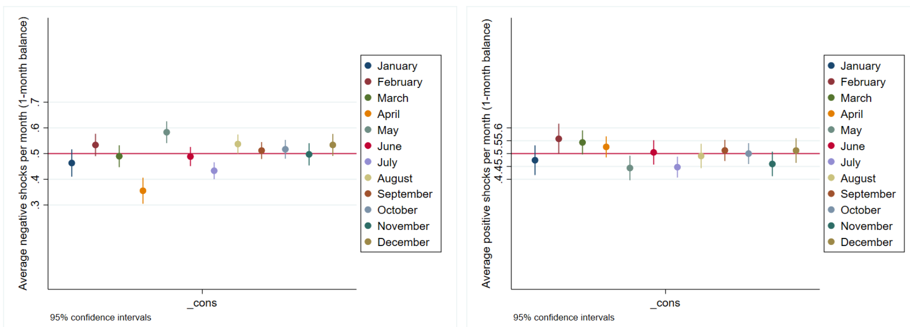


Figure 7: Shocks' distribution among months (2-month balance)

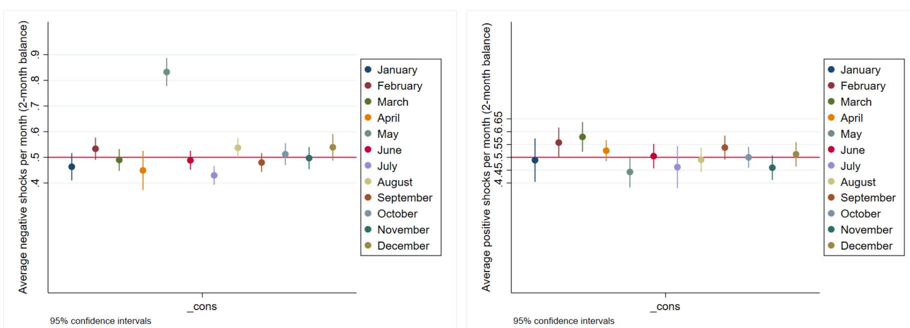


Figure 8: Shocks' distribution among months (3-month balance)

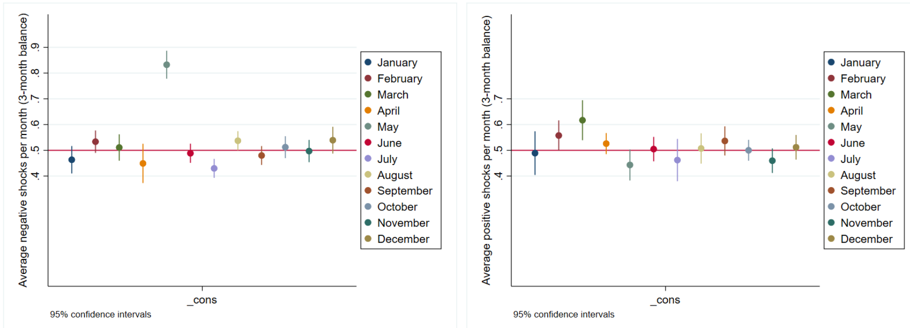


Figure 9: Shocks' distribution among months (4-month balance)

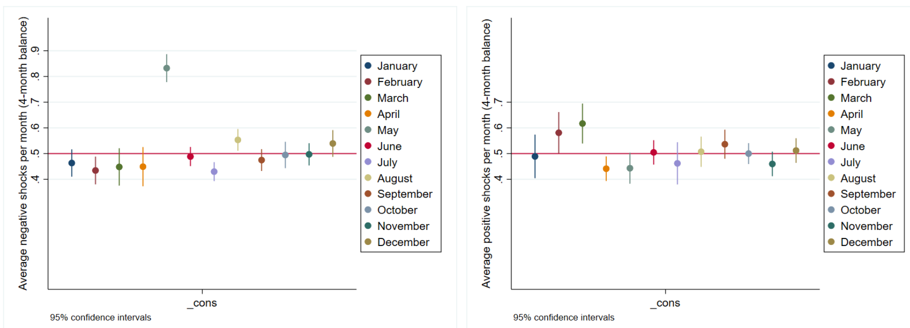


Figure 10: Shocks' distribution among months (5-month balance)

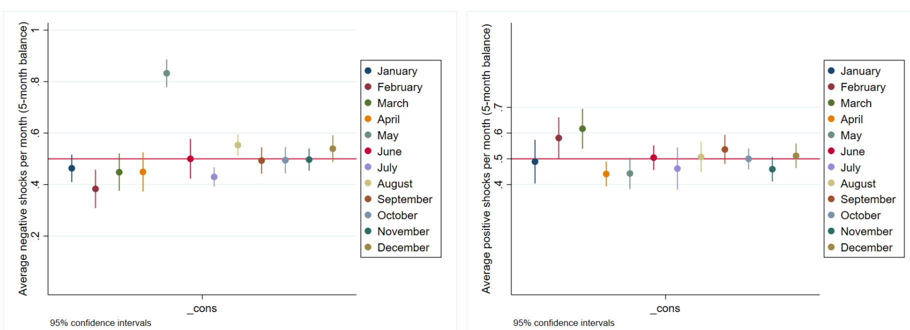


Figure 11: Distribution of news' average areas (treated vs non-treated with 1-month balance)

