Press and Firms Accountability: Evidence from Toxic Emission in the US

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[PRELIMINARY]

Abstract

In this paper I investigate whether newspapers make firms accountable on their environmental standards, extending on the literature on the effect of mass-media on economic and political outcomes. I compare plants that are located in the same county and operate in the same 3-digits industry and year, but have different distances from the closest newspaper. My results suggest that being 9 miles closer to a newspaper with respect to the average distance corresponds to having about 29% less toxic emissions, as measured within Environmental Protection Agency administered Toxic Release Inventory Program. This is consistent with a model in which there is asymmetric information between a firm and agents interested in its plants (communities, regulators, consumers, investors), and plants emit less toxic substances because they are worried about negative coverage that would reveal hidden information. Indeed, I show that in the sample of Top 20 polluters by State the probability that coverage of plant-level TRI statistics arise in the plant's closest newspaper is larger, the lower the distance from the closest newspaper itself.

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1 Introduction

In July 2011 Greenpeace released a report, Dirty Laundry, on two facilities based in China, that were found to be discharging a range of hazardous chemicals with hormone-disrupting properties to the environment. Greenpeace connected the facilities to some major clothing brands, among which Adidas, Nike and Puma. After the release of the report, these three companies engaged in a "virtuous competition" to minimize or erase the production and release of these toxic substances from their entire production chain.

This is only one of many instances of companies committed to corporate social responsibility (CSR hereafter). It is widely discussed why profit maximizing corporations do engage in CSR activities. Among the explanations that have been proposed and explored, one is that CSR can be classified as a risk management strategy, meant to avoid future lawsuits or regulatory interventions. This is directly related to the desire to keep a good reputation among communities and politicians. Moreover, reputation toward consumers and investors seem to play an important role. Consumers have the potential to punish the company for anti-social behavior through boycotts; Hainmueller et al. (2011) find, for instance, a positive effect on sales of the "fair trade" label. Investors can base their investment decisions on companies' social and environmental standards; in the US about 10% of the money in professional funds are managed by funds that have some explicit environmental or social objectives (Heal 2008); Hamilton (1995) finds that stock market prices react negatively to news about the release of toxic substances from US companies within the TRI program, and his result is replicated in different contexts (see Konar and Cohen (2001) for a literature review on firm market value and environmental performance).

If reputation-related concerns are what leads firms to perform well according to social and environmental standards, information must play a key role. If communities, politicians, consumers and investors are not informed about how responsible is a firm, the usage of CSR to build a good reputation cannot be justified. In particular, while news about "positive" initiatives can be easily spread by the firm itself, asymmetric information on negative performance likely exists.

In this paper I investigate the role of local newspapers in the US in delivering information about firms environmental performance, filling a gap between firms and their "constituents", and therefore contributing in making firms accountable on their environmental standards. In particular, I investigate whether firms control their emissions of toxic substances to avoid bad coverage from local newspapers, which would undermine their reputation. In this way, I contribute to different strands of literature in economics. First, I broaden the literature that documents the effects of mass-media on political outcomes (see Pratt and Stromberg (2011) for a review), shedding light on the role of mass-media in creating incentives for CSR effort. Second, I analyze one possible determinant of emissions of toxic substances, which have been shown to be detrimental for health outcomes (see, for instance, Currie (2008)).

Third, I provide some insights for policies aimed at regulating toxic emissions in an "indirect" fashion (like cap and trade policies).

To investigate the role of newspapers in "regulating" emissions, I use data on toxic releases from US-based plants, reported through Environmental Protection Agency (EPA henceforth) administered Toxic Release Inventory program (TRI henceforth). Starting from 1989, every year plants with more than 10 employees that operate in certain sectors and that manufacture, process or otherwise use possibly toxic substances above certain thresholds, must report the quantity of each toxic substance released to the air, to the water and to the land. The reporting requirements were introduced with the Emergency Planning and Community Right to Know Act, following a fatal chemical-release accident in Bophal, India. Every year, statistics on total emissions from plants are published by EPA on its website, and different newspapers, bloggers and environmental activists write stories about these data, usually spotting some top-polluters in a State, in a county, or nation-wide. Emission are not regulated, therefore EPA sanctions plants only when they are caught to have mis-reported their emissions.

I first look at plants that were Top 20 polluters at least once during the sample period, which spans the years between 1998 and 2009. I compare plants that operate in the same State, year and 3-digits industry, and I exploit the variation in distance from the closest newspaper for these plants. I focus on States where coverage of TRI statistics has emerged at least once throughout the period analyzed. I document the relationship between distance from closest newspaper and coverage in the closest newspapers within 5 days from the release of data. My results suggest that being 17 miles more far from a newspaper than the average distance reduces the probability to be covered in the closest newspaper by 20%, once the probability to be covered in any other newspaper (that should measure how "visible" is the firm) is contolled for. One should be aware that coverage is a very rare event, since only 3.7% of the plant-by-year observations in the sample do get coverage in closest newspaper, and 3.5% get coverage in any other newspaper. However, the proability of this event, i.e. the "threat of coverage", is larger, in equilibrium, for plants located nearby a newspaper. It is this "threat of coverage" that can make the firm accountable on its environmental performance, and it is this effect that I aim at measuring in the second part of the paper.

