From Regulators to the Public: Does Information Transparency Enhance Environmental Justice Outcomes?

Grace Fan, Trung Nguyen, and Xi Wu*

Abstract

We study the effect of regulatory disclosure following the sequential internal and public launches of an environmental justice (EJ) mapping tool, focusing on the complementarity of regulatory and public scrutiny in improving EJ related outcomes. During 2010 to 2015, the Environmental Protection Agency (EPA) developed and launched EJScreen, an online tool that aggregates dispersed location-specific demographic and environmental data, and visualizes this information in conspicuous color-schemed mapping tools for identifying locations where vulnerable communities disproportionately bear the brunt of pollution, or areas with high EJ conerns. Using a difference-in-differences estimation approach, we find an increase in regulatory monitoring and NGO activist campaigns targeting areas with high EJ concerns around the internal and public launches of EJScreen, respectively. In response, there is a reduction in regulated toxic chemical releases in high EJ concern areas following the internal use of EJScreen, while a reduction in unregulated greenhouse gas (GHG) emission only after the tool became publicly available. Moreover, the reduction in GHG is greater in areas with larger public and media attention. We complement our results using a stacked difference-in-differences approach and a regression discontinuity design based on a similar tool in California, and find consistent results. The findings provide policy implications for regulatory disclosure to enhance the complementarity of regulators and the public in achieving policy outcomes.

Keywords: Transparency, interactive mapping tool, environmental justice, firm pollution, regulatory scrutiny, stakeholder monitoring

*We thank John Barrios, Matthias Breuer, Ed deHann, Omri Even-Tov, Sehwa Kim, Yun Lou, Thomas Rauter, and workshop participants at the 2025 Bretton Woods Accounting and Finance Ski Conference, 2025 FARS Midyear meeting, 2024 Kellogg Accounting Conference, 2024 ESMT Junior Accounting Conference, 2024 INSEAD Accounting Symposium, 2024 SMU-Xiamen Joint Conference, 2024 DEI Forum at University of Washington, and UC Berkeley for helpful discussions. Muen Zhang, Minghao Chen, and Jeffrey Blossom provided excellent research assistance. Grace Fan is with Singapore Management University. E-mail: gracefan@smu.edu.sg. Trung Nguyen is with the Federal Reserve Bank of Richmond. E-mail: trung.nguyen@rich.frb.org. Xi Wu (corresponding author) is with the Haas School of Business, University of California Berkeley. E-mail: xiwu@berkeley.edu. The views presented in this paper are those of the authors only, and do not represent those of the Federal Reserve Bank of Richmond or the Federal Reserve System.

1 Introduction

Recent years have witnessed growing emphasis on regulatory disclosure as a critical mechanism for improving transparency, accountability, and effectiveness in government regulation.[1] A key objective of regulatory disclosure is to promote complementarity between regulators and corporate stakeholders in driving corporate behavior and outcomes. However, there remains a limited understanding of whether and how regulatory disclosures affect these groups, particularly regarding their complementary interactions. In this paper, we study a specific regulatory disclosure – the disclosure of environmental justice (EJ) information by the Environmental Protection Agency (EPA) – and analyze its effects on both regulators and corporate stakeholders, with a particular focus on their complementary roles.

Vulnerable communities bear a disproportionate burden of environmental damage caused by corporate pollution (e.g., Jbaily et al. (2022); Currie et al. (2023)). Environmental inequality and the roles of government entities and corporations in mitigating such disparities are subjects of intense debate and media attention. The call for "environmental justice," or the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies, has led to several environmental justice initiatives by the government. One important initiative is the launch of the Environmental Justice Screening and Mapping Tool (EJScreen) by the EPA, which is an online mapping tool that disseminate information related to EJ. Using the unique features of the setting, we examine whether the disclosure of EJ information lead to changes in regulatory monitoring efforts and public attention toward areas of high EJ concerns and the subsequent environmental quality in disadvantaged communities.

EJScreen is developed as a EPA's tool to map and screen for areas with environmental

[1] Prominent examples of this trend include the 2013 executive order issued by the Obama administration, mandating open and machine-readable formats as the standard for disseminating government information, and the public disclosure of Securities and Exchange Commission (SEC) comment letters, which increased regulatory transparency in financial markets.

justice (EJ) concerns, or locations where vulnerable communities disproportionately bear the brunt of pollution. It offers a standardized platform that integrates environmental (e.g., air toxics cancer risk indicators) and socio-economic (e.g., people of color and low income) indicators nationwide and presents the discrepancy in environmental exposure of vulnerable communities across the United States. Although EJScreen has been developed by the EPA since 2010, it was only internally used by the EPA for their regulatory purposes since 2012. In June 2015, the first public version of EJScreen was launched. This version featured twelve distinct EJ Indexes, each addressing a different type of pollution. Even though the environmental and socio-economic inputs used to calculate EJScreen indices were publicly-available data, they were dispersed and difficult to compile. EJScreen consolidates these data and presents them on a map with color-schemes that makes it easier to identify areas of high EJ concerns (e.g., areas with indices above the 80th percentile). The specific features of EJScreen, including its initial exclusive release to regulators followed by public access, provide a valuable context for studying the impact of both the internal use and external disclosure of EJ information. Moreover, the EJScreen also offers us an opportunity to study the role of information visualization and display aided by an advancement in information technology, and provides insights into how it is not only the content of information that is disclosed, but the way information is visually displayed and highlighted, that can impact the processing of and response to such information.

Both environmental regulators and the public may potentially be affected by the launch of EJScreen. Starting from the internal usage of EJScreen in 2012, environmental regulators may incorporate EJ information and increase their scrutiny and monitoring efforts against firms that pollute in areas with high EJ concerns, while public scrutiny could only intensify after the public launch of EJScreen in 2015. If EJScreen has the intended effects to influence the regulator's and the public's behavior and enhance environmental justice, we would expect firms to decrease their pollution in the areas that are identified to have EJ concerns where vulnerable communities disproportionately bear the brunt of pollution. However, it is unclear

whether EJScreen can have the effect. First, the information used to create the EJ scores was already publicly available before the launch of EJScreen. Thus, such a policy tool might not add incremental benefits to the internal and external users who already actively searched for and utilized the underlying information before the launches. Furthermore, even if EJScreen can attract more regulatory and public attention to areas with EJ concern, it may still be unclear whether such attention would lead to actions from regulators or the public that eventually improve environmental outcomes in these locations. Thus, the effectiveness of such policy tool is unclear and is an empirical question.

To explore the impact of EJScreen, we first show that the launch of EJScreen affects the intensity of scrutiny on firms from both internal environmental regulators, i.e., EJScreen staff, and external stakeholders, i.e., individuals and non profit organizations (NGOs), in high EJ-concern areas. We indeed find that the EPA is more likely to inspect facilities located in areas with greater EJ concerns after the years 2012 and 2015, which correspond to when the EPA started using EJScreen internally and when EJScreen first became publicly available, respectively. This finding is consistent with the view that regulators target areas with high EJ concerns when such information is easier to obtain. In addition, we show that following the public launch of EJScreen, there are more people searching for the keyword "environmental justice" in states with greater EJ concerns, suggesting increased public attention. Furthermore, there are more NGO activist campaigns targeting facilities' parent companies in areas with higher EJ concerns, suggesting that the public launch of EJScreen induces increased NGO scrutiny. The evidence suggests that the launch of EJScreen has an impact on both internal (environmental regulators) and external (NGOs and the public) stakeholders, and guide their attention and efforts to areas identified by the EJScreen to have greater EJ concerns.

Next, we examine the effectiveness of EJScreen in improving environmental outcomes in high EJ-concern areas. We expect that the effectiveness of regulatory and public scrutiny may vary depending on the type of pollutants. For instance, regarding toxic chemicals,

the Toxic Substances Control Act (TSCA), enacted in 1976, gives the EPA the authority to regulate toxic chemicals that are harmful to human health. Following the TSCA, the EPA has developed a comprehensive regulatory system to monitor and regulate facilities' toxic chemical releases. Given the early focus on toxic chemicals, the immediate and direct threats that they pose to human health and as an extension, environmental justice, and the more stringent regulation and detailed reporting requirements, chemical releases may be most sensitive to regulatory scrutiny. On the other hand, greenhouse gas (GHG) was historically not subject to direct federal environmental regulation; only later when concerns about climate change became more prominent and the Clean Air Act (CAA) was enacted did the EPA start to regulate GHG. Relative to toxic chemicals, GHG are less stringently regulated even though it receives significant media and public attention due to rising concerns about climate change. Therefore, the public launch of EJScreen may lead to significant greater scrutiny of GHG emission and ensuing firm responses. Consequently, we perform difference-in-differences analyses by comparing facilities' different pollution emissions in areas identified by EJScreen as having more vulnerable communities to emission of other areas, focusing on the periods around both the internal usage of EJScreen in 2012 and the public disclosure in 2015.

Our results suggest that, following the internal (public) launch of EJScreen in 2012 (2015), facilities located in areas with a larger percentage of EJ indexes that are ranked among the top 80th percentiles, the threshold above which areas on the EJScreen mapping tool are colored and displayed more conspicuously to users, significantly reduce their toxic chemical releases (greenhouse gas emissions). The differential effects of toxic releases occur only after the internal launch of EJScreen in 2012, whereas the effects of greenhouse gas emission reduction only appear after the public launch of EJScreen in 2015. Further analyses reveal that the effect in pollution reduction is driven by the EJ indexes rather than their components of environmental indexes or demographic indexes alone.

In cross-sectional results, we show that public attention and media attention is important

in driving the reduction of GHG in areas with high EJ concerns, subsequent to the public launch of EJScreen. Specifically, we show that the documented effect of greenhouse gas emission reduction is more pronounced for facilities located in areas with greater public attention to environmental issues and higher local media circulation.

So far, our results suggest that the launch of EJScreen leads to increases in regulatory and public attention, and subsequent improved environmental outcomes in areas with more concerns about environmental justice. However, we are aware that other concurrent changes might also contribute to enhanced environmental outcomes. For example, other concurrent events such as the passage of the Paris Agreement in 2015 might contribute to the reduction in pollution for facilities in the United States. We believe that our research design can help address these concerns. First, we observe that the pollution reduction only occurs in places with high EJ concerns highlighted by the EJScreen, but not areas with just high environmental concerns. Thus, any concurrent changes that only affect firms' incentives to improve the environment but not their incentives to specifically improve the disproportionately poor environmental conditions in areas with more disadvantaged groups would not fully explain our results. Second, we explore the internal and external launches of EJScreen, and we observe predictable responses of regulatory and public attention towards areas with more EJ concerns. Last but not least, our measure captures the features of the coloring scheme of the EJScreen map, which directly links the observed outcomes to the usage of EJScreen.

To further enhance our inference of the effect of transparency on EJ outcome, we complement our existing analyses by examining the effectiveness of a similar environmental screening tool developed by the California state environmental regulators. The California Communities Environmental Health Screening Tool (CalEnviroScreen) is developed by the California Environmental Protection Agency. The first version of CalEnviroScreen was launched in 2013, which was before both the Paris Agreement and the public launch of EJScreen, and was the only state-level tool that was available before 2020. CalEnviroScreen incorporates indicators including air and water quality, pesticides, hazardous waste, population charac-

teristics, and public health outcomes. While the federal EJScreen has a wider geographic coverage and is hence more generalizable, CalEnviroScreen produces and displays only one simple index for California in each of its released version, providing a setting in which we can conduct more robust research designs including both stacked difference-in-differences design and a regression discontinuity design (RDD). An important feature of CalEnviroScreen enables us to implement RDD to explore the effect of its public launch on EJ outcomes.[2] Unlike EJScreen, CalEnviroScreen provides one composite score (EJScore) that identifies areas with high EJ concerns relating to all pollutants, and one corresponding map with color schemes highlighting areas with EJ concerns above a certain threshold.

