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Social capital, environmental justice and carcinogenic waste releases: US county-level evidence, 1998–2019

Ali Ataullah[a], Simeon Coleman[b], Hang Le[c] and Zilong Wang[d]

ABSTRACT
We examine the role of social capital in explaining the highly unequal regional distribution of firms' carcinogenic releases. Our model predicts that social capital, by enabling information-sharing and coordination among community members, decreases carcinogenic releases. Our analysis, based on the US county-level releases derived from around 2 million chemical-facility-level reports during the period 1998–2019 and the instrumental variables approach, confirms our prediction. However, the impact is reduced when counties rely on waste-releasing firms for economic opportunities. An important policy implication of our study is that the efficacy of initiatives to alleviate environmental injustice is likely to depend on communities' social capital.

KEYWORDS
social capital; carcinogenic waste releases; environmental justice; employment; wages; environmental protection agency

JEL H23, Q52, Q53
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1. INTRODUCTION

Firms in the United States reported releasing over 88 billion pounds of chemical wastes during the period 1998–2019, of which more than 5 billion pounds were carcinogenic wastes,[1] that is, the wastes that contain chemical agents that are known or reasonably anticipated to 'produce or incite cancer' in humans.[2] The empirical evidence on the harmful impacts of such wastes is substantial and growing. For example, firms' toxic wastes negatively affect infant mortality and birth weights (Currie, 2011), and increase the risk of cancer (Fortunato et al., 2011) and cardiovascular mortality (Hendryx et al., 2014). An important finding of the growing 'environmental justice' literature is that firms' toxic releases – and associated harmful health effects – are inequitably distributed (Banzhaf et al., 2019). For example, in 2019, 7.6 million pounds of carcinogenic releases were reported in Harris County, Texas, with a population of 4.7 million, while 30 pounds were reported in Montgomery County, Maryland, with a population of 1 million. Our calculations also suggest that most of the toxic waste releases were concentrated in a small number of counties. In 2019, just over 400 counties accounted for around 90% of the total toxic wastes.

This paper examines the impact of social capital on the highly inequitable regional distribution of carcinogenic wastes released by firms. Figure 1 shows that during the period 2014–19, higher values of social capital and lower values of toxic releases are concentrated in the upper Midwest and Northwest counties, while lower social capital and higher toxic releases are concentrated in the Southeast/Southwest counties.[3] Our theoretical model and empirical analysis examine the relationship between social capital and carcinogenic releases, and, in turn, contribute to two strands of literature. First, we augment the environmental justice literature that lays an emphasis on the significance of community-level characteristics – especially race, education and income – in explaining regional variations in firms' toxic releases. For example, low-income, low-education and non-white members of the US population are more likely to live near toxic-releasing facilities (Collins et al., 2016). Residents with high income can lobby the government for a cleaner environment and reduce the toxic wastes that firms release in the neighbourhoods (De Silva et al., 2021). Our analysis shows that

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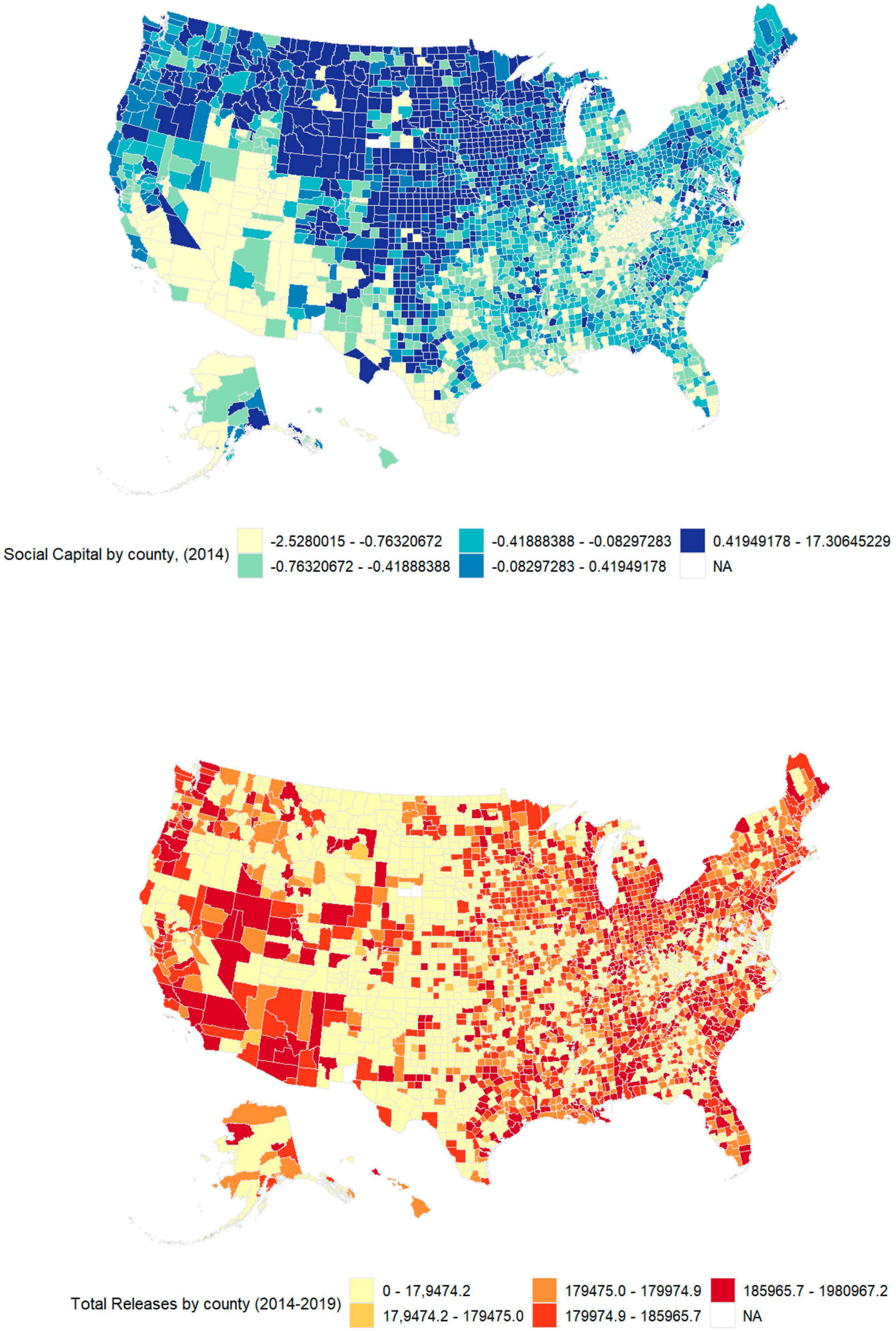

Figure 1. Geographical distribution of (a) social capital and (b) carcinogenic releases in the United States, 2014–19.
Note: Figure (a) uses the 2014 social capital index. For details on how the index is calculated, see Rupasingha et al. (2006). Figure (b) uses the annual average carcinogenic releases for the period 2014–19.
Sources: https://aese.psu.edu/nercrd/community/social-capital-resources; and the Toxic Release Inventory Program (TRI) Basic Data files of the US Environmental Protection Agency (EPA).

communities' social capital is an important determinant of the toxic wastes that firms releases.