I estimate the effect of distance from closest newspaper on emissions for all the plants that report their toxic emissions through the TRI program and that operate in States where coverage of TRI statistics has emerged at least once during the period analyzed. The average distance from closest newspapers for these plants, that include non-polluters (i.e. firms that manufacture, process or otherwise use toxic substances, but that do not release them), is equal to 9 miles. According to my estimates, being 9 miles closer to a newspaper with respect to the average distance translates in about 28% less toxic emissions.

The validity of these results rest on the plausibility of the identifying assumption, i.e. that, once a full set of covariates is controlled for, the variation in distance from closest newspaper is essentially random with respect to other characteristics that determine toxic emissions. Beside including industry and county fixed-effects, I control for a full set of demographics that should capture within county heterogeneity in economic and social conditions. I use Census-block-group data and geographic information systems to calculate averages of these demographics in circles with center at the plant's location and radius equal to 10 miles. Importantly, I control for linear and non-linear effects of population density and income; different pieces of evidence suggest that population and income are indeed the main determinant of newspaper location (see Gentzkow et al. (2011)). Other demographics (share of people who live in an urban area, measures of education, age and racial composition of population) are included.

I use the estimates of the effect of distance when the observables are included to draw some inference on the possibility that selection on unobservables bias the results. In particular, I find that the correlation of the unobservables with distance should be 5.3 times bigger than that of the observables to cancel out the estimated effect. This is remarkable, given that the main determinants of newspaper's presence are included among the observables.

Moreover, I show that distance and emissions are not significantly correlated in States where coverage of TRI statistics has never emerged. This is consistent with distance having an effect on emissions through the "threat of coverage", because this threat does not exist in States in which TRI statistics do not constitute "news".

The rest of the paper is organized as follows: in Section 2 I describe the data. Section 3 presents the equations estimated and the results. Section 4 discusses the identifying assumption. Section 5 presents future development of this project and concludes.

2 Data Description

I use data on toxic releases collected by EPA within the TRI program; starting from 1989, every year plants with more than 10 employees that operate in certain sectors and that manufacture, process or otherwise use (MPOU henceforth) toxic substances above certain thresholds must report the quantity of each toxic substance released to the air, to the water and to the land. However, if the quantity released is lower than 500 pounds, firms can choose to not report the quantity released, and will just submit a form that certifies that they MPOU some of the listed toxic substances; for these cases, emissions are set to zero; this exception does not hold for Persistent, Bioaccumulative and Toxic (PBT) chemicals. Over time firms can update their data on emissions, when they discover some mistakes in previous reporting. Data on updated emissions from 1989 to 2009 can be accessed on EPA website. However, for the purpose of the current research, I use original data on emissions. These data were provided by EPA for years from 1996 to 2009. In 1998 there was a major change in the program, with new sectors being added among those that were required to report their emission statistics. Therefore, I limit my sample to plants observed in the years 1998-2009. I have information on the six digit sector in which a plant operates every year and on its exact geographic location, in the form of latitude and longitude.

I use two different samples for the analysis of the effect of distance on coverage and for that of the effect of distance on emissions.

To select the sample for the analysis of the effect of distance on coverage, I flag plants that were Top 20 polluters in their State at least once in the years in which they appear in the sample, and I follow them throughout the estimation period; these plants reported emissions between 1998 and 2006, i.e. their articles were published between 2000 and 2008, since TRI statistics are released with a two years lag. From this group, I selected plants whose closest newspaper's articles are archived in Newslibrary; I then searched for articles that were written within 5 days after the release of TRI data every year[1]. I searched for a short form of the name of the plant, for the city and the county where the plant is located, and for the word "EPA". Using the output of this search, I created two variables with, respectively, the number of articles in the closest newspaper and the number of articles in any other newspaper; these are meant to be good proxies for the number of articles written about TRI statistics.

As shown in Figure 1, coverage is heterogeneous across States, with 22% of States having coverage equal to 0 in the period studied, meaning that no articles were written reporting TRI statistics for plants located in these States. In the analysis of the effect of distance on coverage I look at States where at least one article on TRI statistics was written througout the sample period. In this way, I focus on States in which there is variation in the variable of interest; while this should not have any implication for the internal validity of the results of my analysis, the external validity is limited to States where some interest from the media on TRI statistics has emerged.

For the analysis of the effect of distance on toxic emissions I consider the entire sample of plants located in States where some coverage has emerged. Given that data are published with a two years lag, and that I look at the effect of distance from closest newspaper on emissions one year later, practically I analyze the determinants of emissions between 2001 and 2009.

The variable distance is constructed using a dataset reporting the name of possibly all the US newspapers, with their city of location, the year they were funded and the year they were closed, if relevant. This dataset is based on information published in the website *Chronicling America*. Given that I have information on the geographic location of each firm in the form of its latitude and longitude, I perform an analysis in ArcGis, where I calculate the distance of each firm from the closest

[1] I limit the search for articles to this restricted sample of plants because the sample size is very large and the coverage in newspaper is most likely focused on Top 20 polluters

newspaper in the dataset.

