Racial Disparities in the Health Effects from Air Pollution: Evidence from Ports

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Abstract

This study examines the uneven effects of air pollution from maritime ports on physical and mental health across racial groups. We exploit quasi-random variation in vessels in port from weather events far out in the ocean to estimate how port traffic influences air pollution and human health. We find that one additional vessel in a port over a year leads to 3.1 hospital visits per thousand Black residents within 25 miles of the port and only 1.1 per thousand for whites. We assess a port-related environmental regulation and show that the policy can help alleviate racial inequalities in health outcomes.

Keywords: air pollution, health, environmental justice, quasi-experiment, instrumental variables, regression discontinuity design.

JEL codes: D63, I14, Q51, Q53, Q58, R41

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1 Introduction

Air pollution is well known to negatively affect human health, most notably by contributing to respiratory and cardiovascular illnesses. More perniciously, the health effects are often unevenly distributed across the population, with some groups facing higher pollution exposures (e.g., Currie, 2011; Colmer et al., 2020; Currie et al., 2020) and worse health outcomes (e.g., Chay and Greenstone, 2003b; Currie and Walker, 2011; Deschênes et al., 2017). There are rising concerns about environmental justice in the United States due to these disproportionate exposures and health outcomes. Indeed, a key plank of President Joseph Biden's campaign platform involved improving environmental and health outcomes for communities of color.[1]

This paper examines racial inequity in health outcomes due to air pollution around a major point source of air pollution: maritime ports.[2] It also explores the sources of this inequity, which could include differences in pollution exposure as well as differing responses to such exposure. Port facilities are especially important to study not only because they produce substantial pollution but also because they tend to be located in highly populated and low-income areas. Around 39 million people live within close proximity to ports in the United States (EPA, 2016), and many are people of color (Houston et al., 2008). For example, Long Beach, California, has one of the largest ports in the country and is 70% non-white. In standard port activities, marine ships, trucks, and cargo-handling equipment often burn highly polluting fossil fuels, such as bunker fuel and diesel fuel. Yet emissions from port activities tend to be poorly regulated in most of the United States, and congestion in ports is as great as it has ever been due to the COVID-19 pandemic-related supply chain challenges.

In this study, we estimate the contemporaneous effects of port activity-related air pollution on physical and mental health, focusing on racial disparities in health outcomes. The analysis consists of three steps. We first leverage quasi-experimental variation from distant oceanic events several days prior that exogenously shift the vessel tonnage or counts in port to identify the causal impact of port traffic on air pollution. The intuition for our identification strategy is that lagged distant storms far out in the ocean will change the path of ships and delay arrivals into port but do not otherwise affect the weather or non-port-related economic activity in areas surrounding the ports.

In the second step, we estimate the causal effect of daily pollution concentrations on hospital visits in port areas using quasi-random variation from the vessel tonnage in ports (as predicted by distant oceanic storms several days prior) and local wind conditions. Our

[1] See https://joebiden.com/climate-communities-of-color/.

[2] Throughout the rest of the paper, we use the term "ports" to refer to oceanic maritime port facilities. We do not consider inland river or lake ports.

results indicate that the health impact on the Black population is three times the impact on the white population (the impact on Hispanics tends to fall in between). We finally use a regression discontinuity design and dynamic simulation to analyze a regulation that reduces fossil fuel use in ports to show how policy can substantially reduce inequality in health outcomes.

We find several compelling results. First, we show that additional tonnage or vessels in port increases pollution concentrations for major air pollutants within a 25-mile radius of the 27 largest ports in the United States. For example, one vessel in port increase fine particulate matter ($PM_{2.5}$) concentrations by 0.53 $\mu g/m^3$, or about 5%. Second, we show that air pollution is responsible for hospital visits related to respiratory, heart, and psychiatric problems near ports, and the Black population is disproportionately impacted. We find that one additional average-tonnage vessel in a port over a year leads to 3.1 hospital visits per thousand Black residents within 25 miles of a major port in California and only 1.1 hospital visits per thousand whites. We also provide evidence showing differences in pollution exposure as well as differences in the response to exposure, indicating that the inequity in hospital admissions likely comes about from both sources. Our results further show that a policy in California to reduce fossil fuel use in ports significantly reduces pollutant concentrations, disproportionately benefiting the Black population. The reduced pollution leads to 5.1 avoided hospital visits per thousand Black residents per year and 2.1 avoided hospital visits per thousand white residents.