We first implement a similar identification strategy as in our main test and continue to find that facility pollution become significantly lower in areas with higher EJ scores after the launch of CalEnviroScreen. Next, we implement a stacked difference-in-differences analysis and identify facilities that are located in areas newly identified as areas with high EJ concerns following each updated version as the treated facilities, and we only use the not-yet treated facilities as the control. We continue to find that greenhouse gas emissions and toxic substance releases in high EJ-concern areas significantly decline in the two and three years following the treatment years. Lastly, we implement an RDD analysis and explore the changes in greenhouse gas emission reduction around the 80th percentile threshold of EJ Score, above which areas will be colored brightly on the CalEnviroScreen map. We find a sharp discontinuity in the level of reduction in GHG emissions above the threshold, suggesting that the improved environmental outcome is associated with the coloring scheme of the mapping tool, cleanly identifying the effect of the CalEnviroScreen tool.

Our paper makes several contributions to the literature. First, we contribute to the accounting literature on the real impact of information transparency. Most of the existing

[2]While the CalEnviroScreen produces only one EJScore and enables us to conduct an RDD design, the federal EJScreen makes an RDD research design impossible as it produces multiple different EJIndexes, each with different corresponding areas for which the EJIndex is above the color-scheme threshold. This makes it possible to calculate an average EJScore based on multiple indexes, but not possible to identify consistent treatment and control areas for all the indexes for an RDD research design.

studies explore how the improvement of transparency of financial-related or security market-related information affect firms and investors (e.g., Blankespoor (2019); Blankespoor et al. (2019); Blankespoor et al. (2020); Cuny et al. (2021)). Recent literature examines how information processing consideration of non-financial information affects stakeholders' actions, such as public procurement (Duguay et al. (2023)), state regulators' enforcement (Belousov et al. (2025); Even-Tov et al. (2024)), and mine safety (Christensen et al. (2017)). Our paper extends this stream of literature in two important ways. First, we examine the implication of improved transparency of EJ-related information on environmental regulators and other stakeholders including NGOs and the public, and assessing the environmental outcomes as a response. Second, we examine how online visualization technologies help disseminate information. Previous research focuses on the availability of online information through the form of websites, such as the launch of open government procurement data (Duguay et al. (2023)) and municipal bond data (Cuny (2018)). Our research stands out from the existing research by highlighting the value of information visualization technology and the role of how information is presented in influencing decisions.

Second, we speak to the literature on the effect of regulator disclosure and scrutiny. Prior research examines the effect of regulator disclosure in municipal government (Cuny et al. (2024)), government procurement (Duguay et al. (2023)), and the Securities and Exchange Commission (Guo and Tian (2024)). Even-Tov et al. (2025) suggest that government procurement promotes corporate climate responsibility by incentivizing firms to undertake climate mitigation actions. Fan et al. (2023) find that regulator scrutiny has a real impact on facilities and toxic emission, and can affect firm disclosure choices. We contribute to this stream of research by documenting how regulator disclosure of EJ information affects government and public scrutiny, and firm environmental strategy.

Third, we contribute to the stream of research on social justice and corporate actions. Several recent papers in accounting have looked at the relationship between minority protest against injustice and corporate behavior. For example, Chen et al. (2022) and Balakrish-

nan et al. (2023) examine the characteristics that make firms express their support for the Black Lives Matter movement. Billings et al. (2022) examine investor responses to #MeToo movement. We document a setting of environmental justice where information on minorities' disproportionate suffering may raise awareness among corporate stakeholders and lead to real actions that affect corporations.

Lastly, we contribute to the recent debate on the effectiveness and cost of regulation. We show that less costly forms of regulation such as providing more transparent information, including aggregating previously publicly available information, to both regulators and the public can help increase scrutiny of firm emission in vulnerable communities. We also show that scrutiny by the public, especially by interest groups, can complement government regulation, leading to reduction in firm emission and better environmental quality in areas where vulnerable communities live.

2 Institutional Background and Hypotheses Development

2.1 Institutional Background

The environmental justice movement emerged during the 1980s, catalyzed by a report that unveiled stark disparities in the burden of environmental degradation and pollution experienced by minority and low-income communities. A notable incident in 1982, involving the dumping of thousands of tons of PCB-contaminated soil in Warren County, North Carolina, within an African American community, sparked extensive research into the health impacts on African American communities. This ultimately led to the publication of the influential study "Toxic Waste and Race" in 1987. Over the subsequent decades, various movements have tirelessly advocated for governmental action to ensure that the brunt of environmental damage is not disproportionately borne by vulnerable communities.

To address these pressing EJ challenges, the United States federal government took a significant step by issuing Executive Order 12898 in 1994. This order established the En-

vironmental Justice Office within the Environmental Protection Agency (EPA) and various other federal agencies. To implement the task, the EPA had been developing and using certain earlier versions of EJ screening tools internally to help them identify areas that they need to pay more attention to. However, such tools were not user-friendly. For example, to use EJView, the latest tool available before the launch of EJScreen, the regulators would have to manually overlay maps with demographic information on top of another map with environmental information to identify communities with EJ concerns, which proved to be time consuming and ineffective. Also, such tools were generally not available to the public (The EPA (2015)).

With the advancement of computer mapping technology, the EPA decided to promote a single, nationally consistent tool that can be used by different parties, including the EPA, its governmental partners, and the public, to understand environmental and demographic characteristics of locations throughout the United States. The EPA first started to develop EJScreen in 2010 and started using an early version of it in 2012. The first version of EJScreen was launched in 2015. Compared to the previous tools, EJScreen is the first tool that allow public access with easy web-based interface and higher resolution maps covering the entire nation. It provides a wide range of demographic information combined with environmental indicators. Moreover, EJScreen also provides standard reports that bring together environmental and demographic data in the form of EJ indexes. These are summarized as percentiles and presented on the map to help users to clearly identify locations with higher EJ concerns. For example, areas with a larger exposure relating to a particular pollutant (e.g., pm2.5) and higher proportion of vulnerable population, i.e., people with color and low income, will have higher EJ indexes, and will be colored and easily identifiable on the map. Thus, EJScreen is the first publicly-available and user-friendly mapping tools that provide users with information on environmental justice.

The Biden administration launched the Justice40 initiative to improve environmental justice. This initiative's primary goal is to allocate 40 percent of the overall benefits derived

from federal investments in climate action, clean energy, affordable and sustainable housing, clean water, and related areas to disadvantaged communities that are marginalized, underserved, and excessively burdened by pollution. As part of this initiative, the government introduced the inaugural version of the Climate and Economic Justice Screening Tool (CEJST) in 2021. This tool serves the purpose of identifying communities that bear an undue burden of pollution and provide easy access of such information to different stakeholders. The overarching hope is that the production and disclosure of such information will lead to concrete actions, both on the part of government regulatory agencies (e.g., in terms of permit approvals, pollution inspections, and more) and within disadvantaged communities through self-advocacy, without enacting new regulations. Additionally, media, investors, and environmental non-profit organizations are expected to engage in advocacy, amplifying the overall impact. Despite the considerable investment and optimism surrounding the EJScreen, the effectiveness of such tools remains a subject of uncertainty. In addition, concerns about the cost and effectiveness of environmental justice related programs has led to doubts and curtail of many of these programs by the current administration, making this an opportune time to study less costly regulatory approaches such as improved information transparency and display with the aid of advanced technology like the EJScreen, and their effectiveness in enhancing both regulatory and public scrutiny, and improving environmental justice.

2.2 Hypothesis Development

Given the debate around the effectiveness of both the federal and state environmental screening tools, we first test whether the internal usage and public launch of EJScreen mapping tool are effective in reducing firm pollution in high EJ concern areas. It is ex-ante unclear whether firms would react to either regulatory or public scrutiny following the launches of environmental screens.

On the one hand, accessible information on the disproportionate environmental burden of minority communities significantly reduces the information processing costs for interested

parties to access and internalize EJ data and identify areas and facilities that require special attention (Blankespoor et al. (2020). First, the introduction of the EJScreen tool enhances awareness of EJ issues. Second, EJScreen significantly reduces the acquisition cost of EJ related information. Previously, although the demographic and environmental information of a certain location is available through various sources, it is costly to acquire and aggregate such information. With EJScreen, users can easily obtain EJ indicators of a certain location with just a few clicks. Lastly, EJScreen also reduces the integration costs for users to understand the implications of EJ issues. In addition, users can obtain a detailed community report that visualizes the various EJ indicators and provides more details about a given community's characteristics. Figure 3 provides an example of such a report. Furthermore, users can now identify a particular facility that are located in a high EJ concern area from the map as shown in Figure 2 and obtain important information such as its parent company. As a result, EJScreen significantly reduces the effort for a user, either a regulatory agent or an individual who cares about the environment, to evaluate a particular facility or firm's environmental impact on the surrounding community. This tool thus may help both internal users (the EPA regulators and its government partners) and external users such as environmental NGOs, institutional investors and other watchdogs such as the local media, to increase environmental monitoring of facilities and firms that are identified as posting threats to environmental justice, thus more effectively pressuring them to improve their environmental outcomes.

On the other hand, information aggregated in the environmental indices have already been available without the introduction of EJScreen. All the data used in constructing the indexes are from public sources, and according to the EPA, "EJScreen simply provides a way to display this information and includes a method for combining environmental and demographic indicators into EJ indexes."[3] Thus, it is unclear whether EJScreen can add incremental value by aggregating and displaying publicly available information in a different

[3]https://www.epa.gov/EJScreen/what-EJScreen

way. We test this empirical question and formally state the below hypothesis in its null form:

H1: After the launch of EJScreen, there is no significant changes in regulatory monitoring efforts and public attention in areas with higher environmental justice concerns (i.e., where there are more vulnerable communities disproportionately exposed to environmental pollution).

If we find results supporting the rejection of H1, we further hypothesize that firms will respond to the enhanced regulatory and public scrutiny by reducing their pollution emissions to avoid costly regulatory penalties and reputation damages. However, as the EJ indexes are a combination of both demographic and environmental indicators, firms might not have direct control over the value of the indexes even if they reduce pollution. Thus, firms might not have incentives to make changes to their operations in response to the disclosure of such information and the pressure that follows thereafter. Therefore, whether we can observe changes in pollution emissions following the introduction EJScreen is an empirical question.

Furthermore, if firms do respond to the enhanced scrutiny following EJScreen's disclosure, we expect that the internal and public launch of EJScreen, which benefits internal and external users, will have different impacts on different types of pollutants. Since the EPA has established a comprehensive regulatory system to monitor and regulate facilities' toxic chemical releases, we expect that toxic releases will be particularly sensitive to regulatory scrutiny such as onsite inspections and enforcement actions following the internal launch of EJScreen in 2012. Conversely, greenhouse gases (GHGs) , which are also significant pollutants that the EPA aims to control as part of its EJ efforts, have not historically been subject to direct federal regulations and are more challenging to monitor directly. Thus, we do not expect that an increase in regulatory monitoring will lead to changes in firms' GHG emissions. On the contrary, firms' GHG emissions have garnered significant attention from the public, including media and investors, and is the central environmental information required to be disclosed in firms' CSR (Corporate Social Responsibility) reports. Thus, we anticipate that firms will be more responsive to public scrutiny following the public launch

of EJScreen in 2015. Thus, we make the following two hypotheses in their null forms:

H2a: After the launch of EJScreen, there is no significant changes in firms' pollution emissions in areas with higher environmental justice concerns.

H2b: The reduction of toxic chemical releases (GHG emissions) in areas with higher environmental justice concerns, if any, is not significantly more sensitive to regulatory (public) scrutiny following the internal (public) launch of EJScreen.