The control variables I use in the analysis are based on Census data. I downloaded block-group data for each of the variables of interest[2]. Using Geographic Information Systems as ArcGis and Geospatial Modelling, I split the US territory in cells with area equal to 1 square kilometer (≈ 0.39 square miles); every cell gets the value of the census block group that has its maximum area in the cell itself, an approximation that does not seem too costly, given the relatively small size of the Census block groups. I then calculate the average across these cells in a circular area with radius equal to 10 miles and center at the plant's location. For the variables population density, percentage of black, percentage of people younger than 20 and percentage of people older than 65 I use Census data for the years 2000 and 2010, and I interpolate the values in between using a cubic spline. For the education variables, income per capita and share of population that lives in an urban area, data for 2010 are not available yet, therefore I linearly extrapolate data in 1990 and 2000 (2010 data will be used as soon as they will be available on US Census website).

Summary statistics for the two samples are shown in Table 1[3]. As expected, average toxic emissions are much larger for the Top 20 polluters; moreover, distance form closest newspaper is definitely larger for the first sample than for the second, which suggests that plants that pollute less are more likely to locate nearby a newspaper. The average distance from closest newspaper is equal to about 17 miles for Top 20 polluters, and about 9 miles for the entire sample used in the analysis of determinants of toxic emissions. The other remarkable difference between the two samples is related to the share of population in urban areas.

As I show in Figure 2, where I represent total emissions in the original TRI sample, TRI emissions declined steadily between 1998 and 2009, the reason for which the program is regarded as a successful one. In the dataset a value of zero is associated with emissions from firms that MPOU monitored toxic substances above TRI thresholds, but do not exceed the prescribed thresholds for releases. These firms are supposed to compile a form without reporting the level of emissions, just certifying that they emit these substances below the minimum threshold, and their emissions are approximated by EPA to 0. Given that I estimate how reported emissions, rather than actual ones, respond to the threat of coverage, I also set emissions equal to zero for these plants. However, in robustness check I run an interval regression, using

[2]A census block group is a cluster of census blocks, that contains between 600 and 3,000 people, with an optimum size of 1,500 people.

[3]From the initial sample of plants, a few observations were dropped because the 6-digits sector was not reported in the original data, or because it was not possible to create the control variables, due to some tabulation errors in Census data; moreover, from the sample used in the analysis on toxic emissions, I dropped, in the order: plants that were observed only for one year or two years, because this complicated the estimation of standard errors clustered by plant; among those that were left, I dropped plants in counties observed only for one plant-by-year observations, because these complicated the estimation of county fixed effects; among those that were left, I dropped plants in industries observed only for one plant-by-year observations, because these complicated the estimation of industry fixed effects.

lower and upper bounds implied by this reporting technique.

The distribution of emissions is very skewed to the right, therefore I perform the analysis on log emissions, which also helps interpreting the results. I add a constant to emissions equal to 0, that is smaller than the minimum non-zero value in the dataset.[4]

Every firm on average during the all sample period gets 0.04 articles in its closest newspaper, and 0.05 in any other newspaper. This is a low number, due mainly to the high number of zeros in the sample: in fact, only about 3.7% of plant-by-year observations get coverage in closest newspaper, and 3.4% get coverage in any other newspaper.

The distribution of articles and distance is skewed to the right, therefore I also transform these two variables with logs. Given that articles take value 0, I first add a constant equal to 0.001 when the variable is equal to 0.

3 Estimation

3.1 Distance from closest newspaper and coverage

I start documenting that plants that are closer to a newspaper get more coverage in the closest newspaper in the 5 days after the release of data from EPA.

There are a number of reasons for which distance should matter for plants' coverage in newspapers. First of all, it is easier for journalists to access information about a plant located nearby their workplace, by visiting the plant, interviewing with plant's employees etc. Moreover, journalists themselves, being very likely to live near their workplace, can be directly affected by a plant activities, and hence they are personally interested in collecting and publishing related news. Finally, journals write stories that a high share of their readers is interested in; this, coupled with the facts that newspapers have high circulation in their surrounding area, and that readers are interested in news about plants located nearby their houses, provides a further intuition for why distance and coverage should be related.

Notice that I abstract from considerations on whether the coverage is positive or negative, although the analysis of a random sample of articles on TRI statistics shows that it is more likely that newspapers cover the topic in a way that would negatively affect the plant's reputation[5].

I estimate the following equation:

$$y_{pt} = \beta_0 + \beta_1 Z_{pt} + \lambda_s + \gamma_t + \eta_i + \epsilon_{pt} \tag{1}$$

[4] Hu (1972) shows that the distortion caused by this type of transformation is smaller the smaller the constant, and it is less severe when the constant is added only to the values that need to be transformed, rather than to the entire sample.

[5] Examples of more "positive" coverage are articles that document substantial decreases in emissions for plants that are historically top polluters; it is evident that also this type of coverage can create incentives for a plant to decrease its emissions

y_{pt} is a dummy taking value one if articles featuring plant p are published within 5 days from the release of TRI data in the closet newspaper in the relevant year; Z_{pt} is distance of plant p from the closest newspaper, λ_s are State fixed-effects, γ_t are year fixed-effects and η_i are three-digits industry fixed effects. I estimate equation 1 with a Linear Probability Model. Results are shown in Table 2.