Second, our analysis adds to the rich and growing economics literature on social capital that lays an emphasis on the significance of ties between people in facilitating information-sharing, trustworthiness and coordination, which, in turn, enable them to undertake collective actions to solve social problems (e.g., Bigoni et al., 2016; Bowles & Gintis, 2002; Ostrom, 1995; Putnam, 2000). Although disagreements and ambiguities around the conceptualization of social capital remain, empirical studies have provided evidence suggesting that regional social capital is related to economic growth (Rupasingha et al., 2006), financial development (Guiso et al., 2004), teaching practices (Algan et al., 2013), innovations (Tura & Harmaakorpi, 2005) and regional development (Iyer et al., 2005). We augment this literature by highlighting the impact of social capital on regional toxic releases that adversely affect public health and the environment. We also add to the literature that examines how government efforts such as environmental tax policies could reduce industrial toxic waste generation (e.g., Vallés-Giménez & Zárate-Marco, 2021) by highlighting the role that community efforts, that is, social capital, could play.

We begin by developing a simple model that offers novel insights into the possible link between social capital and firms' carcinogenic releases. In our model, firms' production activities result in waste releases. Community members can impose a penalty on waste-releasing firms through activities such as organizing protests, boycotting products of polluting firms and lobbying governments. These activities, however, entail costs, which we assume vary inversely with the level of social capital. This assumption is based on the sociology and economics literature that views a community's social capital as a resource that facilitates collective actions through information-sharing and coordination among community members (Bigoni et al., 2016; Bowles & Gintis, 2002; Ostrom & Ahn, 2009; Portes, 1998).[4] Our model predicts that the amount of toxic wastes decreases with the strength of a community's social capital.

We test our prediction using data derived from around 2 million chemical reports in the US Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) during the period 1998–2019. We use the county-level social capital index constructed by Rupasingha et al. (2006). We also test the robustness of our analysis using an alternative measure constructed by the Social Capital Project of the US Congress Joint Economic Committee (JEC). Our analysis seeks to identify the impact of social capital on carcinogenic releases using panel data fixed-effect regressions that include a comprehensive set of county-level time-varying socio-economic variables. We find that the carcinogenic toxic releases are inversely related to the social capital of local communities.

However, despite controlling for a large set of county-level socio-economic differences, the panel data analysis may not be sufficient for identification as there may be other unobservable factors that are correlated with both social capital and toxic releases, or if there is reverse causality. Thus, we use the instrumental variables (IV) approach in which we use a novel instrument for social capital, namely, the county-level annual number of motor vehicle crash deaths. Two justifications for this instrument are as follows. First, the social capital literature suggests that a key source of social capital is the 'internalized norms' of a community such as obeying traffic rules (Portes, 1998, p. 7). As the US Department of Transportation highlights, many serious motor vehicle accidents occur when people disobey traffic rules by driving carelessly or under the influence of alcohol/drugs.[5] Thus, car crash deaths capture the strength of internalized norms pertaining to obeying rules, a source of social capital.

Second, the literature on spatial dispersion of social networks and the importance of commuting in participation and social cohesion suggests that 'travel often produces social capital' while 'insufficient sociality might lead to diminished social capital' (Larsen et al., 2006, p. 262). Within this context, easy and safe travelling may foster the development of social ties (Kamruzzaman et al., 2014). We posit that low motor vehicle crash deaths reflect safe and easy access to social activities, which are important for local residents to coordinate or take part in activities such as meetings to organize protests. Thus, we expect that motor vehicle crash deaths are negatively associated with social capital. Yet, it is very unlikely that motor vehicle crashes have a direct partial effect on carcinogenic wastes that firms release in a particular region. Our IV analysis confirms that social capital has a negative impact on regional carcinogenic releases. We also use the negative binomial hurdle model for the count of facilities as two separate but interrelated processes: the first models the probability density function of a county to have a waste-releasing facility, and the second specifies the probability density function of truncated positive counts. We find that social capital is important in explaining the presence and the number of waste-releasing facilities.

Another novel finding of our analysis is that the magnitude of the relationship between social capital and carcinogenic releases is smaller in counties that rely heavily on waste-releasing firms for employment and economic opportunities than counties that do not. Consider, for example, in 2018, only 5% of the workforce in Blaine County, Oklahoma, was engaged in employment in toxic waste-releasing industries. However, the corresponding percentage for Greenlee County, Arizona, was 79%. We argue that community members in counties such as Greenlee may be reluctant to oppose firms' operations that release toxic wastes if these firms are key sources of employment and other economic opportunities available to the community. Thus, the significance of social capital in reducing toxic wastes could vary with the level of reliance on toxic waste-releasing firms for employment. This evidence is consistent with the notion that the amount of toxic releases may depend on bargaining between communities and firms (Banzhaf et al., 2019). So, even if social capital enables communities to take coordinated actions against waste-releasing firms, their bargaining power is likely to be curtailed due to community members' reliance on such firms for employment.

Our analysis makes an important contribution to the public policy on environmental injustice. A necessary condition for reducing unequal distribution of waste releases, and its disproportionate adverse effects on the health of disadvantaged communities, is the disclosure of information about sources and types of toxic materials released by firms. An important step in such disclosure is the Emergency Planning and Community Right-to-Know Act (EPCRA), passed by the EPA in 1986. The EPCRA's goal is to 'increase the public's knowledge and access to information on chemicals at individual facilities, their uses, and release into the environment' so that communities can use this information to 'improve chemical safety and protect public health and the environment'.[6] Our analysis is relevant to this goal as we suggest that the efficacy of initiatives such as the EPCRA is likely to be contingent upon communities' ability to share information and cooperate/coordinate their activities to take collective actions that influence firms' decisions to determine the location and the amount of their toxic releases. Our evidence also augments recent work that shows that active participation by community members (i.e., 'neighborhood defenders') restricts developers' ability to build affordable housing in different regions of the United States (Einstein et al., 2020).

The rest of the paper is structured as follows. Section 2 presents our simple model and develops our hypothesis. Section 3 describes the data and empirical methods. Section 4 discusses the results. Section 5 concludes.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

The EPA's Right-to-Know Act of 1986 requires facilities to disclose information about the use and releases of hazardous chemicals, to empower communities to protect themselves from the harmful health effects of such chemicals. However, as toxic wastes are normally released in public media (e.g., air, rivers), the disclosure of information to communities alone is not sufficient to reduce inequitable exposures to toxic releases; community members also need to gather and share relevant information about firms' operation, and then coordinate their activities to take collective actions against toxic waste-releasing firms. Even if community members have individual property rights to the level of toxic wastes in their neighborhood and if transaction costs are small, they may not have the incentives to undertake costly actions against toxic-releasing firms. Instead, firms may end up with all the rights to release toxic wastes in the neighborhood, leading to the excess provision of a public *bad* (Helfand et al., 2003, pp. 260–261). This is where social capital of a community plays a role in reducing toxic wastes.

Social capital usually refers to a measure of the strength of ties among community members, which depends on internalized norms or the extent of repeated interactions among community members (Ostrom, 1995; Putnam, 2000; Guiso et al., 2004; Bigoni et al., 2016). The evolution of social capital depends on 'deliberate investment' by community members through engaging in activities that strengthen their ties (Portes, 1998, p. 4). Within this framework, social capital captures community members' concern for the well-being of other members (e.g., Bowles & Gintis, 2002), and reduces costs associated with information-sharing and coordination to take collective actions to mitigate social problems such as the release of toxic wastes by firms (e.g., Ostrom & Ahn, 2009; Portes, 1998). In this section we develop a simple theoretical model to formalize the link between regional social capital and regional toxic releases.