This paper makes several important contributions to the literature. The paper contributes to the economic literature on environmental inequalities by demonstrating how a major point source of pollution leads to unequal health outcomes for minority populations and how policy can ameliorate this inequality. This relates to the literature documenting how low-income, minority groups are more likely than other groups to live adjacent to environmental risks, such as Superfund hazardous waste sites (Currie, 2011) and power plants (Davis, 2011). In addition, an emerging body of economic literature shows heterogeneity in the average effects of air pollution exposure on health across races (e.g., Chay and Greenstone, 2003b; Currie and Walker, 2011; Knittel et al., 2016; Alexander and Currie, 2017), age categories (e.g., Schlenker and Walker, 2016; Deschênes et al., 2017; Halliday et al., 2019), or locations (e.g., Jayachandran, 2009). To our knowledge, our paper is the first to examine inequality due to emissions from a highly relevant setting for environmental justice: port facilities. Further, we are the first to explore the mechanisms behind the inequality in our setting, enriching our knowledge of the drivers of unequal health outcomes across racial groups.

Our paper also contributes to the growing literature identifying the relationship between air pollution and human health using quasi-experimental methods (e.g., Chay and Greenstone, 2003a,b; Currie and Neidell, 2005; Currie and Walker, 2011; Deryugina et al., 2019).[3] In many respects, our paper is most conceptually related to studies that estimate the impact of air pollution on health using transportation traffic as the source of variation in air pollution (Moretti and Neidell, 2011; Schlenker and Walker, 2016; Knittel et al., 2016). For example, Moretti and Neidell (2011) estimate the effect of air pollution on respiratory-related hospital visits, using variation in local air pollution from moving vessels in the Port of Los Angeles. Our paper differs in several fundamental ways. Our focus is on racial disparities in health consequences. But equally importantly, our empirical strategy is quite different in using lagged distant storms far out in the ocean as an exogenous source of variation. In this sense, our empirical strategy can be seen as more conceptually similar to how Schlenker and Walker (2016) use congestion in distant airports (possibly caused by weather) to provide an exogenous source of variation in air pollution around airports. In addition, our port traffic measure is more comprehensive in including both moving and docked vessels. Docked vessels are major emitters of air pollution due to diesel-fired auxiliary electricity generators. We also study a large set of ports and health outcomes, and explore whether disparities come about from pollution exposure or the vulnerability to exposure, providing a rich picture of the causal impacts relevant to policy.

Finally, to the best of our knowledge, we provide the first quasi-experimental evidence that short-term exposure to air pollution influences mental health differently across racial groups using patient-level hospital records in the United States.[4] Related work examines the effects of air pollution on a variety of measures of human physical health, including the studies mentioned above, but neglecting mental health impacts underestimates the overall effect of air pollution in a non-negligible way. By including mental health, our work contributes to the broader literature suggesting that air pollution affects human behavior and well-being (Graff Zivin and Neidell, 2013), such as diminished labor productivity (e.g., Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015; Chang et al., 2016; Borgschulte et al., 2018; Chang et al., 2019), reduced cognitive performance (e.g., Sanders, 2012; Ebenstein et al., 2016; Bishop et al., 2018), increased criminal activities (e.g., Burkhardt et al., 2019; Bondy et al., 2020; Herrnstadt et al., 2021), and inflated road accidents (e.g., Sager, 2019). Some of these outcomes, such as criminal activities and road accidents, may even come

[3]Epidemiological studies have also examined the effect of air pollution on human health. This paper contributes to the literature by providing quasi-experimental evidence on the effect of short-run exposure to air pollution on health that addresses several key estimation challenges.

[4]In concurrent related work, Ordonez (2020) estimates the effects of air pollutants from fossil-fuel power plants on mental health in Colombia using a quasi-experimental framework and patient-level records. Zhang et al. (2017) and Chen et al. (2018) find an effect of air pollution on mental health based on stated evidence (i.e., survey data) in China.

about partly due to the impact of air pollution on mental health.

The paper proceeds as follows. Section 2 provides a brief background on port pollution and human health. Section 3 describes our data and descriptive statistics. Section 4 discusses our empirical strategies and identification. Section 5 presents the main empirical results. Section 6 discusses implications for policy, and Section 7 concludes.

2 Background

2.1 Air Pollution in Ports

Ports serve as a primary conduit for global trade and play a significant role in the local economies for many coastal cities (EPA, 2017). The Organisation for Economic Co-operation and Development (OECD) projects that global marine freight will more than quadruple by 2050, and this expansion is expected to increase port activities further.[5] Docked vessels in ports can be one of the dirtiest emitters in terms of local air pollutants, as they often operate auxiliary engines to generate onboard electricity by burning bunker fuel and diesel (Wan et al., 2016). Other diesel-powered activities in ports, such as cargo handling equipment, automated guided vehicles, and short-haul trucks, also emit a substantial amount of air pollution (Agrawal et al., 2009). Hence, ports can be one of the largest contributors to air pollution in surrounding regions.[6] It is notable that approximately 30% of counties in the United States that are currently out of compliance or previously failed to meet the National Ambient Air Quality Standards (NAAQS) either include or are adjacent to major ports (see Figure B.1).[7]

Most ports are located in urban areas with high population density (e.g., Los Angeles and New York), often surrounded by low-income, minority neighborhoods. For example, around 40% of zip codes within a 25-mile radius of the major ports in California are designated as "disadvantaged" communities, with concentrations of people that are of low income, color, high unemployment, and/or low levels of educational attainment.[8] These low-income households and people of color living or working in port areas can

[5] See https://www.itf-oecd.org/sites/default/files/docs/2015-01-27-outlook2015.pdf.