I compare plants that are located in the same State, industry and year, and that have different distances from closest newspaper[6]. I also exploit differential changes distance across States, but this variation is very small, due to the high persistence of Z_{pt} over time. According to the estimates in column (1), plants whose distance from their closest newspaper is 1% smaller are 0.2% more likely to be covered. However, this estimate could be biased, due to some characteristics that can affect the selection of newspapers and firms, creating spurious correlation among the variables of interest. On one hand, locations with high levels of education are more likely to be headquarter to a newspaper; these locations, if characterized also by high economic activity, could host large plants, that as such have more toxic emissions. On the other hand, large firms that emit toxic substances may settle in locations whose population is less educated, because this decreases the risk that citizens or politicians attempt to limit emissions for given production size. Given that plants with more emissions do in turn attract more articles, both these patterns would induce a spurious correlation between the variables of interest.

In general, any characteristic that is correlated with proximity to a newspaper and with the firm "visibility" would bias the estimates.

In order to guard against this possibility, I adopt two strategies. First, I show in column (2) that the effect of distance on the probability to be covered in any other newspaper is smaller and not precisely estimated. If distance does not matter in increasing the incentives for newspapers to cover a plant, the spurious effect should be estimated also when looking at coverage in other newspapers, because other newspapers should equally react to the plant's visibility. Therefore, the result in column (2) is reassuring on the causal interpretation of my estimates. In column (3) instead I insert the variable "coverage in any other newspaper" among the controls, as a measure of plant's visibility, that could create omitted variable bias in column (1). Strikingly, the coefficient does not change when I include this control, although coverage in other newspapers is significant in explaining the probability that the plant gets covered [7]. In column (4) I add as further controls a full set of demographics measured nearby the plant; importantly, these controls include the two variables that, according to the account reported in Gentzkow and al. (2011), explain most of

[6]Notice that, while in the next section I will exploit county-level variation, in this section I must resort to in-State variation, because there are not many Top 20 polluters that operate in the same industry and that are located in the same county.

[7]Notice that I could also directly control for another important determinant of coverage in newspapers, the actual size of toxic emissions as reported in TRI statistics. While the coefficient does not change when I introduce this control, I do not report this result in my main specification, because, based on the evidence in the next session, size of emissions is a "bad control".

the variation in presence of local newspapers in the US, i.e. population and income (given that the area over which I measure the controls is fixed, I actually control for population density). None of these variables seem significant in explaining coverage in closest newspaper, and the coefficient on distance decreases only slightly.

In columns (5) and (6) I report Logit estimates as robustness check. The estimated elasticity with Logit is slightly larger than that estimated with Linear Probability Model, but also the predicted probability of coverage is smaller.

Overall the results in columns (1), (3) and (4) suggest that, if the distance of a plant from its closest newspaper is 1% smaller, its probability to get some coverage related to TRI statistics is 0.2% larger. While this looks like a small number, one should be aware that a 1% increase in distance with respect to the average is equal to 0.17 miles. Therefore, being 17 miles closer to a newspaper with respect to the average distance increases the probability to be covered by 20%, which is a non-trivial effect[8].

This section shows that the closer is a plant to its closest newspaper, the larger the probability that its performance in the TRI program is featured in the newspaper itself; the size of this relation is not negligible. Even if coverage is a rare event (a bit less than 4% of the plant-by-year observations in the sample are covered), my result nevertheless suggest that the proability of this event is larger, in equilibrium, for plants located nearby a newspaper. In fact, coverage, being an "out of equilibrium" outcome, is perhaps not surprisingly a rare event, because plants located nearby a newspaper tend to pollute less due to the "threat of coverage". It is this "threat of coverage" that can make firms accountable on their environmental performance, and it is this channel that I aim at measuring when analysing the effect of distance from closest newspaper on TRI emissions.

3.2 Distance from closest newspaper and emissions of toxic substances

In order to estimate the effect of being located nearby a newspaper on emissions of toxic substances I run the following regression:

$$Y_{pt} = \beta_0 + \beta_1 Z_{ft} + \lambda_c + \gamma_t + \eta_i + \epsilon_{pt} \tag{2}$$

Y_{pt} are plant-level emissions of toxic substances as reported in the TRI program, λ_c is a county fixed-effect, and the other variables are defined as in equation (1). Equation (2) is estimated on plants that reported their toxic emissions within the TRI program in the years from 2001 to 2009, and that are located in States where newspapers cover TRI statistics at least once in the relevant period [9].

[8] In auxiliary regressions I also estimate a negative effect of distance on the number of articles in the closest newspaper featuring TRI statistics (results available upon request).

[9] As already mentioned, a further selection on the sample is carried on, where in practice plants, industries and counties for which there are few observations are dropped.

The parameter estimates for this equation are shown in Table 3. Column (1) reports a specification where I assume that distance from closest newspaper is random, once I control for county, industry and year fixed effects. In practice, I compare emissions for plants that operate in the same county, industry and year, and total emissions in counties over time (the second source of variation is very small and unlikely to have a big impact on point estimates).