2.1. Firm's production problem

Consider a representative price-taking firm that produces output Y, using labour L and a production process that releases toxic waste E. The firm has the following constant return-to-scale Cobb–Douglas production function:[7]

$$Y = AL^{\alpha}E^{\beta} \tag{1}$$

where $\alpha, \beta \in (0, 1)$, $\alpha + \beta = 1$, and A represents local characteristics that facilitate production. The cost of production is $wL + tE$, where w is wage per unit of labour and t is cost per unit of releasing toxic wastes. These costs may come from sources such as government charges and compensation to community members. To simplify the model we make the production level exogenous.[8] The firm chooses L and E to minimize the cost for a given level of production:

$$\min_{L,E} wL + tE \tag{2}$$

$$\text{s.t. } AL^{\alpha}E^{\beta} = Y \tag{3}$$

The optimal E from the above minimization problem is:

$$E^{*} = \frac{Y}{A}\left(\frac{\beta}{\alpha}\frac{w}{t}\right)^{\alpha} \tag{4}$$

2.2. Local residents' problem

Consider the utility maximization problem for a representative resident i with a concave utility function. The resident chooses effort a_i, captured by a quadratic cost of effort function, to influence firms' cost of releasing toxic wastes. The resident's problem is:[9]

$$\max_{a_i} U = [c + bnt(a)E]^{\theta} - v(nE) - \frac{1}{2}ma_i^2 \tag{5}$$

where c is exogenous consumption of goods and $\theta \in (0, 1)$, n denotes the number of firms in her region, and b is the fraction of the total cost of emission of all polluting firms ntE in the local area paid as compensation to each resident. This compensation could be either in the form of direct compensation or fees paid to local government that provides public goods to local residents. The term $-v(nE)$ denotes the disutility of toxic wastes due to adverse health effects (Muller & Mendelsohn, 2007).

The residents exert effort to claim property rights or compensation which influences the firm's cost of releasing toxic wastes. Thus, the cost of emission t to the waste-releasing firm is a function of $a = a_i + \sum_{k \neq i} a_k$ (collective effort made by all local residents), where k indicates other residents in the area. We assume t is a concave function in a. If local residents have all relevant property rights to claim, they can veto waste-releasing activities. However, even without full property rights, local residents may be able to influence the cost of releasing toxic wastes through tort laws, zoning laws, holding up permitting processes, etc. (Banzhaf et al., 2019). This is a plausible assumption based on the recent evidence that community members actively participate in the decision to control or delay activities such as housing development (Einstein et al., 2020).

In equation (5) the cost of effort is represented by the term $(1/2)ma_i^2$, where $m > 0$. As noted above, community members have to gather relevant information and coordinate their actions to influence the cost of releasing toxic wastes. In this study, we assume that social capital facilitates information gathering and coordination (e.g., Bowles & Gintis, 2002; Ostrom & Ahn, 2009; Portes, 1998), and, in turn, reduces the cost of effort needed by individual community members. This favourable effect of social capital in reducing the cost of effort is captured by the parameter m. Specifically, we posit that the larger the social capital, the lower the value of m. In other words, in a region with higher social capital, the cost of taking action to claim property rights or compensation is lower.

As c is exogenous, the representative resident maximization problem $(c + bntE)^\theta - v(nE) - (1/2)ma_i^2$ is equivalent to the maximization of $(bnE)^\theta t^\theta - v(nE) - (1/2)ma_i^2$. Given that the cost t is a function of collective effort a, the maximization problem becomes:

$$\max_{a_i} (bnE)^\theta [t(a)]^\theta - v(nE) - \frac{1}{2} m a_i^2 \tag{6}$$

where $a = a_i + \sum_{k \neq i} a_k^*$.

The solution to the problem is the following first-order condition:

$$\theta(bnE)^\theta \left[t\left(a_i^* + \sum_{k \neq i} a_k^* \right) \right]^{\theta - 1} t_a - m a_i^* = 0 \tag{7}$$

Let $a^* = \sum a_i^*$ be the optimal level of the total effort of residents, we therefore have:

$$\theta(bnE)^\theta [t(a^*)]^{\theta-1} t_a - m a_i^* = 0 \tag{8}$$

Applying the implicit function theorem to equation (8) obtains:

$$\frac{\partial a_i^*}{\partial m} = -\frac{-a_i^*}{(\theta - 1)\theta(bnE)^\theta (t)^{\theta-2} t_a^2 + \theta(bnE)^\theta [t(a^*)]^{\theta-1} t_{aa} - m} < 0 \tag{9}$$

since $(\theta - 1) < 0$ and $t_{aa} < 0$. Given t is an increasing function of effort level a_i, $(\partial a_i^*/\partial m) < 0$ implies $(\partial t/\partial m) < 0$. The lower the parameter m (higher social capital), the higher the effort made by local residents to impose a penalty on releasing toxic wastes, which, in turn, increases the cost of toxic wastes that firms release. By applying the implicit function theorem again to equation (8) we obtain:

$$\frac{\partial a_i^*}{\partial E} = -\frac{\theta^2 (bn)^\theta [t(a^*)E]^{\theta-1} t_a}{(\theta - 1)\theta(bnE)^\theta (t)^{\theta-2} t_a^2 + \theta(bn)^\theta [t(a^*)E]^{\theta-1} t_{aa} - m} > 0 \tag{10}$$

Since t is an increasing function of effort level a_i. $(\partial a_i^*/\partial E) > 0$ implies $(\partial t/\partial E) > 0$. Thus, the higher the level of emission, the higher the effort made by local residents to impose a penalty on releasing toxic wastes, which, in turn, increases the cost of toxic wastes that firms release.

For a given cost of releases, a firm chooses the optimal level of emission to minimize the production cost. However, the level of emission would affect the effort made by local residents and hence the cost of emission. Thus, the optimal effort level and emission of toxic wastes are simultaneously determined by equations (4) and (8). From equation (8), we know that t is a function of a^* and E^*, and a^* is a function of m and E^*, thus t is a function of m and E^*. Substituting t into equation (4):

$$E^* = \frac{Y}{A} \left(\frac{\beta}{\alpha} \frac{w}{t(m, E^*)} \right)^\alpha \tag{11}$$

The optimal emission E^* is determined by the following equation:

$$E^* [t(m, E^*)]^\alpha - \frac{Y}{A} \left(\frac{\beta}{\alpha} w \right)^\alpha = 0 \tag{12}$$

By applying the implicit function theorem to equation (12) we obtain:

$$\frac{\partial E^*}{\partial m} = -\frac{E^* \alpha t^{\alpha-1} \frac{\partial t}{\partial m}}{E^* \alpha t^{\alpha-1} \frac{\partial t}{\partial E} + [t(m, E^*)]^\alpha} > 0 \tag{13}$$

Recall that in our framework we posit that social capital reduces the cost of effort $(1/2)ma_i^2$ by facilitating information-sharing and coordination. That is, the higher the social capital, the lower the value of m. Thus, equation (13), which suggests a positive relationship between the parameter m and E, implies a negative relationship between social capital and the emission of toxic wastes E.