3 Empirical Design and Data

3.1 Environmental Justice Indexes

We collect the federal environmental indexes from the EPA website, called the EJScreen, which covers the whole US. The EJ indexes are available at each Census block level and are updated annually since its public launch in 2015. Each EJ index is a combination of the Demographic Index and Environmental Indicator. The Demographic Index capture the concentration of low-income population and people of color within a certain Census block. The Demographic Index is calculated as the following:

$$\begin{aligned} EJIndex = {} & Environmental\ Indicator \\ & \times (Demographic\ Index\ for\ Block\ Group - Demographic\ Index\ for\ US) \\ & \times (Population\ count\ for\ Block\ Group) \end{aligned}$$

$$Demographic\ Index = (Low\ Income\ percentage + People\ of\ Color\ percentage)/2 \quad (1)$$

Importantly, all the components that enter the EJIndex are publicly available prior to the launch of the EJScreen to the public. When the first version of EJScreen was launched, 12 environmental indicators were included but only 8 were shown on the mapping tool back

then due to data availability. [4] Later, some more environmental indicators were added (e.g., proximity to underground storage tanks) while some indicators were discontinued (e.g., neurological hazard index). By 2020, there are 13 environmental indicators: the particulate matter 2.5, ozone, diesel particulate matter, air toxics cancer risk, toxic releases to air, traffic proximity, lead paint, RMP facility proximity, superfund proximity, underground storage tanks, and wastewater discharge. Appendix 6 provides a more detailed description of the environmental indicators included in different years and their definitions. Next, the environmental indicator is combined with the Demographic Index to arrive at the final EJ Index for each environmental concern. For example, the air toxics cancer risk index combines the air toxics cancer risk in each Census block with the concentration of low-income population and people of color in a given Census block. The EPA does not provide an overall composite score that contains all information from all the indexes for each geographic location. The reason given is that the EPA believes there is no appropriate weighing scheme that can aggregate the impact of different environmental issues (EPA, 2015).

To present the EJ indexes on the mapping tool, the percentile rankings of each environmental indicator is calculated. In the first version of EJScreen, the ranking of a particular Census Block is benchmarked against the whole United States. In later versions, EJScreen provides the option for users to explore the percentile rankings compared to the whole US or compared to other areas within the same state. Figure 1 presents a snapshot of the map interface. From the map, a user can select the environmental indicator he or she is interested in, and the map will show the areas that have high EJ concerns. For a given environmental indicator, locations whose indexes are at least at the 80th percentile but less than the 90th percentile are shown in yellow on EJScreen maps, while those between the 90th percentile and 95th percentile are colored orange on the maps, and those at the 95th percentile or above are shown in red on maps and reports.

[4] The air toxics cancer risk, neurological hazard index, respiratory hazard index, and diesel PM index, were unavailable in 2015 due to pending data updates from NATA.

3.2 Empirical Design

3.2.1 Differences-in-differences Analyses with Continuous Treatment Variables

We use a difference-in-differences estimation approach. More specifically, we compare the changes in greenhouse gas emitted by facilities located in each Census Block with high versus low environmental indexes (e.g., more minorities exposed to greater pollution), through the following regression:

$$(Attention_{i,t,}\ or\ Emission_{i,t,r}) = \beta_1 EJIndexAbove80_{t,r} \times POST2012 + \beta_2 EJIndexAbove80_{t,r} \times POST2015 + X_{i,t,r} + FEs + e_{i,t,r}$$

$$(Attention_{i,t,} or Emission_{i,t,r}) = \beta_1 EJIndexAbove80_{t,r} \times YearIndicator + X_{i,t,r} + FEs + e_{i,t,r} \quad (2)$$

where $Attention_{i,t,r}$ is either the regulatory attention, proxied by the likelihood of inspecting a given facility ($Inspection_{i,t,r}$), or public attention, proxied by the Google Search Volumes for the keyword "environmental justice" using Google in a state ($lnGoogleSVI_{i,t,r}$), and public scrutiny, proxied by the likelihood of NGO activist campaigns against a facility's parent company ($lnNGOActivites_{i,t,r}$). $Emission_{i,t,r}$is the amount of toxic chemicals (or green house gas) emitted by facility i in year t in area r that has a given EJ index. $EJIndexAbove80_{t,r}$ is the percentage of the EJ indexes that are ranked above the 80th percentile following the first launch of EJScreen in 2015, when the underlying data used to construct all the EJ Indexes were downloadable. For example, if a facility has 4 out of 8 EJ indicators that are ranked above the 80th percentile, then $EJIndexAbove80_{t,r}$ is equal to 0.5. Importantly, we applied the 2015 values of EJ Indexes to periods before 2015 because according to the technical note of EJScreen, the underlying data used to construct the 2015 EJ Indexes were actually based on demographic data from the 2008-2012 ACS 5-year summary file from the 2010 Census Survey and environmental indicators values for the years

2008 to 2012.[5] Thus, we believe that users of EJScreen in 2012 following its internal launch would see the same values of EJ Indexes as the 2015 version. For the analysis of the public launch of the EJScreen, we apply the same EJIndex in 2015 for later years as the index is sticky and we are interested in observing the effect around the public launch of the EJScreen in 2015 when firms are less likely to manipulate rather than the dynamic effect after the launch when firms are more likely to strategic respond to expectations about changes in the index.

The rationale for using the measure $EJIndexAbove80_{t,r}$ is that on the EJScreen mapping tool, only areas with EJ Index that are ranked above the 80th are colored, which are more visible and will likely attract greater user attention. In addition, the EJScreen mapping tool provides a threshold widget that allow users to apply different percentile filters and select specific environmental indicators to be included, as shown in bottom graph in Figure 1. The default option provided is to filter based on the 80th percentile. We also test the robustness of our results using the percentile of environmental indexes that are above the 90th and 95th percentile as the cutoff point. $POST2012$ ($POST2015$) is an indicator variable that equals one if the year is after the year 2012 (2015), which is the internal (public) launch of EJScreen, and zero otherwise. $X_{i,t,r}$ is a vector of control variables for facility i at time t in area r. In all specifications, we include facility and time (year) fixed effects, and the standard errors are clustered at the Census Block-year level to capture the common time trend at the local area.

Our coefficients of interest, β_1 and β_2, capture the differential effects of regulatory and public attention, as well as pollution emission, for facilities located in each Census Block with high versus low environmental indexes after the internal and public launch of EJScreen.

[5] See EJSCREEN Technical Documentation, 2015. https://gaftp.epa.gov/EJSCREEN/2015/EJSCREEN_Technical_Docur
Four of the environmental indicators, namely a facility's proximity to 1) RMP sites, 2) TSDFs, 3) NPL sites, and 4) major direct water dischargers, were based on data retried in 2013. However, since the facility's location wouldn't change from 2012 to 2013, the 2012 values would be the same as the 2013 values.

3.3 Data

3.3.1 Regulator Monitoring Data

We obtain the list of all facilities and their inspection and enforcement histories from the EPA's Enforcement and Compliance History Online (ECHO) database. The ECHO provides integrated compliance and enforcement data for the regulated facilities and includes important information relating to the EPA's regulatory activities, including the identities of the facilities inspected or enforced, the type of regulatory actions, and the duration. We start with all the facilities with identifiers in the ECHO database. These are facilities that are subject to the EPA's regulations under different statutes, such as the Clean Air Act, the Clean Water Act, the National Pollutant Discharge Elimination System, and the Resource Conservation and Recovery Act. We also identify the years of the first appearance and the last appearances of each facility in the databases. Because these facilities need to comply with EPA regulations, they are subject to inspections and enforcement by regional offices.

3.3.2 Public Scrutiny Data

We obtain the Google Search Volume Index (i.e., SVI) with the keyword "environmental justice" from Google Trends. For each year, we separately download the monthly cross-section values of state-level SVI. Moreover, we collect the local newspaper outlets data from Editor and Publisher, where we obtain the data on the title of the newspaper, the city, county, state, zip code, and the years during which a given newspaper are circulated.

For the second measure of public scrutiny, we obtain NGO activities from SIGWATCH, a consultant and data provider on activism who compiles a dataset of NGO activist campaigns around the world. The data provides information on the topics of campaigns and the companies that the campaigns targeted between 2011 to 2023. We focus on environmental-related and equality-related campaigns targeting firms in the United States, and then we match the targeted companies to the parent companies of the facilities reporting to the EPA TRI

and GHG program by their names. In total, 523 parent companies reporting to the EPA TRI program and 146 parent companies reporting to the GHG program in our sample were targeted by NGO activist campaigns during the sample period 2011 to 2018.

3.3.3 Pollution Data

We obtain firms' toxic chemical release data from the Toxic Release Inventory (TRI) program. The TRI data contains information on the release of certain toxic chemicals that may pose potential risks to human health and the environment. A release of a chemical means that it is emitted into the air or water or placed in some type of land disposal. In general, chemicals covered by the TRI database could cause cancer or other chronic human health effects or have significant adverse acute human health and environmental effects. As of 2022, the TRI toxic chemical list contains 787 individually listed chemicals and 33 chemical categories. Industrial facilities are required to report annually to TRI if they are in a covered industry sector (e.g., manufacturing, mining, electric power generation, etc.), employ ten or more full-time equivalent employees, and manufacture, process, or otherwise use a TRI-listed chemical in quantities above threshold levels (Fan et al. (2023)).

We obtain facility-level Greenhouse Gas data from the EPA Facility-level Information on Greenhouse Gas Tool (FLIGHT) developed under the Greenhouse Gas Reporting Program (GHGRP). The data contains the greenhouse gas emission data reported by 8,000 facilities that are subject to mandatory reporting of their greenhouse gas emission starting from 2010. The data includes reporting from both direct emitters and upstream suppliers. Together, they cover 85-90 percent of the total amount of GHG emissions in the U.S.[6] The EPA is required to verify the creditability of the reported data.

[6]See https://www.epa.gov/ghgreporting/learn-about-greenhouse-gas-reporting-program-ghgrp.

3.4 Sample

To construct the facility-level EJ indexes, we first obtain the census block-level EJ data from the EJScreen website. Each census block is identified by a 12-digit FIPS code. In total, there is EJ information for 306,351 unique Census Blocks. Next, we obtain the facility location information from the EPA Facility Report Service (FRS), which provides detailed geographic information for each facility overseen by the EPA. We then match the EJ indexes at the census block to the facility.

We construct different samples for our empirical analysis. For the tests of regulatory monitoring efforts around the adoptions of EJScreen, we construct a panel of all the facilities that the EPA has inspected at one point between 2010 to 2018, which is selected based on the availability of the GHG emissions data that is only available since 2010, and three years following the public launch of EJScreen in 2015. We match each facility with the EJ information based on the Census Block a facility is located in. The inspection sample contains 504,445 facility-year level observations. For the test of public attention using Google Search Volume Index of environmental justice, we construct a state-year sample between 2010 to 2018, and match each state with the mean of all the Census Block-level EJ information within the state in a given year. For the tests of NGO scrutiny, we use the panel data of facilities reporting to the EPA under both the TRI and GHG programs at the facility and year level between the years 2010 and 2018, because we believe that the public will target all facilities that report pollution information to the EPA. For the pollution emissions tests, we separately examine the TRI and GHG sample. The TRI (GHG) sample contains 194,908 (48,687) facility-year observations from 29,611 (8,445) unique facilities during the sample period.

Table 1 Panel A presents the summary statistics for the variable used in the federal EJScreen analyses. The mean of the variable $EJIndexAbove80$, the percentage of EJ indices that are ranked above the 80th percentile, is 0.288 in the TRI sample and 0.180 in the GHG sample, which roughly translates to around two EJ indexes that are above the 80th percentile

compared to the U.S. average. A county on average has around 46 local media outlets.