[6] See https://www.latimes.com/california/story/2020-01-03/port-ships-are-becoming-la-worst-polluters-regulators-plug-in.

[7] The National Ambient Air Quality Standards are specified under the Clean Air Act in the United States, which determines maximum allowable concentrations of criteria air pollutants that have been proved to be harmful to human health.

[8] Disadvantaged communities in California are often disproportionately impacted by environmental hazards. They are determined based on Senate Bill 535 (SB 535). The bill requires a proportion of the revenue from the Cap-and-Trade program auction to be allocated to projects that benefit disadvantaged communities. The designation of disadvantaged communities uses the CalEnviroScreen tool, a scoring system with several factors: pollution burden and socioeconomic characteristics.

be significantly impacted by air pollution (Houston et al., 2014). Many studies have consistently documented differences in air pollution exposure across socioeconomic groups (see recent reviews in Mohai et al., 2009; Banzhaf et al., 2019a,b; Hsiang et al., 2019), and ports are likely one contributing factor for these differences.

2.2 Air Pollution and Health

Air pollution is well known to be detrimental to human health (Dockery et al., 1993). Breathing in polluted air can affect lung development and cause respiratory diseases (Dockery and Pope III, 1994), such as asthma and chronic obstructive pulmonary disease (DeVries et al., 2017; Wang et al., 2019). Epidemiologists have also established an association between air pollution and cardiovascular disease (Seaton et al., 1995), including impairing blood vessel function (Riggs et al., 2020), speeding up artery calcification (Keller et al., 2018), and increasing risk of hemorrhagic stroke (Sun et al., 2019). Moreover, studies have shown an association between air pollution and breast and lung cancer (Cheng et al., 2020).

A growing number of economic studies use quasi-experimental methods to estimate the causal effects of air pollution exposure on human health, using health metrics such as infant mortality and birth outcomes (e.g., Chay and Greenstone, 2003b; Currie and Neidell, 2005; Currie et al., 2009; Currie and Walker, 2011; Sanders and Stoecker, 2015; Arceo et al., 2016; Alexander and Schwandt, 2019), adult mortality (e.g., Deryugina et al., 2019; Anderson, 2020), respiratory problems (e.g., Moretti and Neidell, 2011; Schlenker and Walker, 2016), and cardiovascular diseases (e.g., Schlenker and Walker, 2016; Halliday et al., 2019). While the focus of much of the literature has been on physical health, there is growing epidemiological work showing an association between air pollution and mental health (e.g., Sass et al., 2017; Kim et al., 2018; Brokamp et al., 2019).

Air pollution could adversely affect mental health through several channels. Air pollution can lead to neuroinflammation and oxidative stress linked to anxiety, depression, and cognitive dysfunction (Sørensen et al., 2003; Salim et al., 2011). In addition, people tend to reduce outdoor activities due to pollution, which may induce mental disorders through pathways such as vitamin D deficiency from limited access to sunlight (Anglin et al., 2013), reduced exercise (Suija et al., 2013), restricted access to green space (Cohen-Cline et al., 2015), and less social support (George et al., 1989). Moreover, some studies suggest that worsened physical health caused by air pollution exposure may also lead to fear and stress, which increases anxiety and other mental illnesses (Scott et al., 2007).

3 Data and Descriptive Statistics

This paper compiles a comprehensive data set from multiple sources on port traffic, air pollution, health, local weather, and major oceanic storms.

3.1 Port Traffic

We obtain port data from the US Army Corps of Engineers (USACE) for 2001–2016. The data contain dates on which ships enter and exit from ports, including container ships, bulk carriers, tanker ships, and passenger ships. We match the entrance and clearance records for each vessel visit based on vessel names or identity numbers, from which we can approximate the number of days a vessel is at berth in a port.[9] For each date in a port, we then calculate gross vessel tonnage and the number of vessels, which serve as the core port traffic measures for this study. Since different vessel types have different sizes and weights, the calculated gross vessel tonnage variable represents vessel heterogeneity to some extent.

One minor weakness of these data is that USACE mainly tracks waterborne transportation originating from or heading to foreign ports and does not have complete coverage of ships traveling between domestic ports. According to the Bureau of Transportation Statistics, foreign waterborne freight accounts for 85–90% of total shipping tonnage in maritime ports in the United States.[10] Hence, the USACE data should be a reasonable representation of total vessel tonnage in the included ports in this study, even if it misses a small fraction of the tonnage. This minor caveat about our data is analogous to one in Schlenker and Walker (2016), where the data set they use for airport traffic only accounts for major domestic airline passenger travel.