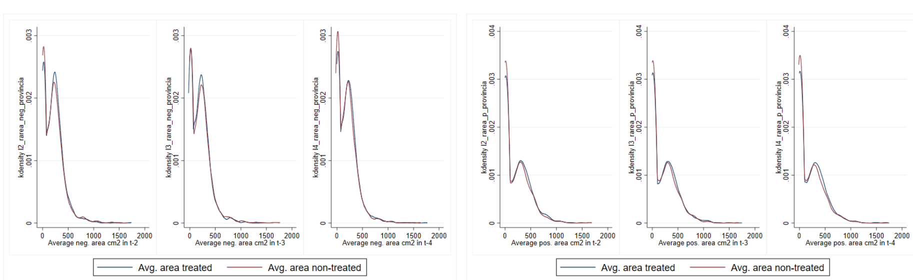


Figure 12: Distribution of news' average areas (treated vs non-treated with 2-month balance)

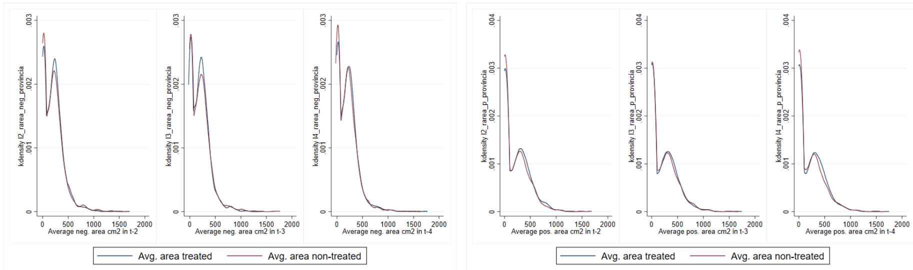


Figure 13: Distribution of news' average areas (treated vs non-treated with 3-month balance)

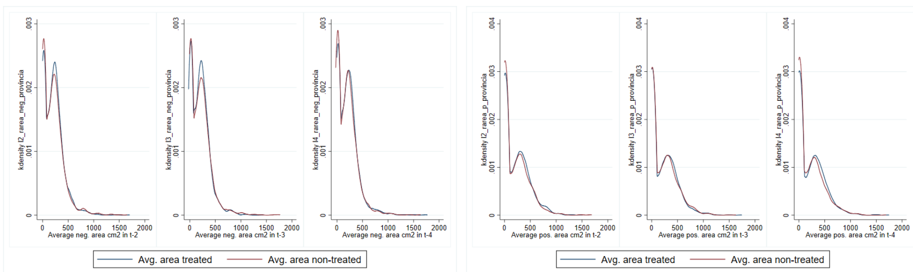


Figure 14: Distribution of news' average areas (treated vs non-treated with 4-month balance)

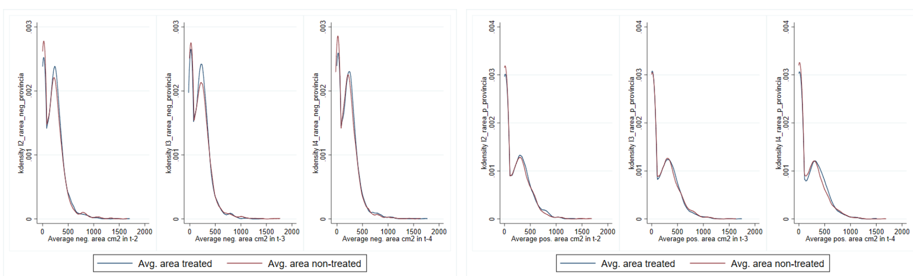
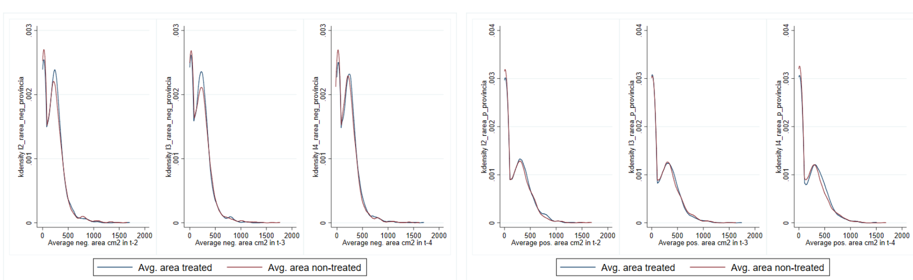


Figure 15: Distribution of news' average areas (treated vs non-treated with 5-month balance)



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. First and foremost, 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 16 depicts the repeated process used to evaluate all pieces of news in the database.

Figure 16: 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:

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

,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.

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 5. 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 departments, 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 5: 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.
Department	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 department's 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 departments. This process is then executed in the same way for provinces and districts. Then,empty lists are removed (departments, 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,lets compare the department 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 is 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 departmental) 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 department. Then, spatial entities are georeferenced through the Google Maps API. In this way, we get the latitude and longitude associated with each news item.