4 Main Empirical Results

4.1 Regulatory Scrutiny Following the Launch of EJScreen in High EJ Concern Places

After documenting the main effects of EJScreen on pollution reduction, we next explore the potential channels through which the EPA's release of EJ information affects firm pollution.

First, we examine whether the EPA's monitoring efforts changes around the internal launch of the EJScreen tool. The EPA states that one of the reasons for developing the tool is to provide more information for the EPA itself, as well as partner government organizations, to identify areas with EJ concerns.[7] Therefore, we expect that, following the internal launch of the mapping tool, the EPA will increase its monitoring efforts in areas with greater EJ concerns.

In Table 2, we find that after 2012, the EPA is more likely to inspect facilities located in areas with higher EJ concerns, i.e., areas with a higher percentage of its EJ indexes ranked above the 80th percentile. In column (2), we find that such an effect starts to show starting from 2012, which is the year when the EPA started to develop the tools. This suggests that the EPA changes their monitoring efforts following their own access to information related to environmental justice in the internal launch of the EJScreen. Interestingly, we also find a significant increase in 2016 following the year when the EJScreen was first launch, suggesting that the EPA may also be responding to the response from the public following the enhanced transparency of EJ information. In untabulated results, we use a two-stage least squared (2SLS) approach, and we find a significant reduction in toxic chemical releases in high-EJ-concern locations following EPA inspections induced by the launch of EJScreen in 2012. The

[7] See https://www.epa.gov/EJScreen/how-was-EJScreen-developed.

evidence suggests that the toxic chemical releases of facilities are responding to the increased regulatory scrutiny by the EPA after the launch of EJScreen.

4.2 Public Scrutiny and Firm Pollution Reduction in High EJ Concern Places

Next, we present the results on changes in GHG emissions, which we hypothesize to be more responsive to the public launch of EJScreen in 2015, and we explore the potential channels through which public stakeholders can influence firm pollution in high-EJ-concern locations.

4.2.1 Attention Towards Environmental Justice Issues

First of all, we explore whether public attention toward EJ changes following the launch of EJScreen. To measure the public's attention to environmental justice, we collect state-level Google Search Volume Index (SVI) for the keyword "environmental justice." The Google Search Volume Index measures the popularity of a particular term or phrase that is searched by users using the Google Search engine and is a popular measure of the public attention (Da et al. (2011), Drake et al. (2012)). In Table 4, we find that in states where a large number of census blocks have high percentages of EJ indexes that are ranked above the 80th percentile, the attention to environmental justice increases significantly, suggesting that the launch of EJScreen potentially leads to increased public attention towards EJ issues.

Next, we explore whether the facilities' pollution reduction is impacted by the public's interest in and/or attention toward EJ issues. We expect that in areas and periods where there is more focus on environmental justice, firms and facilities will have more incentives to respond by cutting pollution emissions due to heightened pressure from different stakeholders following the launch of EJScreen.

In Table 9 panel A, we find that the GHG emission is significantly lower in regions with more attention towards environmental justice. In panel B, we estimate equation (1) for the

subsamples of facilities located in states with above and below median Google SVI relating to environmental justice, respectively. We find that the reduction in GHG emissions is more pronounced in the regions with high public attention towards environmental justice following the launch of EJScreen. In untabulated results, we find that the effect only exists after the year 2015 but not during the years 2012 to 2015, suggesting that public scrutiny rather than regulatory scrutiny is driving the results. The result suggests that the transparency of EJ information can incentivize firms to reduce pollution, especially when the public is more concerned about EJ issues.

4.2.2 NGO Activities

Lastly, we examine whether Non-governmental Organizations (NGOs) increase their activities in areas with high EJ-concern following the launch of EJScreen. NGOs play an important role in influencing corporate ESG practices via activist campaigns and collaborations with companies (Directors' Institute, 2024) . In addition, NGOs are one of the intended users of EJScreen according to the EPA. Evidence suggests that several NGOs are aware of the launch of EJScreen, and have published materials or organized webinars to promote the usage of EJScreen, such as Philanthropy Northwest and Environmental Protection Network. Thus, we expect that one of the channels through which facilities located in high-EJ areas reduce their emissions following the launch of EJScreen is due to the enhanced NGO attention towards corporations.

Table 3 presents the results of the relationship between the launch of EJScreen and the NGO activists campaigns targeting firms with local operations. We find that after the public launch of EJScreen in 2015, the number of NGO activist campaigns that targeted parent firms with facilities in a Census Block with a higher number of EJ Indexes that are ranked above the 80th percentiles increased significantly. In addition, we only find such positive and significant association between NGO campaigns and the EJ concerns of the area after the year 2015. The evidence suggests that the launch of EJScreen induces higher NGO actions

targeting firms with operations in high EJ concern places, potentially contributing to the reduction in emissions we observed in the main tests.

4.3 EJ Indexes Disclosure and Reduction in Emissions

We first test whether after the launch of the EJScreen mapping tool that enhances the transparency of EJ concerns, the facilities in high EJ concern places reduce their pollution emission. To this end, we follow the empirical strategy discussed in Section 3 and we estimate equation (1) using the facility-level toxic chemical releases (TRI) and greenhouse gas (GHG) emission and the EJ concern measures at the Census Block level that the facility is located in. In Table 5 columns (1) and (2), we find that there is a significant decrease in toxic chemical releases from facilities situated in Census Blocks where there are higher percentages of environmental indicators ranked above the 80th percentile following the internal launch of EJScreen in 2012. However, we do not observe significant effects following the public launch of EJScreen in 2015. Conversely, for greenhouse gas (GHG) emissions, we find a different dynamic. Significant reductions in GHG emissions in areas of higher EJ concern are only significant after the public launch of EJScreen in 2015.

We observe that the levels of toxic chemical releases in high EJ concern places experience a slight insignificant increase after 2015, suggesting a reversal of the previous reduction. To further explore the finding, we conduct a subsample analyses focusing only on facilities owned by public companies that usually attract more regulatory and public attention. We find that for public facilities, we only observe a significant reduction in toxic chemical releases after 2012 without future reversal.

4.4 Dynamic Effects of EJ Indexes Disclosure on Reduction in Emission

Next, we explore the dynamic impact of the launch of EJScreen on firm pollution. To test this, we re-estimate equation (1) and we replace the $POST2012$ and $POST2015$ indicators with a set of year dummies that take the value of one for years ranging from the years 2010

to 2018. We use 2011 as the benchmark year, which is one year before the internal launch of EJScreen. Table 6 presents the dynamic effects of EJ indexes disclosure on emission reduction. We find that the reduction in toxic chemical releases become significant since the year 2013, immediately after the internal launch of EJScreen. For GHG emissions, we find that before year 2015, there is no significant difference in GHG emissions between facilities located in high-versus-low percentage of highly-ranked EJ indexes. However, starting in 2017, facilities located in high EJ-concern areas experience a significant reduction in GHG emissions. These results further suggest that EJScreen leads to improved environmental outcomes in high EJ concern areas, but toxic chemical releases are more responsive to the internal launch while GHG emissions are more sensitive to the public launch.

4.5 Demographic and Environmental Characteristics and Reduction in Emission

Next, we explore whether the documented pollution reduction is only driven by the underlying components, namely, the environmental aspect and the demographic aspect, of a location. If this is the case, then the creation of EJScreen merely draw people's attention to the underlying component of EJ Index, rather than "Environmental Justice" as a new piece of information. In Panel A of Table 7, we include the interaction of the $POST2012$ and $POST2015$ indicator and the EJ Index and its components, the environmental indicators and demographic index of a given census block, in the main regressions. We find that the interactions between the percentage of EJ indexes that are above the 80th percentile and the $POST2012$ ($POST2015$) indicators continue to be negative and significant for the level of toxic chemical release (greenhouse gas emissions). Such results suggest that pollution reductions following the launch of EJScreen are not driven purely by the environmental pollution levels or the demographic profiles of the locations. Rather, pollution reduction concentrates n high EJ concern areas. This piece of evidence suggests that the disclosure of EJ information has new effects above the existing environmental and demographic information.

In Table 8, we examine the level of pollution on in subsamples of above-median (High) versus at-or-below median (Low) level of Demographic Index to explore whether the pollution reduction in high EJ places is concentrated in areas with larger percentage of vulnerable community. The results suggest that the pollution reduction for toxic chemical release is significant in both sub samples, with a larger reduction in low Demographic Index areas. For greenhouse gas emissions, the pollution reduction is only significant in areas with high Demographic Index. Overall, the results suggest that following the internal and external launch of EJScreen, there is significant reduction in pollution in areas with higher EJ concerns. However, firms seem to be implementing differential strategies with regards to different pollutants. For greenhouse gas emissions where we expect higher public scrutiny, pollution reduction is concentrated in areas where the high EJ index is driven by high Demographic Index. However, for toxic chemical releases where regulatory scrutiny is more prevalent, pollution reduction is more effective in areas with lower Demographic Index, or lower percentage of vulnerable communities. Such a result might be due to the different nature of the pollutants: toxic chemical release tend to have a more localized impact since it only directly affects nearby regions, whereas greenhouse gases have global influences, which can draw broader public attention beyond local residents. Thus, toxic chemical reduction is more responsive when the local residents have more voice, i.e., when they have higher income status or are of racial majority, but greenhouse gas reduction might be more responsive in more vulnerable regions where there are more public attention.

These findings collectively indicate that the introduction of EJScreen leads to a reduction of facilities' pollution in vulnerable areas with more noticeable EJ concerns. However, the timing of when such reductions became significant varies for different pollutants, suggesting that they may be influenced by different factors.

4.5.1 Local Newspaper Coverage

Second, we explore whether the local media plays a role in disseminating the EJ-related information to the public. Although the EJScreen mapping tool significantly enhances the availability of EJ information, it is unclear whether users will directly use it and in turn pressure firms to react by reducing pollution. However, if journalists and local media utilize such a tool, they can facilitate the dissemination of such information to the public and pressure firms to react. To test this, we obtain the number of local news outlets in each state. If a state has more local newspapers, the information dissemination in the local region will be more efficient.

In Table 10 panel A, we find that the GHG emission is significantly lower in regions with a larger number of local news outlets, suggesting that the media plays a role in curbing firm pollution. In Panel B, we estimate equation (1) for the subsample of facilities located in states with above versus below median number of local newspaper outlets. As expected, we find that the reduction in GHG emissions is more pronounced in the regions with high local newspaper coverage following the launch of EJScreen. In untabulated results, we find consistent evidence when we use local newspaper circulation as the measure for local newspaper coverage. In addition, we find that the effect only exists after the year 2015 but not during the years 2012 to 2015. Such results reveal the potentially important role of the media in promoting environmental justice.

5 Additional Analyses and Robustness Tests

5.1 California EnviroScreen

In the main analyses, we explore the effectiveness of the EJ mapping tool developed by the federal EPA. However, some state governments have also been putting effort into developing similar policy tools to enhance the transparency of EJ information. The front

runner in this area is the state of California that launched the CalEnviroScreen in 2013. It is designed to identify communities in California that are disproportionately burdened by and vulnerable to multiple sources of pollution and environmental hazards.