Table A.1 contains the summary statistics of daily vessel tonnage and counts. In our final data set, we focus on the 27 major maritime ports in the United States, six of which are in California.[11]

3.2 Air Pollution

We obtain daily air pollution concentration data from US Environmental Protection Agency (EPA) Air Quality System (AQS) for five local air pollutants, carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), $PM_{2.5}$, and sulfur dioxide (SO_2), for 2001–2016. The data contain

[9] The data contain some unmatched vessel entrance or clearance records. We treat these entries as a single day in port since most vessels in the data sample enter and exit from ports on the same day.

[10] This estimate is obtained from https://www.bts.gov/content/us-waterborne-freight.

[11] The six major California ports are the Ports of Long Beach, Los Angeles, Oakland, San Diego, Hueneme, and San Francisco.

daily maxima and means of pollution concentrations at the pollution monitoring site level.[12]

Due to advancements in remote sensing technology and machine learning models, researchers are now able to predict granular air pollution concentrations by integrating satellite imagery, chemical transport models, pollution monitor data, land cover, and meteorological data. We obtain daily zip code-level satellite-based $PM_{2.5}$ projection data from Reid et al. (2021), primarily used for robustness checks. The data set includes three projections using various machine learning algorithms: the Ranger algorithm, the extreme gradient boosting tree algorithm, and the generalized linear model that combines the results from the previous two algorithms. We select the data from the third method.

3.3 Health

We obtain patient-level administrative data from the California Office of Statewide Health Planning and Development for 2010–2016. These include three types of data: Patient Discharge Data (PDD), Emergency Department Data (EDD), and Ambulatory Surgery Center Data (ASCD). The PDD consists of overnight stays from all California hospitals. The EDD and ASCD keep track of patients who had single-day emergency treatment in an Emergency Room or licensed freestanding Ambulatory Surgery Centers. Any patient initially logged in the EDD/ASCD that is subsequently admitted to a hospital for overnight stays is dropped in the EDD/ASCD and then added to the PDD to eliminate double-counting and ensure consistency.

These three data sets provide dates for hospital visits, the zip codes of home addresses, demographics (age, sex, and race), one principal diagnosis, and up to 24 secondary diagnoses. In our primary specification, we pool the three data sets and count the daily number of hospital visits at each zip code for patients who had either a principal or secondary diagnosis related to the health problems examined in this paper.[13] We then merge in population data from the 2010 US Census.[14] We next calculate the daily hospital visit rate at the zip code level, indicating the number of hospital visits per million residents per day. We focus on hospital visits of six categories of illnesses: respiratory (asthma, acute upper respiratory, all respiratory), mental (anxiety, all psychiatric), and heart-related. We

[12]The EPA AQS reports various daily means with different time windows that air passes through the monitoring device before it is analyzed. For example, for CO at certain monitoring sites, there are one-hour and eight-hour run daily averages. We take averages for each monitor and day.

[13]We conduct several robustness checks by exploring only principal diagnoses and each of the three data sets separately.

[14]US Census data is based on the zip code tabulation area (ZCTA), so we merge in based on the ZCTA. We exclude the ZCTAs with fewer than 5,000 residents (or those with fewer than 1,000 residents in each socioeconomic group for heterogeneity analysis), which only accounts for 2% of the total California population. For the remainder of the paper, we refer to 'zip codes' for simplicity.

also include two diseases for placebo checks: arterial embolism (i.e., stuck blood clots) and appendicitis.[15] Figure B.2 illustrates that our sample includes large sections of the largest urban areas in California.

3.4 Weather

We acquire weather data from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database for 2001–2016. We construct daily measures of weather variables from hourly readings at the weather station level. These variables include dew point, minimum and maximum temperatures, precipitation, wind speed, and wind direction. The minimum and maximum temperatures are the lowest and highest hourly readings in a day, and the daily precipitation is the summation of hourly records.[16] We then calculate daily means for dew point temperature, wind speed, and wind direction. The wind direction blowing north is normalized to zero, and it increases up to 360 degrees clockwise.

3.5 Tropical Cyclones

Tropical cyclones are rapidly rotating storms that originate in the tropical oceans. Those occurring in the northeastern Pacific Ocean or the Atlantic Ocean are called hurricanes, while those in the northwestern Pacific Ocean are called typhoons. We obtained data on the 578 tropical cyclones near the United States from 2001-2016 from the NOAA National Hurricane Center. The data track dates, times, center locations, maximum wind, central pressure, and wind radii of historical cyclones every six hours in the Northeast and North-central Pacific Ocean and the Atlantic Ocean.