In summary, residents who live in a neighbourhood with a higher social capital are better able to coordinate and undertake collective actions, which impose costs on firms' waste-releasing activities. Cost minimizing firms, in turn, would reduce waste releases. Thus, social capital through collective actions affects the aggregate wastes released in the neighbourhood and benefits and utility of local residents. Figure 2 summarizes this

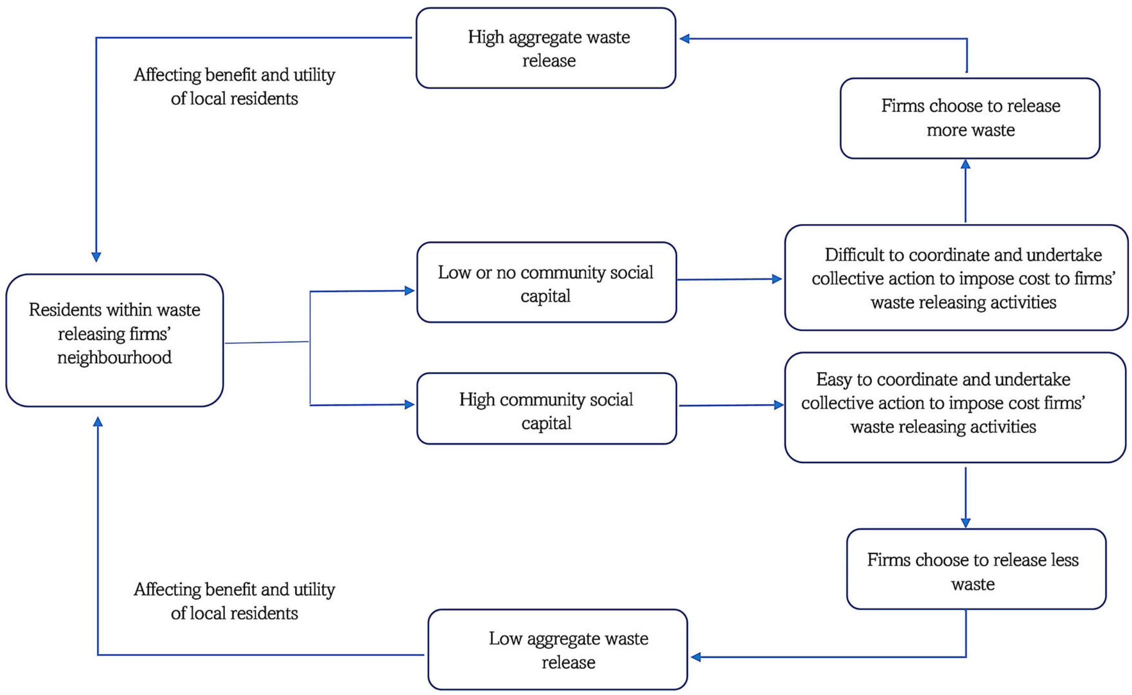

Figure 2. Representation of the theoretical model.

theoretical link between social capital and toxic waste releases.

Given that carcinogenic wastes are an important category of toxic wastes, equation (13) and our discussion above lead to the following testable hypothesis:

Hypothesis 1: An increase in the social capital of a community decreases the emission of carcinogenic wastes in their neighbourhoods, ceteris paribus.

3. METHODOLOGY

3.1. Data

We use several databases for the empirical analysis. The Toxic Release Inventory (TRI) Program of the EPA provides annual emission data for facilities in 409 distinct industry codes (using six-digit North American Industry Classification System – NAICS) for 770 individually listed chemicals and 33 chemical categories. The information is self-reported by facilities using the EPA's standardized form and pertains to releases into the air, ground and water.

The TRI Program went through significant changes in reporting requirements (Gibson, 2019; Hamilton, 2005). Although there are some concerns over the self-reporting nature of the data, it might not lead to under-reporting as the EPA only imposes fines on false reporting but not on high emissions (Gibson, 2019). Over the years, the EPA has strengthened enforcement, and introduced inspectors and attorneys to investigate non-compliance cases.[10] To ensure that our results are not affected by early reporting changes, especially by the addition of seven major industries in 1997, our analysis is based on data for the period 1998–2019.

We use the county-level social capital index developed by Rupasingha, Goetz and Freshwater at Penn State University (Rupasingha et al., 2006). We also use the index developed by the Social Capital Project of the US Congress JEC, which covers a wider range of socio-economic indicators compared with the Rupasingha et al.'s (2006) index.[11] There is only one wave of the JEC index (2018) while there are five waves in the Rupasingha et al.'s index.

We obtain data for county-level control variables from the ERS County Typology of the US Department of Agriculture (USDA), US Census, Bureau of Economic Analysis (BEA), US County Business Patterns, and US County Health Rankings and Roadmaps.

We extract 1,911,256 facility–chemical–year observations from the TRI data files and merge with county-level social capital and other controls to achieve an unbalanced panel of 67,197 county–year observations (3084 counties and 22 years).

3.2. Variables

3.2.1. Outcome variables

We aggregate facility-level annual chemical releases from the TRI and then compute county-level total, on-site and off-site releases using facilities' reported addresses. Our analysis uses seven outcome variables: total, on-site and off-site amounts of carcinogenic chemicals (in pounds) released by firms (*Carcinogen_Total*, *Carcinogen_Onsite* and *Carcinogen_Offsite)*; total, on-site and off-site amounts of all released chemicals (*All_Chem_Total*, *All_Chem_Onsite* and *All_Chem_Offsite*), and the number of releasing-report facilities (*Facilities_Count*).

3.2.2. Measures of social capital

We use the county-level social capital index (*Social_Capital*) from Rupasingha et al. (2006). The index is calculated as the first principal component of four standardized factors: (1) *assn*, the aggregate of the number of religious, civic, social, business, political, professional, labour, fitness and recreational sports clubs, establishments or organizations; (2) *pvote*, presidential voter turnout; (3) *respn*, census response rate; and (4) *nccs*, number of non-profit organizations. We backfill data for each missing year using the social capital index values in the preceding year. For example, we use the 2014 social capital index values for the years 2014–19. Later, we perform an analysis to ensure that our results are not affected by this backfilling method.

3.2.3. Other variables

We include a comprehensive list of county-level variables including economic sector dependency; metro/non-metro status; indicators for low employment, retirement destination and persistent poverty; education attainment; demographic composition variables which are race, origin and age; and employment growth, income level and income growth. To measure the economic significance of polluting industries, we calculate county-level total annual employment and payrolls for each two-digit NAICS industry. We merge this with TRI data to calculate the employment share of all two-digit NAICS industries that report carcinogenic toxic releases in the county total employment. Appendix B in the supplemental data online provides detailed definitions, data sources and summary statistics for all the variables used in our analysis.

3.3. Methods

Our main analysis consists of four parts. First, we use Harrell–Davis quantile estimator (Wilcox et al., 2014) to compare different quantiles of carcinogenic release distribution for the group of counties with the lowest level of social capital (i.e., counties within the 1st quartile of social capital) with the highest level of social capital (i.e., 4th quartile).

Second, we seek to explain the relationship between social capital and the amount of toxic waste releases in counties using panel data fixed-effect regressions. These regressions include a comprehensive set of county-level control variables, along with time and county fixed-effects. Our regression function takes the following form:

$$\log(Release_{ct}) = \beta_0 + \beta_1 Social\_Capital_{ct} + \sum_{k=2}^{p} \beta_k Z_{kct} + \eta_c + \tau_t + \epsilon_{ct} \qquad (14)$$

where $Release_{ct}$ is the amount of toxic releases in county c in year t, $Social\_Capital_{ct}$ is the value of the social capital index in county c in year t, Z_{kct} is the kth control variable, η_c denotes the county-level time-invariant heterogeneity, τ_t is the year fixed-effect, and ϵ_{ct} is the error term. We use county population as weights in all regressions.