The first version of CalEnviroScreen 1.0 was launched in 2013. It incorporated indicators including both air and water quality, pesticides, and hazardous waste, population characteristics and public health outcomes. The second version CalEnviroScreen 2.0 was launched in 2014. the number of indicators and refined the methodology. It included new data layers, such as traffic density and educational attainment, to provide a more comprehensive assessment of environmental and social stressors. CalEnviroScreen 2.0 also allowed users to visualize data through an interactive online mapping tool. In 2017, a third version of CalEnviroScreen was launched. It further refined the methodology and updated data sources. It incorporated additional indicators related to housing, transportation, and climate vulnerability, recognizing the interconnected nature of environmental and social factors. CalEnviroScreen 3.0 also introduced the concept of "screening for climate change vulnerability," considering factors like sea-level rise and extreme heat events. CalEnviroScreen 4.0 is the latest version so far and was released in 2020. CalEnviroScreen 4.0 continues to prioritize equity and community engagement, aiming to identify areas most in need of EJ interventions. It incorporates new indicators related to environmental and public health, as well as social and economic vulnerabilities. Unlike the Federal EJScreen, the CalEnviroScreen calculates only one composite score, the *EJ Score*, which is the average of all the EJ indicators, at the census tract level. The map is also based on the percentile ranking of the EJ Score. Please refer to Figure 4 for a snapshot of the user interface of the most recent CalEnviroScreen.

To explore the implications of CalEnviroScreen, we start by examining the response in facility greenhouse gas emissions following the first launch of CalEnviroScreen. Such a design choice is due to the fact that the second and third versions of CalEnviroScreen was implemented in a very short time frame, and we expect that the effect of the first launch to be the largest. Later, we also examine the staggered launch of the different versions of

CalEnviroScreen. We estimate the following regressions:

$$Emission_{i,t,r} = \beta HighCalEJScore \times POST2013 + X_{i,t,r} + FacilityFE + TimeFE + e_{i,t,r} \quad (3)$$

where $HighCalEJScore$ is an indicator variable that equals 1 if the EJ Score of the census tract that a facility is located is ranked at the top decile in a given year, and 0 otherwise. On the map, the locations with EJ Scores ranked at the top decile will be marked as red. $POST2013$ is an indicator variable that equals 1 if the year is on or after the year 2013, and 0 otherwise. $X_{i,t,r}$ is a vector of control variables for facility i at time t. i and t are facility and time fixed effects. Our coefficient of interest, β, captures the differential effect of pollution emission for facilities located in each census tract with high versus low environmental indexes.

Table 11 presents the result of greenhouse gas emissions in communities with high-versus-low EJ concerns after the launch of CalEnviroScreen. In column (1), we find that there is a significant reduction in greenhouse gas emissions in facilities that have above median EJ Score after 2013, which is the year in which CalEnviroScreen 1.0 was introduced. This translates to a 1.56% reduction in greenhouse gas emissions compared to the sample mean. In column (2), we find that the reduction in greenhouse gas emission in areas with high EJ Score only started in 2013, suggesting that the launch of CalEnviroScreen drives the pollution reduction results. In untabulated results, we find that when the facility is located in the areas with above 90th percentile EJ Scores, there is a significant reduction in greenhouse gas emissions which translates to a 1.72% relative decrease compared to the sample mean.

5.2 Other Robustness Tests

5.2.1 Stacked Difference-in-differences Analysis

We follow Callaway and Sant'anna (2012) stacked difference-in-differences approach and exploit the effect of the transparency of EJ information on pollution reduction in California.

We identify treated facilities as those that are ranked in the high-EJ score group and identify the treatment years as the year when a facility enters into the high EJ score group. For example, if a facility's EJ Score is above the sample median in the first (second) version of the CalEnviroScreen, its treatment year will be 2013 (2014).

Table 12 presents the results. Before the Census Tract, we find that a facility is located in is identified as having high EJ-concern, there is no significant change in its GHG emission. However, following the inclusion in the high-EJ group, greenhouse gas emissions reduce significantly in the next two to three years. The analysis provides additional support that the launch of CalEnviroScreen leads to a reduction of pollution in places identified as having high EJ concerns.

5.2.2 Regression Discontinuity Analysis

Next, to explore the robustness of our results, we utilize the CalEnviroScreen setting, and we exploit the effects of the discontinuity in EJ scores on pollution reduction in California. To this end, we continue to use the same threshold of above 80th percentile to identify areas with severe EJ concerns. Based on the CalEnviroScreen map, the areas with above the 80th percentile scores will be colored as deep orange, giving a more salient visual effect on the users of the CalEnviroScreen web-based tool. Thus, we compare the discontinuity in the California EJ score around the 80th percentile cutoff and its relationship with pollution reduction after the initial launch of CalEnviroScreen.

We first plot the average level of the changes in greenhouse gas emission in tons for ten evenly spaced bins, the 95th confidence interval, and the fitted polynomial trends, during the periods between 2014 and 2018, which is after the launch of CalEnviroScreen 1.0. In Table 13 Panel A, we find that right after passing the 80th percentile in the EJ Score, the reduction in greenhouse gas emissions exhibits a significantly downward trend. This result indicates that there is a significant negative association between the EJ score and pollution levels when the EJ concern is considered to be more severe due to the coloring scheme of the

online mapping tool.

Table 13 Panel B presents the results using parsimonious local linear and quadratic regressions. We find that moving past the 80th percentile in the EJ Score is associated with a significant reduction in greenhouse gas emissions in periods after the launch of CalEnviroScreen 1.0. The results suggest that the transparency of EJ information contributes to pollution reduction in vulnerable areas.

5.2.3 Additional Robustness Tests

In our main results, we use the percentage of environmental indexes that are ranked above the 80th percentile ($EJIndexAbove80$) for a given facility (location) as the continuous treatment variable in the DiD analyses. In untabulated robustness tests, we use alternative measures. First, we use the percentage of environmental indexes that are ranked above 90th and 95th percentile ($EJIndexAbove90$ and $EJIndexAbove95$) as the treatment variables. Second, we use an indicator variable, $HaveEJIndexAbove80$, which represents that at least one of the environmental indexes is ranked above the 80th percentile, as the treatment variable. Our inferences remain robust to these alternative specifications.

We also explore whether the significant reduction in emission in areas with greater EJ concerns affects local employment and income due to the reduction in production activities. In untabulated analyses, we find that there is no significant differences in employment and income between areas of high and low indices. Lastly, we explore whether firms shift their pollution to places with low EJ concerns. In untabulated results, we do not observe evidence suggesting such shifting behaviors.

6 Conclusion

In this paper, the effect of information transparency, as well as the role of online visualization technologies that highlight areas with EJ concerns, on firm emissions. More specifically,

we examine the effect of the launch of web-based mapping tools that reveal the disproportionate environmental impact of vulnerable communities in certain areas in the United States on firm pollution. We find that after the internal launch and the public launch of EJScreen, there is an increase in regulatory monitoring effort and the EPA become significantly more likely to inspect facilities located in areas with high EJ concern. We also find that following the public launch of EJScreen in 2015, there is an increase in public attention and scrutiny in places in high EJ concern areas. Specifically, there are more NGO activist campaigns targeting parent firms of facilities located in high EJ concern areas. Exploring the environmental outcomes of the launch of EJScreen, we find a significant reduction in toxic chemical release following the increase in regulatory scrutiny in 2012, and a significant reduction in greenhouse gas emission following the public launch of EJScreen in 2015. In addition, we find that the reduction in greenhouse gas emissions is more pronounced in areas with more local newspaper outlets and in areas with more public attention on EJ issues. Furthermore, we find similar results that enhanced transparency of EJ related information leads to a reduction of pollution in areas with higher EJ concerns using the launch of CalEnviroScreen in California.

Our findings highlight the importance of the aggregation and disclosure of information on environmental justice, as well as the significance of reducing information processing costs through regulators' disclosure of EJ information in facilitating the usage of such information of other stakeholders, who can then take actions to better monitor firms to improve environmental justice. The results of this study is especially timely and relevant as concerns about the cost and lack of effectiveness of government environmental regulation has led to doubts and the curtail of many programs, especially programs related to environmental justice. We provide evidence showing that less costly forms of regulation, i.e., regulation through improved information transparency, with the aid of advanced technology, can help increase both regulatory and public scrutiny, thereby leading to a reduction in firm emission and improved environmental quality for vulnerable communities.

References

Balakrishnan K, Copat R, De la Parra D, Ramesh K. 2023. Racial diversity exposure and firm responses following the murder of george floyd. *Journal of Accounting Research* **61**: 737–804.

Belousov I, Nakhmurina A, Samuels D. 2025. Newspaper notice as governmental transparency mechanism: Evidence from florida. *Working Paper* .

Billings MB, Klein A, Shi YC. 2022. InvestorsâĂŹ response to the# metoo movement: does corporate culture matter? *Review of Accounting Studies* **27**: 897–937.

Blankespoor E. 2019. The impact of information processing costs on firm disclosure choice: Evidence from the xbrl mandate. *Journal of Accounting Research* **57**: 919–967.

Blankespoor E, deHaan E, Marinovic I. 2020. Disclosure processing costs, investorsâĂŹ information choice, and equity market outcomes: A review. *Journal of Accounting and Economics* **70**: 101344.

Blankespoor E, Dehaan E, Wertz J, Zhu C. 2019. Why do individual investors disregard accounting information? the roles of information awareness and acquisition costs. *Journal of Accounting Research* **57**: 53–84.

Chen A, Dechow P, Tan S. 2022. Corporate response to the black lives matter movement: Determinants of speaking out in support of social causes. *Working Paper* .

Christensen HB, Floyd E, Liu LY, Maffett M. 2017. The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records. *Journal of Accounting and Economics* **64**: 284–304.

Cuny C. 2018. When knowledge is power: Evidence from the municipal bond market. *Journal of Accounting and Economics* **65**: 109–128.

Cuny C, Even-Tov O, Watts EM. 2021. From implicit to explicit: The impact of disclosure requirements on hidden transaction costs. *Journal of Accounting Research* **59**: 215–242.

Cuny C, Li K, Nakhmurina A, Watts E. 2024. Muni disclosures. *Working Paper* .

Currie J, Voorheis J, Walker R. 2023. What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality. *American Economic Review* **113**: 71–97.

Da Z, Engelberg J, Gao P. 2011. In search of attention. *The journal of finance* **66**: 1461–1499.

Drake MS, Roulstone DT, Thornock JR. 2012. Investor information demand: Evidence from google searches around earnings announcements. *Journal of Accounting research* **50**: 1001–1040.

Duguay R, Rauter T, Samuels D. 2023. The impact of open data on public procurement. *Journal of Accounting Research* **61**: 1159–1224.

Even-Tov O, She G, Wang LL, Yang D. 2025. How government procurement shapes corporate climate disclosures, commitments, and actions. *Review of Accounting Studies* : 1–47.

Even-Tov O, Su JA, Wang KP. 2024. Do information processing costs matter to regulators? evidence from the us mortgage companies' supervision. *Working paper* .

Fan G, Nguyen T, Wu X. 2023. Beyond the disaster zone: How disruptive climate events shape epa oversight and firm behavior. *Working Paper* .

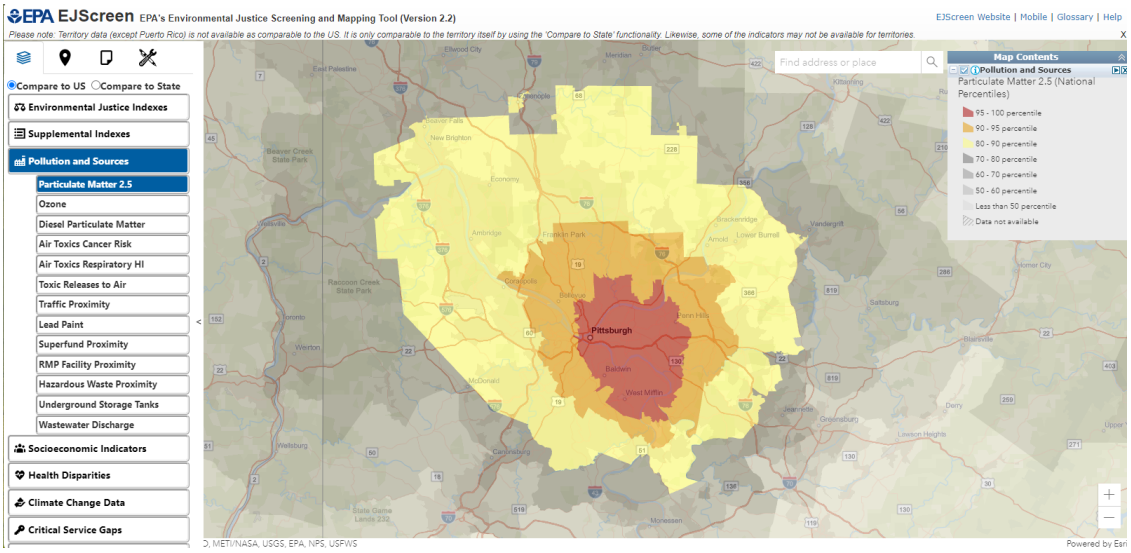
Guo R, Tian X. 2024. Regulatory transparency and regulatorsâĂŹ effort: Evidence from public release of the sec's review work. *Journal of Accounting Research* **62**: 229–273.