Figure 1(a) shows all hurricanes that occurred in 2016 and the locations of the 27 major ports in the United States. The figure shows that cyclones can strike ports, which may directly impact local weather and air pollution. Our primary results only use data when cyclones are at least 500 miles away from the 27 major ports. We chose 500 miles because cyclones are documented to have a typical radius in the range of 125–310 miles, so we can be assured that the ports are well outside the scope of the cyclones included in our study.[17]

[15]The administrative data sets adopt what are called 'ICD codes' to record diagnoses. In October 2015, the codes were upgraded from ICD-9-CM codes to the ICD-10-CM codes. Table A.2 presents the ICD codes for this study. The codes that fall into the psychiatric categories follow Brokamp et al. (2019) by excluding those associated with suicides. The table also presents the corresponding Medicare Severity Diagnosis Related Group (MS-DRG) codes for calculating the medical costs of illnesses from the Medicare data.

[16]For missing hourly precipitation readings, we assume they are the same as the most recent available reading.

[17]See https://public.wmo.int/en/our-mandate/focus-areas/natural-hazards-and-disaster-risk-reduction/tropical-cyclones.

The path of cyclones at least 500 miles away from ports can be seen in the colored dotted lines in Figure 1(a).

Tropical cyclones are especially useful for our study because they can dramatically affect the number of ships and gross tonnage in port. For example, StormGeo—a global weather service provider—observes that "[t]ropical cyclones [raging in the ocean] have an enormous impact on ships and shipping logistics. Entire supply chains can be disrupted when ships are delayed due to the presence of a cyclone."[18] To illustrate this effect, Figure 1(b) shows how two paths of ships headed for US ports were taken off track by Hurricane Leslie from August 30 to September 12, 2012. Typically, vessels would take the efficient routes following the shortest distances (the dashed lines) to travel between ports. In this case, we have ships traveling from the Port of Marseille, France, to the Port of Houston and the Port of Santos, Brazil, to the Port of New York and New Jersey. Around September 8, 2012, the vessels took longer alternative routes (the solid lines) to avoid Hurricane Leslie, which led to additional transit time and delays in reaching their final destinations. This influence of distant storms on shipping paths will provide an exogenous source of variation in our study, as will be discussed.

3.6 Data Compilation

We compile two data sets for this study. For the analysis of air pollution, we construct the data at the paired monitor-port level with the following steps: (1) we map all pollution monitors within a 25-mile radius of the 27 major ports;[19] (2) we calculate the Vincenty distance and direction between a monitor and its mapped port based on their latitudes and longitudes;[20] (3) we select all weather stations within a 50-mile radius of pollution monitors and calculate inverse distance-weighted averages of weather measures at the monitor level; and (4) we calculate the relative wind direction between a monitor and a port to determine whether a monitor is downwind or upwind of its paired port, i.e., the difference in angles between the wind direction observed at a monitor and a perpendicular ray from the port to the monitor.

[18]See https://www.stormgeo.com/products/s-suite/s-routing/articles/the-effects-of-tropical-cyclones-on-shipping/.

[19]In our data set, a monitor can be mapped to multiple ports, since ports can be close to each other (e.g., Ports of Los Angeles and Long Beach).

[20]Vincenty distance is a commonly used distance measure between two points on the surface of a spheroid developed by Thaddeus Vincenty (for examples of economics papers adopting this distance measure, see Auffhammer and Kellogg (2011) and Currie et al. (2017)). The distance measure assumes that the shape of the Earth is an oblate spheroid, which is more accurate than other distance measures, such as great-circle distance, which assume a spherical Earth.

For our analysis of health impacts, we construct the data at the paired zip code-port level with similar steps: (1) we select all zip codes within a 25-mile radius of the six major ports in California; (2) we calculate the Vincenty distance between a paired zip code and port; (3) we calculate the zip code-level pollution measures by taking inverse distance-weighted averages of the monitor-level data within 25 miles of zip code centroids; (4) we calculate zip code-level weather measures by selecting all weather stations within 50 miles of zip code centroids and take inverse distance-weighted averages.

Table 1 contains the summary statistics for the main variables in this study, with hospital visit rates broken down by race. Tables A.3–A.7 present the supplementary summary statistics of pollution and hospital visit rates for various slices of the data.

3.7 Descriptive Statistics on Racial Disparities

Before diving into the empirical modeling, we present descriptive statistics on racial disparities in pollution exposure and hospital visits near ports in California. Following Currie et al. (2020), we primarily focus on comparing non-Hispanic white and Black populations. The Hispanic ethnic identity is often described as more fluid over time than non-Hispanic white or Black groups, which may introduce measurement errors in comparing Hispanics and non-Hispanics (Liebler et al., 2017). However, for the interested reader, we also present some descriptive statistics for Hispanics in Figure B.3.

Figure 2(a) shows distributions of the Black and white populations residing in California port areas by distance to their nearest mapped ports. We observe that the Black population tends to live closer to ports, while the white population is more uniformly distributed, suggesting that ports may disproportionately impact Blacks simply due to differences in exposure to air pollution.