According to the estimates in column (1), being 1% more distant from a newspaper translates in 0.34% more emissions. The identifying assumption is that plants that are located in the same county and that operate in the same 3-digits industry are located at different distances from a newspaper for reasons that are random with respect to their emission levels. County fixed effect control mainly for differences in institutions and regulatory environment that most likely affect the size of the threat that a plant is allowed to pose to the community located nearby. Industry fixed effects are also important because some industries are "naturally" more polluting than others, and location decisions are expected to be more homogenous within industry rather than across industries.

However, different parts of a county in the USA can exhibit very different demographics, a long list of which can be correlated with distance and emissions. Moreover, some plants may be located at the county border, so that demographics of nearby counties also matter. As already pointed out in Subsection 3.1, Gentzkow et al. (2011) document the importance of population size and income for the location decision of newspapers; it is not unlikely that these variables also affect the decision of a newspaper to remain in a location; indeed, population size and income must affect the profitability of a newspaper, being positively correlated with potential readers and advertisers. In absence of an ideal experiment that would solve this identification issue, I adopt a control-based approach, creating a newly-created dataset where different demographics are measured in circles with radius equal to 10 miles and with center at the plant's location; in this way, I aim at measuring the economic and social environment that is mostly relevant for the plant. Beside log population density and log income, I control for: two measures of educational achievement (share of people with high school diploma or some year of college and share of people with college and more), two measures of the age composition of the population (share of people older than 65 and share of people younger than 20), share of black people and share of people who live in an urban area.

Importantly, the coefficient in column (2), where these controls are accounted for, decreases, as expected, but not dramatically so. This is interesting especially because some of the controls included are significant in explaining toxic emissions, and most of them enter the model with the expected sign.

The results in Table 3 also contribute in shading light on other determinants of toxic emissions, measured for the first time, to the best of my knowledge, in an area relatively close to the plant. More specifically, toxic emissions appear to decrease with population density, share of people with high levels of education and share of people younger than 20, and to be increasing in degree of urbanism. As compared to previous work on "environmental justice", the share of black people in the population does not appear to affect emissions in a statistically significant way.

To account for non-linearities in the relation between emissions and the variables that are most correlated with distance from closest newspaper, in column (3) I control for quartiles in log population density and log income per capita, and the coefficient estimate is basically unaffected; in column (4) instead I allow for State-specific shocks, which again has little impact on the estimated effect of distance on emissions.

In column (5) I implement a robustness check, running an interval regression; the lower bound of emissions is calculated as the sum of all the substances released by the plant, assuming that any time the plant reports emissions lower than 500 pounds they are actually equal to 0; the upper bound is calculated assuming instead that these emissions are equal to 499. The coefficient decreases only slightly, showing that the effect estimated is robust to alternative specifications.

Overall, the estimates in Table 3 show that a plant emit between 0.27% and 0.29% less toxic substances if its distance from the closest newspaper is 1% smaller that that of another plant that is located in the same county and that operates in the same 3-digits industry, once year effects are accounted for. Therefore, being 9 miles closer to a newspaper with respect to the average distance translates in about 29% less toxic emissions.

The causal interpretation of these estimates relies on the assumption that, once the included demographics are controlled for, there are not characteristics of the area where the firm is located that are correlated both with the presence of a newspaper and with emissions.

In the next Section I discuss this assumption and I provide some evidence that the estimated effect may indeed be causal.

4 Identification

I am mainly worried about two types of bias, one related to the characteristics of the plant, and one related to the characteristics of the location of the plant.

Regarding the first, larger plants, that are very likely the largest polluters, attract more attention and thus more media coverage. Newspapers may decide to locate close to a large plant for this reason, but this is an extremely unlikely outcome, given the very limited space dedicated to firms in newspapers'coverage. The same can be said more in general for plants that are known polluters.

Another concern related to the characteristics of the plant is that plants that intend to pollute more self-select in areas where there are no newspapers, to avoid coverage of their pollution statistics; however, more than a concern this is part of the effect that I want to estimate.

More substantial are the worries related to the characteristics of the location of the plant, that can be correlated both with plant's emissions and with the presence of a newspaper. The identifying assumption is that, when making their location decision, newspapers and plants take into account different variables, or that these variables are not correlated with emissions, or that we are able to control for these variables.

In what follows I suggest two types of analysis to get a sense of how likely it is that the identifying assumption is met.

Using observables to infer the degree of selection on unobservables.The coefficient for distance in the specification that includes controls, though smaller than in the baseline, is not dramatically so. This may suggest that the correlation of distance with the covariates is not very strong; while it is impossible to test whether there are unobservable determinants of emissions that are also correlated with distance from the closest newspaper, the correlation of the observables with distance can be used to infer how strong should be the correlation of the unobservables to cancel out the estimated effect. Using the method developed by Altonji et al. (2005), and adapted to the continuous case by Bellows and Miguel (2008), I find that the correlation of distance with the unobservables should be 5.3 times bigger than its correlation with the observables to cancel out the effect of distance on emissions. This is remarkable, because, as already pointed out, variables that intuitively and from previous accounts seem to explain most of the variation in newspaper presence in the US are included among the observables.