Third, we use the IV approach in which we instrument social capital with county-level annual number of motor vehicle crash deaths. A large number of serious motor vehicle accidents occur when people disobey traffic rules by driving carelessly (e.g., speeding) or under the influence of alcohol/drugs.[12] Thus, car crash deaths capture the strength of internalized norms pertaining to obeying rules, a source of social capital (Portes, 1998). Second, the literature highlights the spatial dispersion of social networks and the importance of commuting in participation and social cohesion. Specifically, 'travel often produces social capital' while 'insufficient sociality might lead to diminished social capital' (Larsen et al., 2006, p. 262). Within this context, easy and safe travelling may foster the development of social ties (Kamruzzaman et al., 2014). We posit that low motor vehicle crash deaths reflect safe and easy access to social activities, which are important for local residents to cooperate and coordinate activities such as meetings to organize protests or take part in other social activities. Yet, it is very unlikely that motor vehicle crashes have a direct partial effect on local carcinogenic releases. Due to data availability, we have a reduced sample for IV regressions.

Fourth, we use a negative binomial hurdle model for our count variable $Facilities\_Count_{ct}$, which is the number of facilities releasing carcinogenic wastes in county c in year t. The use of a hurdle model is motivated by the fact that several counties have zero reporting facilities. Consequently, we model the count of facilities in counties as two separate but interrelated processes. Specifically, the first part models the probability density function $f_{zero}(Facility\_Count; X, \gamma)$ of a county to have a release-reporting facility, where X denotes regressors (including social capital), and γ denotes the parameters to be estimated. The second part of our model specifies the probability density function $f_{count}(Facility_{Count}; X, \beta)$ of truncated positive counts once the hurdle of zero counts is crossed (i.e., counties have reporting facilities), and β denotes the parameters to be estimated. The hurdle model combines the two parts, as follows (Zelleis et al., 2008, p. 6):

$$f_{hurdle}(Facility_{Count}; X, \gamma, \beta) = \begin{cases} f_{zero}(0; X, \gamma) & \text{if } Facility.Count = 0 \\ (1 - f_{zero}(0; X, \gamma)).\dfrac{f_{count}(Facility.Count; X, \beta)}{(1 - f_{count}(0; X, \beta))} & \text{if } Facility.Count > 0 \end{cases}$$

We use the same regressors in both parts of the model. The unconditional variance of our count variable is much larger than the mean. This 'overdispersion' motivates our use of the negative binomial distribution in the second part of our hurdle model.

4. RESULTS

4.1. Comparison of quantiles of carcinogenic release distribution

Using TRI data, we calculate that in the US the annual average chemical release is 1.3 million pounds per county, of which 78,741 pounds is carcinogenic. Figure 3 shows a declining trend in the total toxic releases in the United

Figure 3. Number of (a) releasing facilities and (b) amount of carcinogenic releases by social capital quartiles in the United States, 1998–2019.
Note: Figure (a) uses the annual county-level aggregate number of facilities that report releasing carcinogenic toxic wastes for the period 1998–2019. Figure (b) uses the annual county-level aggregate total carcinogenic toxic wastes (thousands of pounds) for the period 1998–2019.
Sources: Toxic Release Inventory Program (TRI) Basic Data files of the US Environmental Protection Agency (EPA); and https://aese.psu.edu/nercrd/community/social-capital-resources.

States in the past few decades. Yet, a considerable gap remains between the amount of toxic releases and the number of toxic-releasing facilities in counties with high social capital and in counties with low social capital.

In panel A of Table 1, we group counties into four quartiles based on the social capital levels and then calculate the amount of toxic releases during the period 1998–2019 in each quartile of social capital. The difference across quartiles is substantial with the annual average of carcinogenic releases in counties in the last quartile of social capital being nearly five times that in counties in the top quartile of social capital. Panel B of Table 1 shows different quantiles of carcinogenic release distribution for the lowest social capital counties with the highest social capital counties using the Harrell–Davis quantile estimator. Differences between low and high social capital

Table 1. Summary statistics and quantile comparisons of toxic release across low and high social capital counties.

Panel A: Summary Statistics

	All counties		Q1: *Social_Capital* counties		Q2: *Social_Capital* counties		Q3: *Social_Capital* counties		Q4: *Social_Capital* counties	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Carcinogen_Release	78,741.11	529,283.30	124,172	849,133	85,486	449,524	78,498	315,463	26,836	305,717
Carcinogen_Onsite	67,309.30	505,339.90	111,320	819,934	71,555	423,031	62,425	274,107	23,966	302,557
Carcinogen_Offsite	11,431.81	108,854.30	12,852	114,215	13,931	121,588	16,073	136,052	2870	30,899
Facilities_Count	4.004	10.229	4.77	15.50	4.89	9.00	4.97	8.89	1.39	3.05

Panel B: Quantile Comparison

Quantiles	1998		2003		2008		2013		2019	
	Low–high	*p*-value	Low–high	*p*-value	Low–high	*p*-value	Low–high	*p*-value	Low–high	*p*-value
0.10	967.59	0.672	6558.41	0.002	2579.15	0.014	3115.30	0.002	3459.12	0
0.25	8982.88	0.232	15,267.06	0.002	11,350.98	0	6695.77	0	6713.36	0
0.50	43,143.68	0	53,692.98	0	27,890.52	0	23,069.67	0	22,800.73	0
0.75	187,773.82	0.002	125,447.25	0	92,321.19	0	102,152.18	0	102,908.45	0
0.90	989,859.94	0.002	442,260.50	0	256,429.13	0	286,697.10	0.014	426,370.66	0
N (Q1 – counties)	286		283		266		250		234	
N (Q4 – counties)	135		143		168		142		144	

Note: In panel A, counties are grouped into quartiles by the value of the social capital index. In panel B, low–high is the difference between the *q*th quantile of carcinogenic releases in counties in the 1st quartile of social capital and releases and the corresponding quantiles of carcinogenic releases in counties in the 4th quartile of social capital.

Table 2. Social capital and carcinogenic toxic release – panel data estimation.

	Carcinogenic toxic releases			All chemical releases		
	Carcinogen_Total **(1)**	***Carcinogen_Onsite*** **(2)**	***Carcinogen_Offsite*** **(3)**	***All_Chem_Total*** **(4)**	***All_Chem_Onsite*** **(5)**	***All_Chem_Offsite*** **(6)**
Social_Capital	−0.254***	−0.322***	−0.109***	0.018	−0.014	0.007
	(0.023)	(0.024)	(0.029)	(0.018)	(0.019)	(0.026)
Low_Emp	0.157***	0.279***	0.363***	−0.097***	−0.067**	−0.219***
	(0.042)	(0.043)	(0.052)	(0.032)	(0.034)	(0.046)
Emp_Growth	1.015***	1.166***	−0.290	0.369	0.287	1.069***
	(0.320)	(0.328)	(0.398)	(0.245)	(0.257)	(0.355)
Income	1.732***	1.426***	1.287***	1.345***	1.263***	1.306***
	(0.120)	(0.123)	(0.150)	(0.092)	(0.097)	(0.133)
Income_Growth	−0.358*	−0.507**	−0.618**	−0.490***	−0.825***	−0.207
	(0.206)	(0.212)	(0.257)	(0.158)	(0.166)	(0.229)
Economic dependence indicators	Yes	Yes	Yes	Yes	Yes	Yes
Other county typology variables	Yes	Yes	Yes	Yes	Yes	Yes
Race/origin variables	Yes	Yes	Yes	Yes	Yes	Yes
Age variables	Yes	Yes	Yes	Yes	Yes	Yes
Education attainment variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	67,197	67,197	67,197	67,197	67,197	67,197
R^2	0.008	0.009	0.002	0.012	0.010	0.004