Jbaily A, Zhou X, Liu J, Lee TH, Kamareddine L, Verguet S, Dominici F. 2022. Air pollution exposure disparities across us population and income groups. *Nature* **601**: 228–233.

The EPA UEPA. 2015. Environmental justice mapping and screening tool. *EJSCREEN Technical Documentation* .

Figure 1: EJScreen Mapping Tool Interface

This graph presents the EJScreen mapping tool interface as seen by the users in the year 2024. The upper graph presents the overall view showing the detailed breakdown of EJ indexes. The bottom graph presents the interface relating to the selection of indicators and relevant thresholds relating to the EJ indexes.



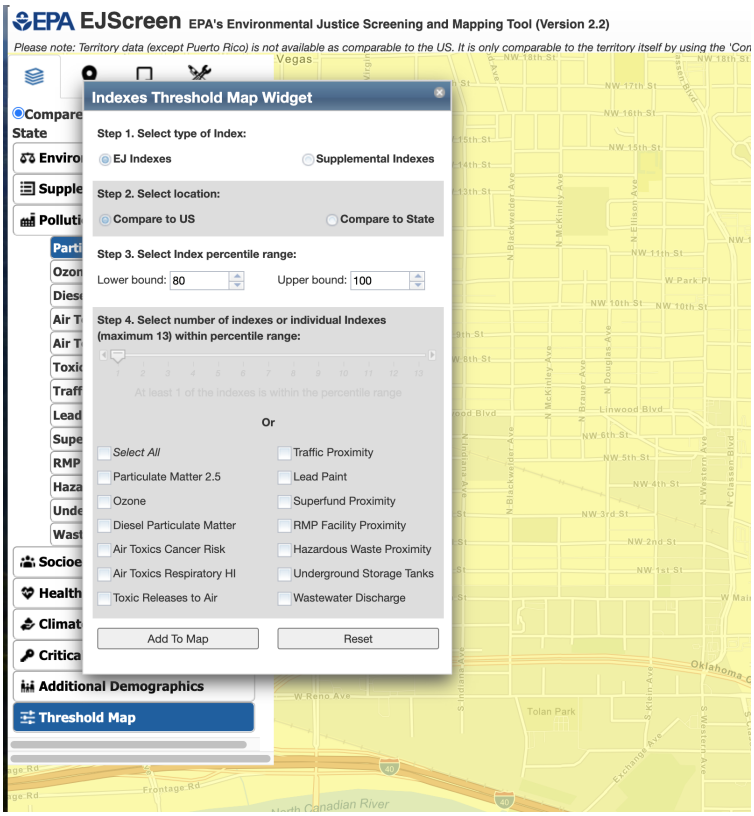


Figure 2: EJScreen Mapping Tool Interface - Facilities and Firms

This graph presents the EJScreen mapping tool interface with facilities information as seen by the users in the year 2024.

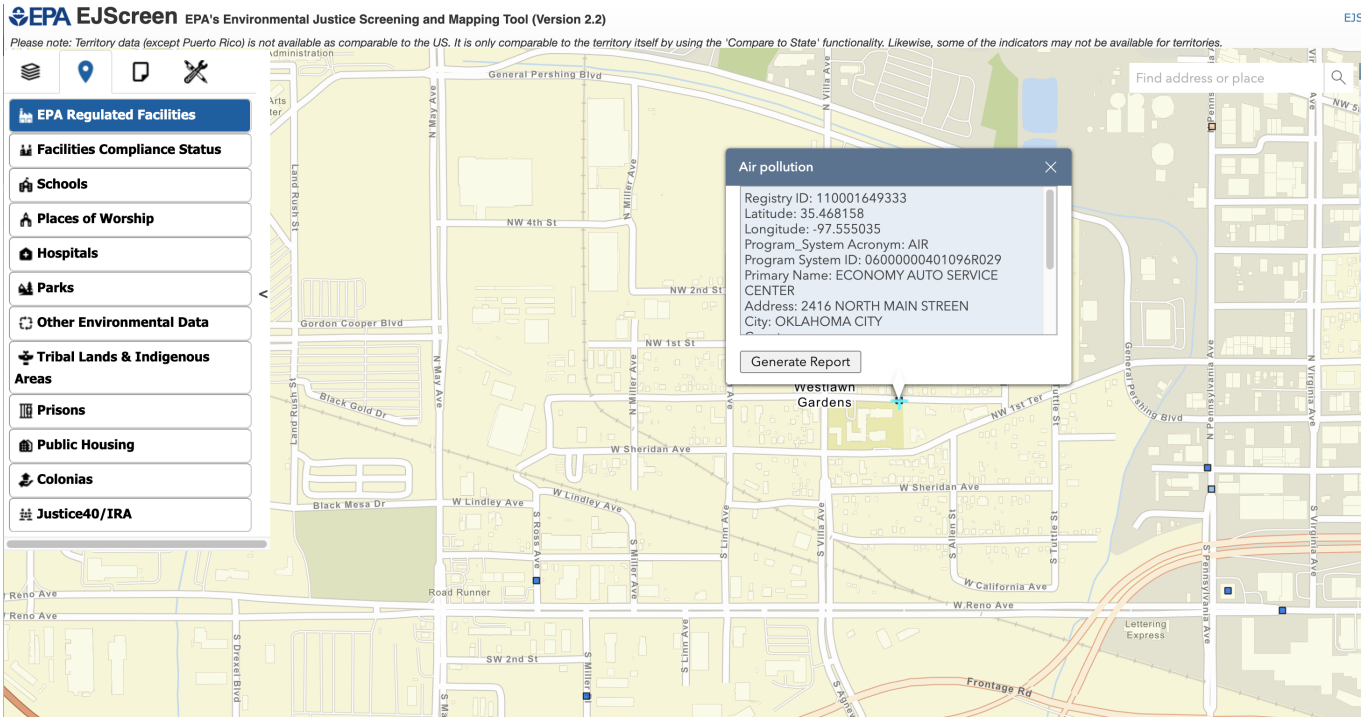


Figure 3: EJScreen-Generated Community Report

This graph presents a snapshot of the EJScreen community report generated from the EJScreen mapping tool. Users can obtain a report relating to the environmental justice for a given location by double-clicking the area on the map.

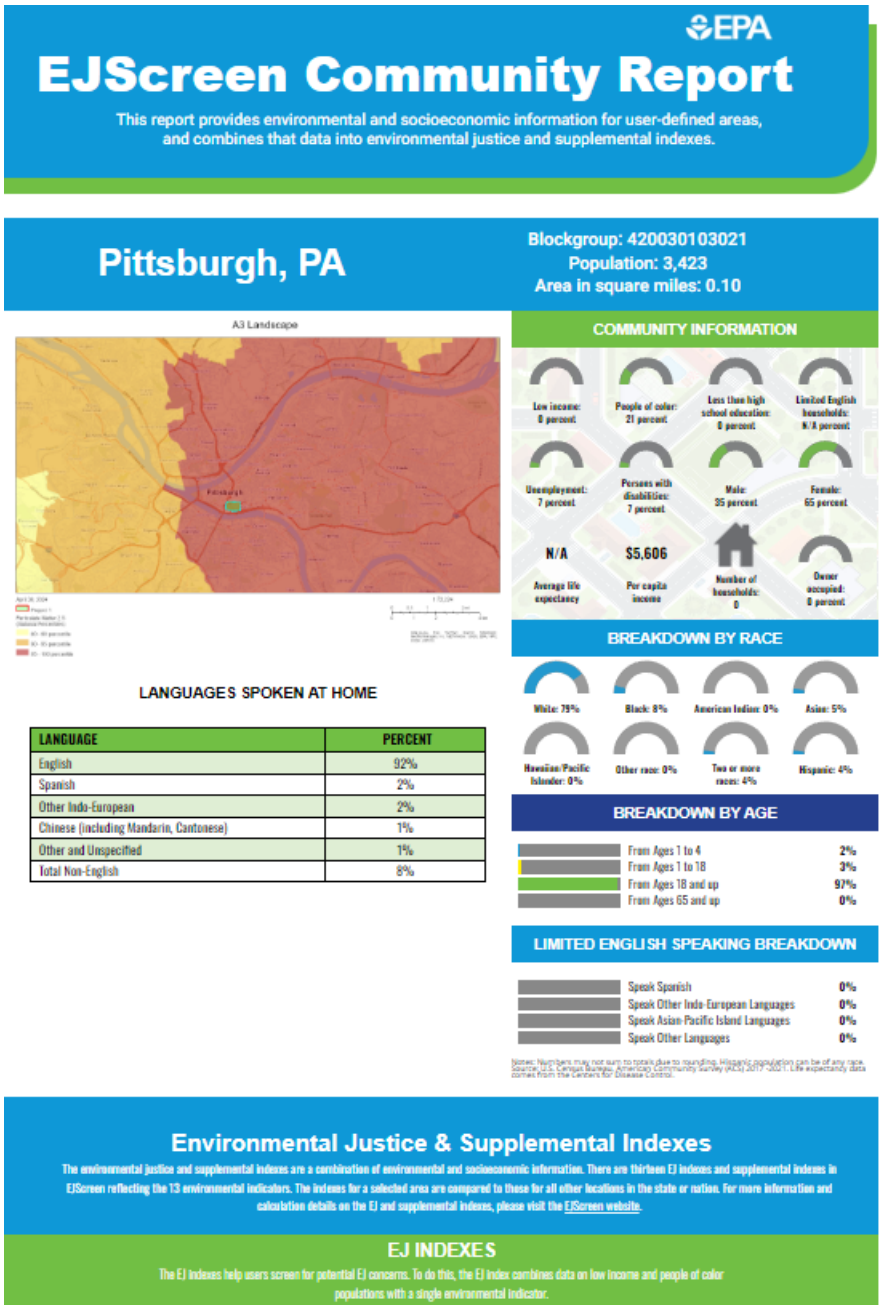


Figure 4: CalEnviroScreen Mapping Tool Interface

This graph presents the CalEnviroScreen 4.0 mapping tool interface as seen by the users in the year 2024.