Running placebo regression to evaluate the identifying assumption. Table 4 provides another test to assess the validity of my identification strategy. As explained in Section 2, the number of total articles on TRI statistics written in the period analyzed is actually null in about 20% of the States. This means that TRI statistics are considered news only in certain States, presumably those where there is more concern around environmental issues, or where average emissions are larger. I document, indeed, that in these States being closer to a newspaper translates into less emissions, and I argue that this finding is relatd to the other result in this paper, i.e. that being closer to a newspaper increases the probability that articles about TRI statistics are written.

In States where TRI statistics do not constitute a "news" instead, the presence of a newspaper nearby should not represent a "threat" for plants' reputation on environmental performance. Therefore, if the effect of distance on emissions is due at least in part to the "threat of coverage", rather than to spurious correlation with other characteristics of the plant's location, the effect should be smaller or null once we look at plants in States where coverage does not arise at any point in time.

Table 4 shows that this is indeed the case. The effect of distance on emissions is not precisely estimated, and its magnitude and sign change across specifications, when equation 2 is estimated on plants located in States where coverage does not emerge.

This test shows that the data satisfy a necessary, although not sufficient condition for identification. Indeed, this finding is also consistent with an alternative scenario in which there are other variables (such as general interest in the population about environmental issues) that correlate with distance of newspaper and that matter only in certain States. In particular, in States where coverage has never arisen emissions have lower average and standard deviation. If both interest and coverage arise only once emissions exceed a certain level, the pattern observed in Tables 3 and 4 is consistent with both coverage and interest determining the correlation between distance from closest newspaper and emissions. However, one should consider that these two variables are intertwined; it is not unlikely that interest is determined, at least in part, by coverage itself; moreover, local newspapers were funded mostly in the 19th or early 20th century, and it is thus less likely that people's interest in getting informed about environmental issues (and about socio-political local issues in general) drove the location decision of the newspaper.

5 Conclusion and Future Developments

In this paper I have shown that plants that are located closer to a newspapers emit less toxic substances than plants that are more distant from their closest newspaper and that operate in the same industry, county and year. Population density, income per capita, urbanization, educational, demographic and racial composition of the county population do not completely explain this correlation.

I argue that there is a direct causal effect of distance from closest newspaper on emissions, through the "threat of coverage" coming from the local press. I show that, indeed, plants located nearby a newspaper are more likely to get covered and are featured in a larger number of articles.

I also show that distance from closest newspaper and emissions are not correlated in States where coverage of TRI statistics has not emerged.

The main concern on identification is that locations where there are newspapers are different than those where there are not, for reasons that are correlated with emissions, and that we are not able to control for.

At this proposal, different solutions to the identification problem will be explored in future development of this paper.

I will control for measures of distance of the firm from the closest university, arguing that this is a good proxy for non accounted for differences in economic, social and cultural development of the place where the plant is located. For the same purpose, I plan to collect data on total newspapers circulation at zip-code level, and to control for newspapers penetration in the area around the plant; arguably, the share of people who read newspapers is another good indicator of social and cultural local development and of local civic attitudes.

Moreover, I plan to search for coverage of environmental issues in newspapers, and to test whether the estimated effect is larger for plants whose closest newspaper covers environmental issues more heavily.

Finally, based on economic theory and empirical evidence I argue that certain plants are supposed to care about reputation more than others; more specifically, these are plants that: operate in industries with lower concentration (i.e. less competition) (see Heal (2008)); operate in industries where the average distance traveled by goods is lower (see Heal (2008)); are listed in the stock market (see Hamilton (1995)); produce goods with a higher "consumer proximity" index (see Heal (2008)).

Testing these predictions will show whether the effect estimated can be generated by plant's concerns about reputation, as formed through newspapers coverage; moreover, these tests will shed light on what are the "constituents" that these firms are mostly worried about (mainly, local investors, local consumers, or more in general their "neighbors").

Bibliography

Altonji, Joseph G., Elder, Todd E. and Taber, Christopher R. (2005). Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy*, University of Chicago Press, vol. 113(1), pages 151-184, February.

Currie, J., and Johannes F. Schmieder (2009). Fetal Exposure to Toxic Releases and Infant Health. *American Economic Association Papers and Proceedings*, 99(2), May 2009, 177-83

Eisensee, T. and Stromberg, D. (2008). News Floods, News Droughts, and U.S. Disaster Relief. *Quarterly Journal of Economics*, 122(2), 2007.

Gentzkow, M., Shapiro, Jesse M. and Sinkinson, M. (2011). The Effect of Newspaper Entry and Exit on Electoral Politics. *American Economic Review.* Vol. 101 (7).

Hainmueller, J., Hiscox, Michael J. and Sequeira, S. (2011). Consumer Demand for the Fair Trade Label: Evidence from a Field Experiment. Mimeo

Heal, G. (2008). *When Principles Pay-Corporate Social Responsibility and the Bottom Line.* Columbia Business School Press, 2008. - Blog posting on FairerGlobalization

Hamilton, James T. (1995). Pollution as News: Media and Stock Market Reactions to the Toxics Release Inventory Data. *J Environmental Economics and Management.* Vol. 28, 98-113.