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Standard errors are shown in parentheses. All specifications are weighted with county population. County and year fixed effects are included.

counties for all quantiles of the carcinogenic release distributions are statistically significant. More importantly, differences between low and high social capital counties are much larger in the upper part of the distribution. For example, in 2019, the difference between the low and the high social capital counties at the 10th quantile was only 3459 pounds of carcinogenic wastes. However, the corresponding difference for the 90th quantile was 426,370 pounds, and similar results hold for all years. This suggests that inequality between low and high social capital communities is larger in counties that have high carcinogenic releases. This is consistent with the literature that highlights environmental injustice in the United States (Banzhaf et al., 2019; Banzhaf & Walsh, 2013; Chakraborty et al., 2016; Ringquist, 2005; Timmins & Vissing, 2022) and offers evidence of a new potential causal factor of environmental injustice. For brevity, we only report the results for five years here; however, the results are similar in all other years (reported in Appendix C in the supplemental data online).

4.2. Panel data estimation

Table 2 presents the results of the panel data fixed-effect regressions, with models 1–3 using one of the three measures of carcinogenic releases, that is, total, on-site and off-site. All models include the full set of control variables as described in section 3.3 and county and year fixed effects. For brevity, we only report the coefficients of low employment indicator, employment growth, income and income growth. The estimated coefficient of *Social_Capital* is negative and statistically significant in model 1, which suggests that social capital is inversely related to total carcinogenic wastes released in the area. Similarly, the negative and significant coefficients of *Social_Capital* in models 2 and 3 confirm that facilities in counties with higher values of the social capital index release less carcinogenic wastes both on-site and off-site of their production locations. The large difference between the *Social_Capital* coefficients in models 2 and 3 indicates that the impact of social capital in reducing toxic releases is larger for toxic wastes released near a community (on-site releases) than away from a community (off-site releases).

The above analysis does not distinguish between different types of wastes. However, not all wastes released by firms are equally harmful. Indeed, the EPA has invested considerable resources in analysing the health effects of different types of chemicals released by firms. Communities may be more willing to tolerate releases of wastes that are less harmful to health to gain from economic opportunities created by firms. However, such assessment of less versus more harmful wastes requires even more information-sharing and coordination. From this perspective, we expect that the magnitude of the relationship between social capital and toxic wastes is higher for more harmful wastes than

Table 3. Social capital and carcinogenic toxic release – instrument variables (IV) estimation.

Dependent variable	*Social_Capital* (1)	*Carcinogen_Total* (2)	*Carcinogen_Onsite* (3)	*Carcinogen_Offsite* (4)
Crash_Deaths	−0.617***			
	(0.022)			
Social_Capital		−2.245**	−2.721***	−1.201
		(0.893)	(0.914)	(0.810)
Low_Emp	0.001	0.238*	0.288**	0.250*
	(0.009)	(0.142)	(0.146)	(0.129)
Emp_Growth	0.177**	0.710*	0.904**	0.077
	(0.070)	(0.383)	(0.393)	(0.348)
Income	0.099***	1.412***	1.370***	0.627***
	(0.026)	(0.171)	(0.175)	(0.155)
Income_Growth	0.338***	−0.637***	−0.589***	−0.296*
	(0.039)	(0.196)	(0.201)	(0.178)
Economic dependence indicators	Yes	Yes	Yes	Yes
Other county typology variables	Yes	Yes	Yes	Yes
Race/origin variables	Yes	Yes	Yes	Yes
Age variables	Yes	Yes	Yes	Yes
Education attainment variables	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	43,958	43,958	43,958	43,958
R^2	0.099	0.001	0.001	0.0001

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Standard errors are shown in parentheses. All specifications are weighted with county population. County and year fixed effects are included.

for less harmful wastes. We repeat the panel data regressions using total, on-site and off-site releases of all chemicals as the dependent variables (i.e., not just carcinogenic releases, as in models 1–3). Results of this analysis are reported in models 4–6 of Table 2. The coefficients of *Social_Capital* are statistically insignificant, which, in conjunction with results in models 1–3, suggests that the relationship between social capital and toxic wastes is primarily due to carcinogenic releases and not due to all waste releases. This finding is very intuitive in the sense that social capital seems to facilitate community members' action to reduce wastes that is known to be harmful to human health and not for all types of waste releases. Overall, the results support our hypothesis that regions with higher social capital are associated with less carcinogenic wastes released in the neighborhood.

4.3. Instrumental variables (IV) approach

We use the IV approach in which we instrument social capital with the county-level annual number of motor vehicle crash deaths. Model 1 in Table 3 shows that *Crash_Deaths* satisfies the requirement of a valid instrument, that is, it correlates with social capital. Models 2–4 report the second-stage regression results where *Social_Capital* is the fitted value estimated from the first-stage regression. We use all county-specific control variables and county and year fixed-effects in all models. The coefficient of the fitted *Social_Capital* remains negative and significant, similar to the results of the panel data regressions in Table 2. These findings lend some support for possible causal evidence of social capital's effect on carcinogenic releases.

4.4. The importance of polluting industries to the local economy

Banzhaf et al.'s (2019) proposition is that the Coasean bargaining process may lead to circumstances where communities with low incomes and low employment accommodate higher toxic releases in their community. It is plausible that local residents weigh the harmful health effects of toxic releases against the economic opportunities created by releasing firms. Consequently, communities that rely heavily on waste-releasing firms may find it difficult, or economically infeasible, to impose a penalty on such firms. Within this context, we expect that the magnitude of the relationship between social capital and toxic releases decreases with the importance of polluting industries in the community's economy.

In the analysis reported in Table 2, we find that carcinogenic waste releases are higher in counties with persistent poverty and low employment, which is consistent with Banzhaf et al.'s (2019) proposition (also Hackbarth et al., 2011; Tessum et al., 2021). Yet, we also find that counties with higher personal income also have higher toxic releases. This evidence points to the role those economic

Table 4. Social capital and carcinogenic toxic release – share of polluting industries in total county employment and wages.