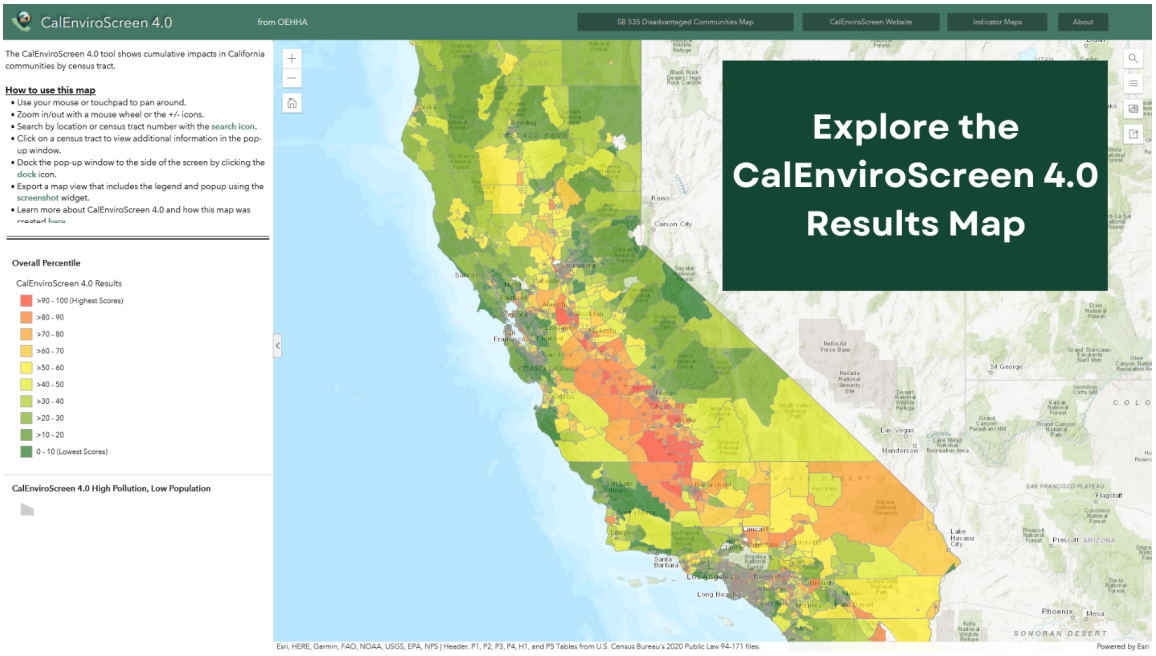


Table 1: Summary Statistics

This table presents the summary statistics of variables used in the different tests. Variable definitions are included in Appendix A.

Panel A. Federal EJScreen Tests					
	Mean	S.D.	p25	Median	p75
State-level sample					
lnGoogleSVI	1.283	0.791	0.651	1.253	1.897
StEJAbove80	129.836	142.837	37.500	107.000	163.000
Census-Block level sample					
NumNGOActivity	0.163	2.192	0.000	0.000	0.000
TRI sample					
EJIndexAbove80	0.288	0.401	0.000	0.000	0.625
lnTRI	5.699	4.450	0.378	6.229	9.389
GHG sample					
EJIndexAbove80	0.180	0.314	0.000	0.000	0.250
lnGHG	11.289	1.735	10.366	11.065	12.108
GoogleSVI	4.902	5.249	1.167	3.000	7.417
LocalMediaOutlets	46.524	28.252	22.000	37.000	75.000

Panel B. California CalEnviroScreen Tests					
	Mean	S.D.	p25	Median	p75
CalEJScore	50.670	28.680	26.000	51.000	76.000
lnGHG	11.016	1.707	10.150	10.894	11.996

Table 2: EJScreen and EPA Inspection

This table presents the results of EPA monitoring activity around the development and launch of EJScreen during the years 2010 to 2018. *Inspect* is an indicator that equals 1 if the facility is inspected in a given year, and 0 otherwise. *PastInspect* is an indicator that equals 1 if the facility is inspected last year, and 0 otherwise. *EJIndexAbove*80 is the percentage of the facility's EJ indexes that are ranked above the 80th percentile. *POST*2012 is an indicator that equals 1 if the year is at or after the year 2012, and 0 otherwise. All regressions include facility and year fixed effects. Standard errors are clustered at census block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

VARIABLES	(1) Inspect	(2) Inspect
EJIndexAbove80×POST2012	0.014*	
	(0.008)	
EJIndexAbove80×Year2010		-0.002
		(0.006)
EJIndexAbove80×Year2012		0.005
		(0.006)
EJIndexAbove80×Year2013		0.014**
		(0.006)
EJIndexAbove80×Year2014		0.007
		(0.006)
EJIndexAbove80×Year2015		-0.005
		(0.007)
EJIndexAbove80×Year2016		0.011*
		(0.006)
EJIndexAbove80×Year2017		0.009
		(0.006)
EJIndexAbove80×Year2018		0.002
		(0.006)
PastInspect	-0.105***	-0.083***
	(0.004)	(0.002)
Observations	504,445	504,445
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.037	0.068

Table 3: EJScreen and NGO Activist Campaigns

This table presents the results of public's attention on EJ issue around the development and launch of EJScreen during the years 2011 to 2018 for facilities reporting to the EPA TRI and GHG programs. *lnNGOActivities* is the natural log of one plus the number of NGO activist campaigns targeting the parent company of a facility each year. *EJIndexAbove*80 is the percentage of the facility's EJ indexes that are ranked above the 80th percentile. *POST*2015 is an indicator that equals 1 if the year is at or after the year 2015, and 0 otherwise. All regressions include state and year fixed effects. Standard errors are clustered at the EPA regional office level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

VARIABLES	(1) lnNGOActivities	(2) lnNGOActivities
EJAbove80×POST2012	0.003	
	(0.002)	
EJAbove80×POST2015	0.004**	
	(0.002)	
EJAbove80×Year2012		0.000
		(0.003)
EJAbove80×Year2013		0.005
		(0.005)
EJAbove80×Year2014		0.004
		(0.003)
EJAbove80×Year2015		0.004
		(0.003)
EJAbove80×Year2016		0.008**
		(0.003)
EJAbove80×Year2017		0.006*
		(0.003)
EJAbove80×Year2018		0.008*
		(0.004)
Observations	217,961	217,961
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.882	0.897

Table 4: EJScreen and State-level Attention on Environmental Justice

This table presents the results of public's attention on EJ issue around the development and launch of EJScreen during the years 2010 to 2018. *lnGoogleSVI* is the natural log of one plus the Google Search Volume Index of the keyword "environmental justice" in each state each year. *HighStEJAbove*80 is an indicator that equals one if the state has an above-median number of census blocks with above-median percentages of EJ indexes that are ranked above the 80th percentile, and zero otherwise. *POST*2015 is an indicator that equals 1 if the year is at or after the year 2015, and 0 otherwise. All regressions include state and year fixed effects. Standard errors are clustered at the EPA regional office level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

VARIABLES	(1) lnGoogleSVI	(2) lnGoogleSVI
HighStEJAbove80×POST2015	0.077*	
	(0.043)	
HighStEJAbove80×Year2010		0.104
		(0.221)
HighStEJAbove80×Year2012		-0.028
		(0.053)
HighStEJAbove80×Year2013		-0.042
		(0.082)
HighStEJAbove80×Year2014		0.127
		(0.123)
HighStEJAbove80×Year2015		0.033
		(0.096)
HighStEJAbove80×Year2016		0.090
		(0.121)
EJIndexAbove80×Year2017		0.117
		(0.100)
HighStEJAbove80×Year2018		0.124*
		(0.059)
Observations	408	408
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.813	0.810

Table 5: Launch of EJScreen and Pollution Reduction

This table presents the results of regressing firms' facility-level toxic substance release around the development and launch of EJScreen during the years 2010 to 2018. $lnTRI$ ($lnGHG$) is the natural logarithm of the amount of toxic chemical release (green house gas emission) at the facility level. $EJIndexAbove80$ is the percentage of the facility's EJ index that is ranked above the 80th percentile. $POST2012$($POST2015$) is an indicator that equals 1 if the year is at or after the year 2012 (2015), and 0 otherwise. All regressions include facility fixed effects and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

	(1)	(2)
VARIABLES	$lnTRI$	$lnGHG$
EJIndexAbove80×Post2012	-0.147***	0.013
	(0.042)	(0.018)
EJIndexAbove80×Post2015	0.053	-0.043**
	(0.065)	(0.019)
Observations	194,908	48,687
Facility FE	YES	YES
Year FE	YES	YES
Adj.R-squared	0.896	0.864

Table 6: Dynamic Trends of EJScreen and Pollution Reduction

This table presents the results of regressing firms' facility-level greenhouse gas emission around the development and launch of EJScreen during the years 2010 to 2018. *lnGHG* is the natural logarithm of the amount of green house gas emission at the facility level. *EJIndexAbove*80 is the percentage of the facility's EJ index that is ranked above the 80th percentile in year 2015. *POST*2015 is an indicator that equals 1 if the year is at or after the year 2015, and 0 otherwise. All regressions include facility fixed effects and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

	(1)	(2)
VARIABLES	*lnTRI*	*lnGHG*
EJIndexAbove80×Year2010	0.053	-0.057
	(0.035)	(0.062)
EJIndexAbove80×Year2012	**-0.078****	0.037
	(0.035)	(0.052)
EJIndexAbove80×Year2013	**-0.092****	-0.006
	(0.036)	(0.051)
EJIndexAbove80×Year2014	**-0.079****	-0.079
	(0.038)	(0.058)
EJIndexAbove80×Year2015	0.010	**-0.094***
	(0.041)	**(0.050)**
EJIndexAbove80×Year2016	-0.063	-0.087
	(0.040)	(0.053)
EJIndexAbove80×Year2017	0.001	**-0.089***
	(0.039)	**(0.053)**
EJIndexAbove80×Year2018	0.022	**-0.110****
	(0.040)	**(0.053)**
Observations	194,908	48,687
Facility FE	YES	YES
Year FE	YES	YES
Adj.R-squared	0.914	0.864

Table 7: EJ Index Components and Pollution Reduction

This table presents the results of regressing firms' facility-level toxic substance release and greenhouse gas emissions around the development and the components of EJ Index during the years 2010 to 2018. $lnTRI$ ($lnGHG$) is the natural logarithm of the amount of toxic chemical release (green house gas emission) at the facility level. $EJIndexAbove80$ is the percentage of the facility's EJ index that is ranked above the 80th percentile. $AvgEnvIndex$ is the average scores of all the environmental indicators for a given census block. $DemographicIndex$ is the demographic index for a given census block, which is the average of the percentage of people of color and people of low income. $POST2012$($POST2015$) is an indicator that equals 1 if the year is at or after the year 2012 (2015), and 0 otherwise. All regressions include facility fixed effects and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

Panel A. Pollution reduction and EJ Index components		
	(1)	(2)
VARIABLES	lnTRI	lnGHG
EJIndexAbove80×POST2012	**-0.169*** **	
	(0.026)	
AvgEnvIndex×POST2012	0.001	
	(0.001)	
DemographicIndex×POST2012	0.145***	
	(0.040)	
EJIndexAbove80×POST2015		**-0.040*** **
		(0.014)
AvgEnvIndex×POST2015		-0.001*
		(0.005)
DemographicIndex×POST2015		0.024
		(0.057)
Observations	194,908	48,687
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.896	0.865

Table 8: Pollution Reduction Conditional on Demographic Indexes

This table presents the results of regressing firms' facility-level toxic substance release and greenhouse gas emissions around the development conditional on the Demographic Index of the Census Block during the years 2010 to 2018. *lnTRI* (*lnGHG*) is the natural logarithm of the amount of toxic chemical release (green house gas emission) at the facility level. *EJIndexAbove*80 is the percentage of the facility's EJ index that is ranked above the 80th percentile. *DemographicIndex* is the demographic index for a given census block, which is the average of the percentage of people of color and people of low income. *POST*2012(*POST*2015) is an indicator that equals 1 if the year is at or after the year 2012 (2015), and 0 otherwise. All regressions include facility fixed effects and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