Pratt, A. and Stromberg, D. (2011). The political economy of mass-media. Mimeo.

Cohen, M. and Konar, S. (2001). Does the Market Value Environmental Performance? *The Review of Economics and Statistics.* Vol. 83, No. 2, 281-289

Appendix

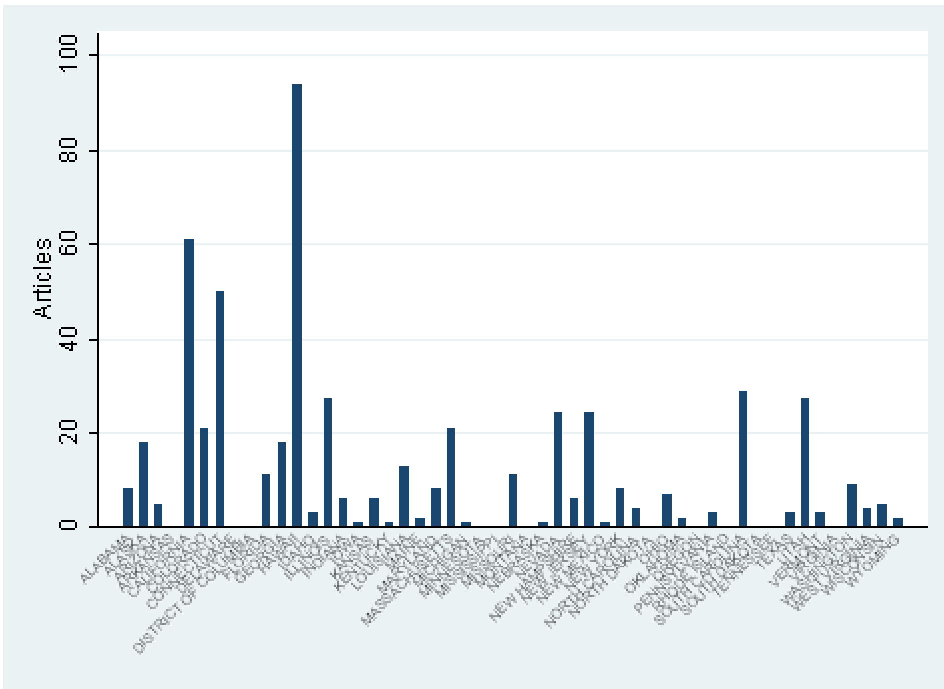

Figure 1
Total number of articles by State

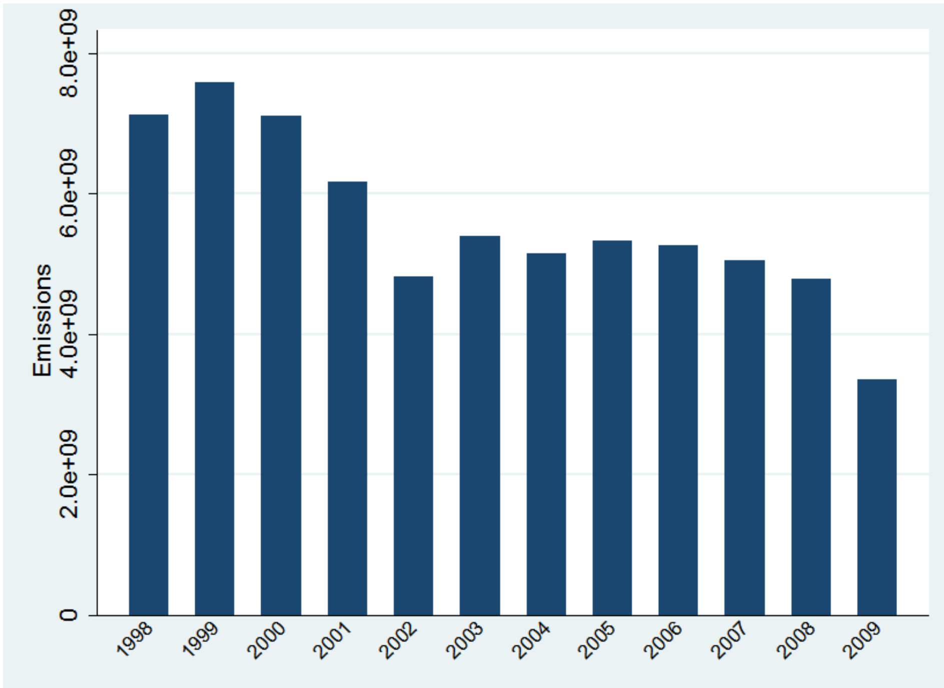

Figure 2
Total emissions by year

Table 1
Summary Statistics

	Top 20's			Full Sample		
Variable	**Mean**	**Stand Dev**	**N**	**Mean**	**Stand Dev**	**N**
toxic emissions	3808006	30969749	5838	231161	6004950	166751
distance closest newspaper	17.185	38.059	5838	9.396	11.557	166751
log pop density	5.636	1.957	5612	6.203	1.551	166724
log income pc	10.049	0.274	5610	10.132	0.263	166719
share black	0.107	0.19	5612	0.102	0.163	166724
share urban	0.452	0.333	5612	0.517	0.338	166724
share high school and some college	0.555	0.085	5612	0.54	0.091	166724
share college and more	0.288	0.112	5612	0.302	0.114	166724
share younger 20	0.293	0.036	5612	0.288	0.028	166724
share older 65	0.123	0.033	5612	0.129	0.028	166724
articles closest newspaper	0.043	0.228	5838			
coverage closest newspaper	0.037	0.188	5838			
articles others	0.05	0.301	5838			
covered others	0.035	0.184	5838			