	Employment share of polluting industries			Wage share of polluting industries		
	< 10% (1)	≥ 10% (2)	≥ 20% (3)	< 10% (4)	≥ 10% (5)	≥ 20% (6)
Social_Capital	−0.362***	−0.175***	−0.078**	−0.382***	−0.188***	−0.150***
	(0.041)	(0.031)	(0.032)	(0.042)	(0.030)	(0.032)
Low_Emp	−0.426***	0.490***	0.414***	−0.492***	0.485***	0.351***
	(0.064)	(0.059)	(0.063)	(0.065)	(0.058)	(0.061)
Emp_Growth	0.918**	1.137**	0.712	0.234	1.397***	−0.196
	(0.449)	(0.471)	(0.534)	(0.457)	(0.460)	(0.511)
Income	3.132***	0.936***	0.716***	2.724***	1.153***	1.131***
	(0.196)	(0.171)	(0.184)	(0.195)	(0.170)	(0.183)
Income_Growth	−1.279***	0.018	0.257	−1.349***	0.005	0.240
	(0.323)	(0.301)	(0.310)	(0.325)	(0.297)	(0.306)
Economic dependence indicators	Yes	Yes	Yes	Yes	Yes	Yes
Other county typology variables	Yes	Yes	Yes	Yes	Yes	Yes
Race/origin variables	Yes	Yes	Yes	Yes	Yes	Yes
Age variables	Yes	Yes	Yes	Yes	Yes	Yes
Education attainment variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37,862	29,335	20,935	35,980	31,217	25,511
R^2	0.005	0.008	0.013	0.004	0.010	0.011

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Standard errors are shown in parentheses. All specifications are weighted with county population. County and year fixed effects are included.

opportunities, such as employment, generated by polluting industries play. To examine further, we divide counties into two subsamples, those where employment in polluting industries accounts for at least 10% of the county's total employment and those where the employment is less than 10%. We repeat our panel data estimations for these two subsamples. We report the results for total carcinogenic releases in models 1 and 2 of Table 4. The coefficients of social capital are still negative and significant, but the magnitudes of the coefficients are substantially smaller in counties where the employment share of polluting industries is greater than 10%. We report the estimated result for the subsample of counties where the employment of polluting industries is greater than 20% (model 3). The sizes of the *Social_Capital* coefficient in models 1–3 indicate that the impact of social capital on total carcinogenic releases in the counties where the employment share of polluting industries is less than 10% is more than double the impact in the counties where the employment share of polluting industries is greater than 10% and more than four times the impact in the counties where the employment share is greater than 20%. This result supports our proposition that the role of social capital in reducing toxic releases is lessened when polluting industries are important in the local economy. The results are similar when we split the counties based on the wage share of polluting industries (models 4–6). All additional results are reported in Tables D1 and D2 in Appendix D in the supplemental data online.

4.5. The hurdle model estimation

To examine if social capital has any impact on the number of releasing facilities present in a county, we use a negative binomial hurdle model in which the first part models the probability density function of a county to have a release-reporting facility and the second part specifies the probability density function of truncated positive counts once the hurdle of zero counts is crossed (i.e., counties have reporting facilities). We use the same regressors in both parts of the model. As the unconditional variance of our count variable is much larger than the mean, that is, 'overdispersion', we use the negative binomial distribution in the second part. The results, reported in Appendix E in the supplemental data online, from the Vuong's test for the appropriateness of the negative binomial distribution and the no-zero hurdle test confirm our choice of distribution (Zelleis et al., 2008).

Table 5 reports the hurdle model results. The significant and negative coefficient of *Social_Capital* in the logistic models (models 1 and 2) implies that the presence of polluting facilities decreases with county-level social capital while results in the negative binomial models (models 3 and 4) show a negative and significant association between

Table 5. Social capital and carcinogenic toxic release – hurdle model analysis.

	Logistic model		Negative binomial model	
	(1)	(2)	(3)	(4)
Social_Capital	−0.379***	−0.308***	−0.400***	−0.210***
	(0.010)	(0.014)	(0.013)	(0.011)
Low_Emp		−0.317***		−0.301***
		(0.032)		(0.019)
Emp_Growth		0.223		−1.030***
		(0.322)		(0.234)
Income		1.421***		1.130***
		(0.086)		(0.059)
Income_Growth		−1.381***		−0.954***
		(0.202)		(0.177)
Constant	−0.717***	−21.466***	−0.508**	−13.255***
	(0.171)	(0.929)	(0.211)	(0.639)
Economic dependence indicators	No	Yes	No	Yes
Other county typology variables	No	Yes	No	Yes
Race/origin variables	No	Yes	No	Yes
Age variables	No	Yes	No	Yes
Education attainment variables	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	67,197	67,197	67,197	67,197
Log-likelihood	−146,761	−129,132	−146,761	−129,132

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Robust clustered (by county) standard errors are shown in parentheses. All specifications are weighted with county population. State and year fixed effects are included.

Table 6. Social capital and carcinogenic toxic release – robustness check without backfilling methods.

	Three years with available social capital index			County averages – four periods		
Dependent variable	***Carcinogen_Total*** **(1)**	***Carcinogen_Onsite*** **(2)**	***Carcinogen_Offsite*** **(3)**	***Carcinogen_Total*** **(4)**	***Carcinogen_Onsite*** **(5)**	***Carcinogen_Offsite*** **(6)**
Social_Capital	−0.206***	−0.228***	−0.149*	−0.158***	−0.274***	0.033
	(0.073)	(0.074)	(0.087)	(0.047)	(0.050)	(0.058)
Low_Emp	0.152	0.303**	0.169	0.064	0.143	0.349***
	(0.119)	(0.121)	(0.142)	(0.083)	(0.088)	(0.103)
Emp_Growth	−0.632	0.145	−3.295***	0.828	1.563	−1.885
	(1.000)	(1.019)	(1.196)	(1.402)	(1.495)	(1.738)
Income	3.197***	3.440***	2.066***	1.761***	1.974***	1.105***
	(0.404)	(0.411)	(0.483)	(0.290)	(0.309)	(0.360)
Income_Growth	−0.488	−1.540**	0.396	−3.268***	−4.092***	−2.716**
	(0.599)	(0.611)	(0.717)	(0.991)	(1.057)	(1.229)
Economic dependence indicators	Yes	Yes	Yes	Yes	Yes	Yes
Other county typology variables	Yes	Yes	Yes	Yes	Yes	Yes
Race/origin variables	Yes	Yes	Yes	Yes	Yes	Yes
Age variables	Yes	Yes	Yes	Yes	Yes	Yes
Education attainment variables	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year/period FE	Yes	Yes	Yes	Yes	Yes	Yes
N	9171	9171	9171	12,214	12,214	12,214
R^2	0.004	0.006	0.002	0.010	0.012	0.002

Note: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.
Standard errors are shown in parentheses. All specifications are weighted with county population. County and year fixed effects are included.

Table 7. Social capital and carcinogenic toxic release – US Joint Economic Committee's (JEC) measurement.

Dependent variable	*Carcinogen_Total* (1)	*Carcinogen_Onsite* (2)	*Carcinogen_Offsite* (3)	*Social_Capital* (4)	*Carcinogen_Total* (5)	*Carcinogen_Onsite* (6)	*Carcinogen_Offsite* (7)
Social_Capital_JEC	−0.717***	−0.654***	−0.439***		−7.635***	−7.002***	−5.731***
	(0.106)	(0.105)	(0.067)		(0.701)	(0.669)	(0.491)
Crash_Deaths				−0.367***			
				(0.025)			
Low_Emp	−0.271	−0.340	−0.207	−0.135***	−1.363***	−1.358***	−1.035***
	(0.220)	(0.217)	(0.138)	(0.033)	(0.358)	(0.342)	(0.251)
Emp_Growth	11.536**	11.648***	0.592	2.775***	33.797***	32.797***	12.262**
	(4.585)	(4.514)	(2.882)	(0.808)	(8.255)	(7.876)	(5.780)
Income	0.895**	0.739*	0.380	0.808***	9.378***	8.714***	5.678***
	(0.427)	(0.420)	(0.268)	(0.082)	(1.024)	(0.977)	(0.717)
Income_Growth	−2.000	−2.397	−1.074	−2.621***	−12.968	−11.969	−14.604**
	(3.716)	(3.658)	(2.336)	(0.800)	(8.334)	(7.952)	(5.835)
Constant	−14.242***	−12.781***	−4.937*	−10.456***	−126.628***	−118.115***	−74.858***
	(4.422)	(4.354)	(2.780)	(0.828)	(11.679)	(11.144)	(8.177)
Economic dependence indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other county typology variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race/origin variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education attainment variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2934	2934	2934	2731	2731	2731	2731
R^2	0.249	0.224	0.206	0.693	−0.604	−0.531	−0.862

Note: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.
Standard errors are shown in parentheses. All specifications are weighted with county population. County and year fixed effects are included.

the count of polluting facilities and social capital. Again, this implies that counties with higher social capital are less likely to have polluting facilities present, and among counties with facilities that report the use/production/release of carcinogens, those with higher social capital have fewer such facilities.