Figure 2(b) presents distributions of populations for the two racial groups by percentile of mean $PM_{2.5}$ exposure at the zip code level over 2010–2016. We see that Blacks live in areas that are exposed to higher pollution concentrations than whites. As further evidence, Table A.8 presents the average pollution exposure for Blacks and whites in port areas, weighted by the population of each race at the zip code level.[21] The evidence indicates that Blacks face substantially higher exposure to air pollution in areas around ports than whites.

[21]This analysis focuses on differences in exposure across zip codes and ignores any within-zip code differences in exposure, so it may slightly underestimate disparities in pollution exposure. That said, this approach is standard in the literature (see a review of this approach in Banzhaf et al. (2019b)). Figures B.4 and B.5 further illustrate the locations of $PM_{2.5}$ monitors and ports, computed average pollution concentrations, and race-specific population shares at the zip code level surrounding two major urban areas in California.

Next, we examine the racial gaps in health outcomes. Figure 3 plots probability density functions of annual hospital visit rates for the Black and white populations for zip codes within 0–12.5 miles to ports and zip codes within 12.5–25 miles to ports. In both panels, the distributions for the Black population lie to the right of the distributions for whites. The gaps in mean hospital visit rates between Blacks and whites become slightly wider closer to ports. Further, Figure B.6 shows that annual air pollution exposure for individuals visiting hospitals is notably higher for Blacks than whites. These figures provide descriptive evidence of racial disparities in pollution exposure and health outcomes in port areas.

4 Empirical Strategy

4.1 Effect of Vessels in Ports on Air Pollution

We begin our analysis by estimating the effect of port traffic on daily air pollution concentrations. Our empirical specification is as follows:

$$P_{ipt} = \beta V_{pt} + \mathbf{X}_{it}\theta + \delta_t + \mu_{ip} + e_{ipt}, \tag{1}$$

where P_{ipt} refers to local air pollutant concentrations at monitor i that is mapped to port p on day t. The variable V_{pt} is either the gross vessel tonnage or the number of vessels in port. The set of variables $\mathbf{X}_{it}$ includes weather controls consisting of maximum, minimum, and dew point temperatures; precipitation; wind speed; and relative wind direction (indicating whether a monitor is downwind or upwind of the mapped port). $\mathbf{X}_{it}$ also includes quadratic terms for each of the weather controls (except for the relative wind direction). We incorporate temporal fixed effects δ_t that consist of county-by-year, month, day-of-week, and holiday fixed effects.[22] Since there may be unobserved time-invariant effects, we further include monitor-port fixed effects μ_{ip}. e_{ipt} is the error term. The parameter of interest, β, can be interpreted as the effect of port traffic on local air pollutant concentrations for a given day.

There are several potential concerns in estimating equation (1) using ordinary least squares (OLS) that may lead to biased estimates of β. One concern is that there may be some measurement error in the port traffic measures because we observe vessels originating from or heading to foreign ports (85-90% of tonnage), so we miss some vessels in our analysis. A second concern is the possibility of omitted variables, such as unobserved economic or weather factors that affect port traffic and local air pollution.

[22] The holidays include New Year, Martin Luther King Jr. Day, Presidents Day, Memorial Day, Independence Day, Labor Day, Columbus Day, Veterans Day, Thanksgiving, and Christmas, as well as the three-day prior and post the holiday.

To address these concerns, our empirical approach leverages quasi-random variation from distant tropical cyclones several days prior to the day under consideration. Specifically, we instrument for V_{pt} using the existence of lagged tropical cyclones far out in the ocean. As mentioned above, these cyclones often disrupt travel for marine vessels, delaying their arrival into ports, leading to fewer ships and less tonnage in ports several days later (recall Figure 1). The first stage relies on this disruptive impact on shipping.

To be precise, the first stage of our instrumental variables approach is:

$$V_{pt} = \alpha TC_{t-m} + \mathbf{W}_{ipt}\lambda + \epsilon_{ipt}, \tag{2}$$

where TC_{t-m} is an indicator variable equal to one if there are one or more tropical cyclones far out in the ocean (i.e., at least 500 miles away from ports) on day $t - m$. We use a seven-day lag ($m = 7$) in our primary specification, but we run robustness checks with different lags. A cyclone can last anywhere from a few days to weeks. Thus, to create this lagged variable, we first identify the days when there are one or more cyclones that are at least 500 miles away from ports, and then take the seven-day lag.[23] The variable $\mathbf{W}_{ipt}$ includes the exogenous variables defined in equation (1): weather controls, temporal fixed effects, and monitor-port fixed effects.

To be a valid instrument, TC_{t-m} must satisfy the exclusion restriction, i.e., it is uncorrelated with the error term e_{ipt} in equation (1).[24] A direct threat to the exclusion restriction would be if the tropical cyclones hit the ports several days later, directly affecting pollution. We avoid this concern by removing the observations for the days when cyclones appear within a 200-mile radius of ports. We also remove observations two days prior and after the cyclones are within a 200-mile radius. Further, we perform a robustness check removing all observations within 21 days after a cyclone is last within 200 miles of ports in case it takes ports weeks to recover after a storm.