Table 2

Distance from closest newspaper and coverage

Model	(1) covered closest LPM	(2) covered others LPM	(3) covered closest LPM	(4) covered closest LPM	(5) covered closest Logit	(6) covered closest Logit
log distance	-0.007**	-0.003	-0.007**	-0.006*	-0.187**	-0.242**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.086)	(0.103)
covered others			0.150***		1.621***	
			(0.028)		(0.258)	
log pop density				0.002		-0.021
				(0.005)		(0.115)
log income pc				0.038		1.340*
				(0.026)		(0.754)
share black				0.023		1.137*
				(0.016)		(0.589)
share urban				-0.006		0.238
				(0.025)		(0.632)
share high school and some college				-0.027		0.672
				(0.057)		(1.680)
share college and more				-0.069		-1.882
				(0.077)		(2.201)
share younger 20				0.098		0.893
				(0.165)		(4.094)
share older 65				-0.253		-9.079
				(0.164)		(5.562)
Observations	5,838	5,838	5,838	5,610	3,971	3,712
R-squared	0.107	0.049	0.127	0.095		
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Elasticity	-0.20	-0.10	-0.19	-0.17	-0.18	-0.24
$Pr(\overline{x'}\widehat{\beta})$	0.0368	0.0351	0.0368	0.0353	0.0244	0.0256

Standard errors are clustered by plant

Table 3

Distance from closest newspaper and toxic emissions

Model	(1) log emissions OLS	(2) log emissions OLS	(3) log emissions OLS	(4) log emissions OLS	(5) log emissions Interval Regression
lag 1 log distance	0.339***	0.274***	0.284***	0.285***	0.263***
	(0.0829)	(0.0901)	(0.0905)	(0.0907)	(0.0770)
log pop density		-0.640***	-0.558***	-0.572***	-0.358**
		(0.163)	(0.185)	(0.187)	(0.153)
log income pc		-0.593	-0.122	-0.148	-0.0226
		(0.926)	(0.945)	(0.951)	(0.791)
share high school and some college		0.116	0.524	0.0982	-0.368
		(2.147)	(2.228)	(2.310)	(1.837)
share college and more		-6.315**	-6.008**	-6.193**	-5.055**
		(2.544)	(2.566)	(2.599)	(2.119)
share older 65		-3.450	-3.567	-4.028	1.117
		(5.784)	(5.810)	(5.897)	(4.750)
share younger 20		-16.34***	-17.64***	-18.23***	-8.257*
		(5.621)	(5.663)	(5.816)	(4.753)
share black		-0.782	-0.740	-0.778	-0.216
		(0.680)	(0.682)	(0.685)	(0.578)
share urban		1.842**	2.100**	2.160**	1.127
		(0.751)	(1.000)	(1.016)	(0.833)
Observations	166,751	166,719	166,719	166,719	166,719
R-squared	0.176	0.178	0.178	0.179	
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Dummies for quartiles	No	No	Yes	Yes	Yes
State-by-year FE	No	No	No	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors are clustered by plant

Table 4

Distance from closest newspaper and toxic emissions: test of identifying assumption

Model	log emissions OLS	log emissions OLS	log emissions OLS	log emissions OLS	log emissions Interval Regression
lag 1 log distance	0.00263	-0.167	-0.172	-0.181	0.217
	(0.238)	(0.277)	(0.278)	(0.279)	(0.220)
log pop density		-0.0687	-0.178	-0.152	0.647
		(0.563)	(0.637)	(0.639)	(0.479)
log income pc		-5.630	-6.384	-6.217	-4.373
		(3.867)	(3.907)	(3.940)	(2.991)
share high school and some college		5.459	4.007	5.542	3.963
		(7.394)	(7.624)	(8.286)	(6.295)
share college and more		-0.0389	0.463	0.948	-1.789
		(11.07)	(10.99)	(11.12)	(8.318)
share older 65		-50.89**	-50.89**	-51.14**	-46.43***
		(20.41)	(20.46)	(21.83)	(17.02)
share younger 20		-57.88***	-56.70***	-53.95**	-58.49***
		(19.88)	(19.90)	(21.82)	(17.27)
share black		-3.058*	-2.991*	-2.833*	-1.516
		(1.705)	(1.702)	(1.708)	(1.303)
share urban		-1.912	2.130	2.078	0.507
		(2.426)	(3.199)	(3.232)	(2.521)
Observations	24,252	24,252	24,252	24,252	24,252
R-squared	0.215	0.219	0.221	0.223	
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Dummies for quartiles	No	No	Yes	Yes	Yes
State-by-year FE	No	No	No	Yes	Yes

Standard errors are clustered by plant