4.6. Robustness checks

We conduct a range of analyses to check if our results are sensitive to alternative measures or sampling methods. First, to check if our results are affected by the backfilling method that we employ due to the limited availability of the Rupasingha et al.'s (2006) social capital datapoints, we do the following: (1) we run the regressions for the years during the period of study for which the values of the social capital index are actually available, that is, 2005, 2009 and 2014; and (2) we construct a panel dataset with the county–period dimension in which we use the value of 1997 social capital index and the annual average for the period 1998–2004 for all other variables for period 1. Similarly, for periods 2–4 we use the values of the 2005, 2009 and 2014 social capital index and for all other variables the annual averages for the periods 2005–08, 2009–13 and 2014–19, respectively. The results reported in Table 6 are essentially similar to the main results, confirming that the backfilling method we employ in the main analysis does not overstate the significance of the estimates.

Second, instead of using economic sectoral dependency indicators from the USDA, we obtain data from the BEA to calculate county-level annual proportions of sector employment. Since data on employment is only available from 2001, we have a reduced sample. The results, reported in Table D3 in Appendix D in the supplemental data online, regarding the association between social capital and toxic releases remain unchanged.

Third, we perform an analysis using the social capital index (*Social_Capital_JEC*) developed by the US Congress JEC. As only one wave of *Social_Capital_JEC* was available, we perform a cross-sectional analysis with the average values for the period 2014–19 for all variables except social capital.[13] We have a sample of 2934 observations for this analysis. Models 1–3 in Table 7 show that the coefficient of *Social_Capital_JEC* is negative and statistically significant. We report the IV estimation results, where the coefficient of *Crash_Deaths* is negative and significant in model 4, and the coefficient of the fitted *Social_Capital_JEC* is negative and statistically significant in models 5–7. The IV estimation results are similar to those using Rupasingha et al.'s (2006) index and confirm that our findings are not sensitive to the selected measures of social capital.

5. CONCLUSIONS

The existing literature on environmental justice has documented that pollution exposure is related to variations in racial and income profiles of local communities (Banzhaf et al., 2019; Ringquist, 2005). Other factors that might also affect environmental justice include the location siting of polluting companies (De Silva et al., 2021; Wolverton, 2009), household willingness to pay for a clean environment (Banzhaf & Walsh, 2013; Hamilton, 1995), negotiation between firms and landowners (Timmins & Vissing, 2022), and government and environmental regulations (Shadbegian & Gray, 2012). We contribute to this growing and policy-relevant literature by highlighting the role of social capital on environmental justice.

In this paper we propose and test hypotheses regarding the relationship between social capital and the amount of carcinogenic releases by firms and the number of releasing firms in US counties. Using county-level data derived from the TRI, we show that high social capital reduces the amount of carcinogenic releases, but not all chemical releases. Further, the magnitude of the negative relationship between social capital and on-site carcinogenic releases is larger than that between social capital and off-site releases. We also show that social capital reduces the probability of the presence (and the count) of toxic-releasing facilities in counties. Yet, we also highlight the economic importance of polluting firms and how it is likely to curb the waste-release reducing impact of social capital. The role of social capital in reducing toxic releases is lessened when polluting industries are important in the local economy.

Our analysis has policy implications related to the EPA's Right-to-Know Act of 1986, which requires facilities to disclose information about the use and releases of hazardous chemicals. The Act is designed to help local communities protect public health, safety and the environment from harmful chemicals. However, communities may differ in terms of their resources to use public information to limit harmful releases and to protect residents from adverse health effects of firms' releases. Our study suggests that the effectiveness of environmental regulations and policy initiatives such as EPCRA is likely to be contingent upon social capital, a key resource that enables community members to effectively exchange information and coordinate their activities to pursue collective actions. Our analysis highlights the possible role of developing social capital to protect public health and environmental sustainability. Our analysis and findings are also relevant to the EPA's 2015 initiative EJScreen,[14] which provides a graphical analysis of issues related to environmental justice in the US. Our analysis is relevant as it highlights the importance of communities' social capital, along with other demographics such as race and gender, in determining the regional distribution of carcinogenic waste releases.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. Computed from the Toxic Release Inventory data of the US Environmental Protection Agency (EPA).
2. The definition is from the Chemical Emergency Preparedness and Prevention Glossary published by the Office of Land and Emergency Management (https://sor.epa.gov/sor_internet/registry/termreg/searchandretrieve/glossariesandkeywordlists/search.do?details=&vocabName=Chemical%20Emrgcy%20Prep%20and%20Prev&filterTerm=carcinogenic&checkedAcronym=false&checkedTerm=false&hasDefinitions=false&filterTerm=carcinogenic&filterMatchCriteria=Contains). For more information on hazardous chemicals, see the Material Safety Data Sheets (MSDS) requirement for determining the applicability of the Emergency Planning and Community Right-to-Know Act (EPCRA) 311/312 of the US EPA (https://www.epa.gov/epcra/definition-hazardous-chemical-and-oshas-msds-requirement-determining-applicability-epcra). For more information on the listing and evaluation of carcinogens, see the Reports on Carcinogens published by the National Toxicology Program (https://ntp.niehs.nih.gov/whatwestudy/assessments/cancer/roc/index.html).
3. For more visualizations, see Appendix A in the supplemental data online.
4. We do not claim that 'social capital' is a universally agreed-upon term to capture the role of community members in resolving social problems. Indeed, the term 'community governance' in Bowles and Gintis (2002) may be more suitable. Also, for recent evidence on the potential 'dark side' of social capital, see Gannon and Roberts (2020).
5. See https://www.nhtsa.gov/risky-driving and https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812115.
6. See https://www.epa.gov/epcra.
7. A similar production is adopted by Beladi et al. (2013).
8. Since we are interested in a firm's emission decision, a cost minimization problem for a given level of output would give us a neat solution. Otherwise, we could endogenize the level of production and solve the profit maximization problem; the solution is more complex but would not affect our conclusions.
9. A more generalized function form with concave utility function from consumption and convex cost of effort function would give the same results.
10. See https://www.epa.gov/toxics-release-inventory-tri-program/tri-compliance-and-enforcement.
11. The correlation between the 2014 *Social_Capital* and *Social_Capital_JEC* is 0.56.
12. See note 4.
13. The visualization of the *Social_Capital_JEC* and toxic releases in Appendix A in the supplemental data online shows a similar pattern to those using Rupasingha et al.'s (2006) social capital index.
14. See https://www.epa.gov/ejscreen.

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