Another concern could be that lagged distant cyclones not only impact vessel tonnage or counts in ports but also substantially influence the composition of vessels, which may, in turn, affect air pollution in ports. Figure B.7 shows that lagged tropical cyclones far out in the ocean do not appear to have any notable effect on the composition of vessel types in ports. In addition, when a storm is slated to arrive at a port, vessels tend to depart earlier to avoid or weather the storm at sea and avoid potential collisions, so later departures should not be a threat to identification.

[23]The choice of seven days is motivated both because it is a week after the storm was out at sea and because we observe a drop in vessel tonnage in ports seven days later.

[24]We expect lagged distant tropical cyclones always to reduce the number of vessels and gross tonnage in ports, so the monotonicity condition should hold.

A more modest threat could be if lagged tropical cyclones far out in the ocean sufficiently impact meteorological patterns that they indirectly affect current-day weather in the ports. We explore this by dividing the sample into month-days when $TC_{t-7} = 1$ and those when it is zero. Figure 4 shows distributions of the six weather variables across the two subsamples.[25] The distributions between the two grouped samples are almost identical, confirming that the weather in the ports is no different when there are tropical cyclones in the distant ocean seven days prior than when there are not.[26]

Thus, for there to be remaining identification concerns, there would have to be some other localized source of air pollution that happens to be correlated with distant storms seven days earlier. This seems unlikely to us. But we will also perform a placebo test and a set of robustness checks to further support the instrument's validity.

4.2 Effect of Air Pollution on Health

To estimate the relationship between air pollution and health outcomes in port areas, we specify the following linear regression model for the overall population and separately for Blacks and whites:

$$y_{ipt} = \beta P_{ipt} + \mathbf{X}_{it}\theta + \delta_t + \mu_{ip} + e_{ipt}, \tag{3}$$

where y_{ipt} is the hospital visit rate (i.e., hospital visits per million residents) associated with an illness in zip code i that is mapped to port p on day t. The variable P_{ipt} is the air pollutant concentration. We run the regression separately for each of four pollutants—CO, NO_2, $PM_{2.5}$, and SO_2—that are shown to be detrimental to human health.[27] Because these pollutants have different scales, we standardize them by their sample means and standard deviations to facilitate comparisons. In an extension in Section 5.4, we also consider including sets of these pollutants that might be co-emitted. The remaining variables are similar to those specified in equation (1), where $\mathbf{X}_{it}$ is a set of weather controls (not including wind variables). δ_t is the set of temporal fixed effects. μ_{ip} denotes zip code-port fixed effects, which are especially useful for controlling for time-invariant factors that affect health and pollution levels (e.g., poor households with lower baseline health have previously sorted into in polluted areas). The coefficient of interest β indicates the effect of a one-unit increase in air pollution concentrations on the daily hospital visit rate associated

[25] Because the number of observations in the two subsamples is different, we randomly draw a subset of observations in the second subsample, so the number of observations is the same between the samples, but statistical tests of differences in means are no different if we use the each of the full subsamples.

[26] To provide further evidence, Table A.9 presents the standardized mean differences, variance ratio, and Kolmogorov-Smirnov statistics for the weather variables.

[27] In this choice of pollutants to study, we follow the existing evidence of the health effects of common air pollutants (e.g., Dominici et al., 2006; Bell et al., 2008; Brokamp et al., 2019).

with an illness.

However, estimating equation (3) using OLS may still lead to a biased estimate of β. One potential concern is that exposure to air pollution is not randomly assigned to residents, and thus people with preferences for better air quality may adjust their daily activities based on pollution forecasts. Another potential concern is that there may be measurement errors in pollution exposure. Our pollution measures at the zip code level may deviate from residents' actual exposure since we do not observe their exact home addresses, and people are also unlikely to be stationary all the time. In addition, there may be time-varying omitted variables correlated with both air pollution and health.

To address these concerns, we employ an over-identified instrumental variables approach (Knittel et al., 2016; Schlenker and Walker, 2016; Deryugina et al., 2019), where the first-stage regression is specified as:

$$\begin{aligned} P_{ipt} =& \alpha_1 \widehat{V}_{pt} + \alpha_2 WS_{it} + \sum_{s=1}^{7} \alpha_{3s} WD_{it}^{s} + \alpha_4 \widehat{V}_{pt} \times WS_{it} + \sum_{s=1}^{7} \alpha_{5s} \widehat{V}_{pt} \times WD_{it}^{s} + \\ & \sum_{s=1}^{7} \alpha_{6s} WS_{it} \times WD_{it}^{s} + \sum_{s=1}^{7} \alpha_{7s} \widehat{V}_{pt} \times WS_{it} \times WD_{it}^{s} + \mathbf{W}_{ipt}\lambda + \epsilon_{ipt}. \end{aligned} \tag{4}$$