	High Demographic Index (poor)	Low Demographic Index (rich)	High Demographic Index (poor)	Low Demographic (rich)
	(1)	(2)	(3)	(4)
VARIABLES	lnTRI	lnTRI	lnGHG	lnGHG
EJIndexAbove80×POST2012	-0.068**	-0.381***		
	(0.033)	(0.048)		
EJIndexAbove80×POST2015			-0.012**	0.019
			(0.021)	(0.072)
High-Low	**0.313***		**-0.031****	
Observations	96,922	97,058	27,269	27,090
Year FE	YES	YES	YES	YES
Facility FE	YES	YES	YES	YES
Adj. R-squared	0.889	0.904	0.860	0.851

Table 9: EJScreen and Pollution Reduction Conditional on Public Attention

This table presents the cross-sectional results of greenhouse gas emission for places with high EJ concerns around the development and launch of EJScreen in the sub samples of high versus low attention on EJ issues during the years 2010 to 2018. Attention on EJ issue is measured as the annual mean of monthly state-level Google Search volume index (SVI) on searches of the keyword "environmental justice". High (low) attention is the state-year observations that have above (below) median values of Google SVI index. *lnGHG* is the natural logarithm of the amount of green house gas emission at the facility level. *EJIndexAbove*80 is the percentage of the facility's EJ index that is ranked above the 80th percentile. *POST*2015 is an indicator that equals 1 if the year is at or after the year 2015, and 0 otherwise. All regressions include facility and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

Panel A. Descriptive Statistics

lnGHG	Obs.	Mean	S.D.
High Google SVI	23,079	11.205	1.739
Low Google SVI	23,133	11.354	1.726

Panel B: Regression results

	High Public Attention	Low Public Attention
	(1)	(2)
VARIABLES	lnGHG	lnGHG
EJIndexAbove80×Post2015	-0.053*	0.018
	(0.028)	(0.026)
Diff. (High – Low)	**-0.071****	
Observations	23,079	23,133
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.856	0.881

Table 10: EJScreen and Pollution Reduction Conditional on Environmental Local News Coverage

This table presents the cross-sectional results of greenhouse gas emission for places with high EJ concerns around the development and launch of EJScreen conditional on the number of local newspaper outlets in the county that the facility is located in. The sample period for this test is from 2010 to 2018. *lnGHG* is the natural logarithm of the amount of green house gas emission at the facility level. *EJIndexAbove*80 is the percentage of the facility's EJ index that is ranked above the 80th percentile. All regressions include facility fixed effects and year fixed effects. *POST*2015 is an indicator that equals 1 if the year is at or after the year 2015, and 0 otherwise. All regressions include facility and year fixed effects. Standard errors are clustered at the Census Block and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

Panel A. Descriptive Statistics

lnGHG	Obs.	Mean	S.D.
High Local News Outlet	23,916	11.224	1.738
Low Local News Outlet	23,522	11.352	1.730

Panel B: Regression results

	High Local News	Low Local News
	(1)	(2)
VARIABLES	lnGHG	lnGHG
EJIndexAbove80×Post2015	-0.086***	0.025
	(0.029)	(0.028)
Diff. (High – Low)	**-0.111***	
Observations	23,916	23,522
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.853	0.881

Table 11: CalEnviroScreen and Greenhouse Gas Emission

This table presents the results of regressing firms' facility-level greenhouse gas emission around the development and launch of CalEnviroScreen during the years 2010 to 2018. $lnGHG$ is the natural logarithm of the amount of greenhouse gas emission in tons at the facility-chemical level. $CalEJScoreAbove80$ is an indicator variable that equals 1 if the EJ Score of the census tract that a facility is located is ranked above the 80th percentile at a given year, and 0 otherwise. $POST2013$ is an indicator that equals 1 if the year is at or after the year 2013, and 0 otherwise.All regressions include facility fixed effects and year fixed effects. Standard errors are clustered at the census tract and year level and presented in parentheses below the coefficients. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

	(1)	(2)
VARIABLES	lnGHG	lnGHG
CalEJScoreAbove80×POST2013	-0.172**	
	(0.088)	
CalEJScoreAbove80×Year2010		0.000
		(0.000)
CalEJScoreAbove80×Year2012		0.013
		(0.105)
CalEJScoreAbove80×Year2013		-0.081
		(0.106)
CalEJScoreAbove80×Year2014		-0.089
		(0.103)
CalEJScoreAbove80×Year2015		**-0.352****
		(0.143)
CalEJScoreAbove80×Year2016		**-0.241***
		(0.134)
CalEJScoreAbove80×Year2017		-0.035
		(0.134)
CalEJScoreAbove80×Year2018		-0.135
		(0.134)
Observations	3,600	3,600
Year FE	YES	YES
Facility FE	YES	YES
Adj. R-squared	0.803	0.814

Table 12: CalEnviroScreen and Greenhouse Gas Emission - Stacked DID

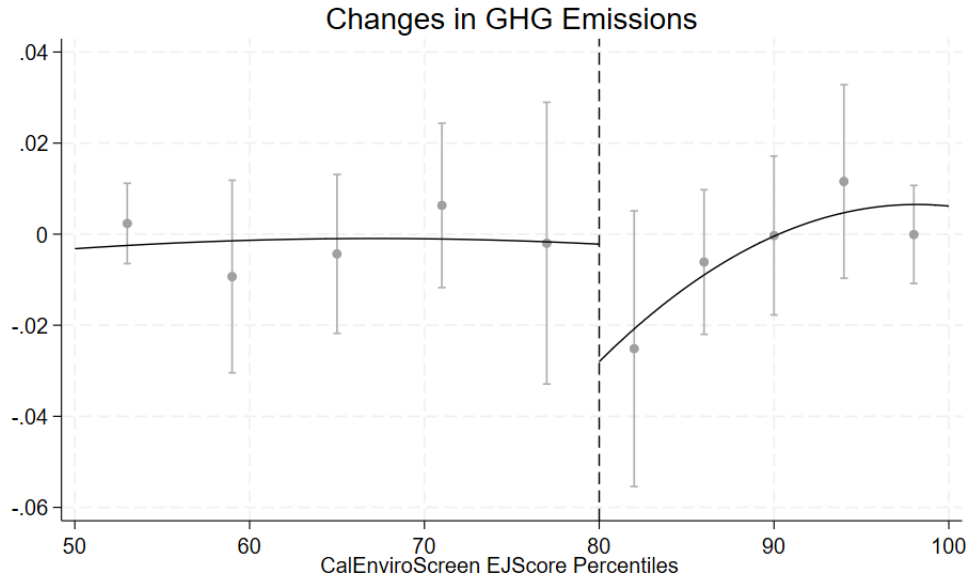
This table presents the results of the stacked regression of the Callaway and S'anna (2021) facility-level greenhouse gas emission around the development and launch of CalEnviroScreen. The estimation is based on the Doubly Robust IPW method with Wildbootstrap standard errors. $lnGHG$ is the natural logarithm of the amount of greenhouse gas emissions in tons at the facility level. $EJScreen$ is a variable that equals 1 since the establishment of EJScreen, and equals 0 otherwise. $CEScoreAbove80$ is an indicator that equals 1 if the average percentile of the facility's environmental justice index is above the 80th percentile, and equals 0 otherwise. $t0$ is the year where a facility has a value of $CEScoreAbove80$ being one. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

	Coefficient	Std. err.	z	P>z
Tm3	-0.222	0.147	-1.51	0.132
Tm2	0.066	0.121	0.540	0.586
Tm1	-0.079	0.069	-1.160	0.248
Tp0	-0.066	0.056	-1.190	0.235
Tp1	-0.063	0.074	-0.850	0.394
Tp2	**-0.369**	0.175	-2.110	0.035
Tp3	**-0.316**	0.170	-1.860	0.062

Table 13: Regression Discontinuity of CalEnviroScreen Environmental Justice Score

This table presents the regression discontinuity tests of greenhouse gas emission during the periods 2014 to 2018, which is after the launch of CalEnviroScreen 1.0. Panel A plots the average values and their 95 percent confidence intervals of the level of greenhouse gas emissions for 10 evenly spaced bins of the census block's EJ scores. Panel B presents the regression results of estimating non-parametric local linear regressions with mean squared error optimal bandwidths using the 80th percentile cutoff, following Calonico et al. (2014). *chgGHG* is the changes in the amount of green house gas emission at the facility level between year *t* and year *t*-1. All continuous variables are winsorized at the top and bottom 1% levels. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively. Variable definitions are included in Appendix A.

Panel A. Reductions in Greenhouse Gas Emissions



Panel B. Regression		
	(1)	(2)
VARIABLES	Linear chgGHG	Quadratic chgGHG
Above 80th	-0.317*	-0.365**
	(-1.743)	(-1.973)
Observations	1,854	1,854

Appendix A: Variable Definitions

Variable	Description (Source)
EJIndex_Above80	The percentage of the EJ indexes that are ranked above the 80th percentile of a given year for a given Census Block.
HaveEJIndex_Above80	An indicator variable that equals 1 if at least one of the EJ indexes is ranked above the 80th percentile of a given year for a given Census Block.
AvgEnvIndex	The average scores of all the environmental indicators for a given census block
Demographic Index	The Demographic Index for a given census block, calculated as the mean of the percentage of minimum income population and the percentage of people of color.
lnTRI	The natural log of the amount of toxic chemical releases (in pounds) of a given facility.
lnGHG	The natural log of the amount of green house gas emission (in tons) of a given facility.
Inspect	An indicator variable that equals 1 if a facility is inspected by the EPA at a given year, and equals 0 otherwise.
lnGoogleSVI	The natural log of one plus the annual mean of the monthly Google Search Volume Index of the keyword “” in a given state.
NumNGOActivities	The number of NGO activist campaigns targeting the parent company of a given facility.
NumLocalNewsOutlet	The number of local news outlets in a given state.
CalEJScore	The Environmental Justice Score at the census tract level developed by the CalEnviroScreen.
CalEJScoreAbove80	An indicator variable that equals 1 if the EJ score in CalEnviroScreen is ranked above the 80th percentile at a given year, and equals 0 otherwise.
chgGHG	The changes in the level of total greenhouse gas emissions at the facility level.

Appendix B: EJ Indexes Development

Environmental Indicators	Version	Description
PM2.5	2015	PM 2.5 levels in air measured using an annual average
Ozone	2015	Ozone annual mean top 10 of daily maximum 8-hour concentration in air.
Diesel PM	2015	Diesel PM level in air.
Cancer Hazard Index	2015	Lifetime cancer risk from inhalation of air toxics.
Neurological Hazard Index	2015 (discontinued since 2018)	Ratio of exposure concentration to RfC
Air toxics respiratory HI	2015	Ratio of exposure concentration to health-based reference concentration.
Traffic Score	2015	Count of vehicles (annual average daily traffic [AADT]) at major roads within 500 meters, divided by distance in meters (not kilometers [km]).
Lead paint	2015	Percent of housing units built before 1960in-differences approach. We identify treated facilities as those that are ranked in the high EJ score group and we identify the treatment years as the year when
Superfund Proximity	2015	Count of proposed and listed NPL sites within 5 km (or nearest one beyond 5 km), each divided by distance in km. Count excludes deleted sites.
RMP Facility Proximity	2015	Count of RMP (potential chemical accident management plan) facilities within 5 km (or nearest one beyond 5 km), each divided by distance in km.
Hazardous Waste Proximity	2015	Count of hazardous waste management facilities (TSDFs and LQGs) within 5 km (or nearest one beyond 5 km), each divided by distance in km.
Proximity to Major Direct Water Discharges	2015 (discontinued since 2016)	Count of NPDES major facilities within 5 km, divided by distance
Waste Water Toxic Concentration	2016	Toxic Concentrations at stream segments within 500 meters, divided by distance in km.
UST Proximity	2018	Count of LUSTs (multiplied by a factor of 7.7) and the number of USTs within a 1,500- foot buffered block group.
Toxic Release to Air	2021	RSEI modeled toxicity-weighted concentrations in air of TRI listed chemicals.