In this equation, WS_{it} represents wind speed. WD_{it}^{s} is an indicator variable for wind direction, which is equal to one if the daily mean wind direction in zip code i falls in each 45-degree interval [45s, 45s+45), where $s \in \{1, ..., 7\}$ is the interval.[28] The variable $\widehat{V}_{pt}$ is the fitted vessel tonnage in port p on day t, which is obtained using the following regression:

$$V_{pt} = \sum_{p} \gamma_p \mathbb{1}_p \times TC_{t-m} + \xi_{pt}, \tag{5}$$

where TC_{t-m} is the tropical cyclone indicator variable. The variable $\mathbb{1}_p$ is an indicator for port p, which allows the effect of the instrument to vary across locations.

The intuition for the identification in this empirical strategy is that we are isolating and leveraging the variation in vessel tonnage that comes about because of distant tropical cyclones several days prior.[29] This approach avoids using any variation in vessel tonnage related to factors that may also influence hospital visit rates. For example, people

[28] We exclude the interval [0, 45) in regressions as the base, and no observations fall in the interval [315, 360) in our data set, so this interval is also excluded. $\mathbf{W}_{ipt}$ includes the same weather controls (except for wind direction and wind speed) and fixed effects as in equation (2).

[29] Wooldridge (2002, p. 117) discusses the assumptions for using fitted variables as instruments, which requires the exogenous regressors for generating fitted instruments to be orthogonal with the error term in the main estimation equation, i.e., equation (3). See Dahl and Lochner (2012) and Schlenker and Walker (2016) for recent papers using fitted variables as instruments.

may observe or possess information about port traffic and adjust their activities and pollution exposure accordingly. For there to be a remaining identification concern, one must believe that tropical cyclones in the distant ocean several days prior influence hospital visits in areas around ports through a channel outside of port traffic. This seems unlikely.

Our specification also includes local wind direction and wind speed in the set of instruments, which adds statistical power because local wind affects the spatial distribution of air pollutants. A large body of meteorological literature has shown that wind direction and speed are strong predictors of local pollutant concentrations (e.g., Chaloulakou et al., 2003; Kukkonen et al., 2005; Karner et al., 2010). Based on this scientific evidence, a growing number of studies in the economics literature exploit variation in local wind as the driver for air pollution (e.g., Moeltner et al., 2013; Schlenker and Walker, 2016; Keiser et al., 2018; Deryugina et al., 2019; Bondy et al., 2020; Anderson, 2020; Herrnstadt et al., 2021).

5 Results

5.1 Effect of Vessels in Port on Air Pollution

We begin our analysis by demonstrating a causal relationship between port traffic and air pollution. We estimate the model given in equation (1) using two-stage least squares, with the existence of distant tropical cyclones seven days prior as the instrument. We perform this estimation using all 27 major ports in the United States. The standard errors are two-way clustered by monitor-port and day.[30]

In the first stage, we estimate equation (2). We find a strong first-stage relationship, consistent with lagged distant tropical cyclones affecting vessel tonnage and the number of vessels. The first-stage F-statistics reported in Panel A of Table 2 range from 13 to 35.[31] These are well above standard thresholds for weak instruments to be a concern (e.g., Andrews et al. (2019) suggest that instruments are weak below a threshold of ten). The point estimates shown in Table A.10 are all significant, indicating that the existence of lagged distant tropical cyclones results in 20,000 metric ton (Mt) less tonnage (or 0.5 fewer vessels) in ports per day.[32] We also present two tests for weak instruments, the Anderson-Rubin Wald statistic and the related Stock and Wright (2000) LM S statistic. The null hypothesis of the two tests is that the coefficient of the endogenous variable is equal to

[30]We cluster by monitor-port because we exploit the relative wind direction between a port and monitor, and a monitor can be mapped to multiple ports.

[31]All first-stage F statistics reported in this paper are cluster-robust Kleibergen-Paap Wald F statistics (Kleibergen and Paap, 2006), which are much smaller than the standard Cragg-Donald Wald F statistics assuming i.i.d. errors (not reported in the paper) (Cragg and Donald, 1993).

[32]The specifications are the same across the columns. The number of observations differs across columns due to the minor differences in data availability for each pollutant.

zero in the structural equation (i.e., we have a weak instrument). The p-values for these two tests indicate that the null hypothesis is rejected at the 1% or 5% levels for most columns.

Estimating the second stage shows the effect of port traffic on the concentration of the four major air pollutants, which are shown in Panel A of Table 2. Each entry is a separate estimation. Columns (1)–(4) show the results using vessel tonnage as the covariate of interest, while columns (5)–(8) shows the results using the number of vessels as the covariate of interest. Using vessel tonnage accounts for the fact that larger ships with greater capacity are more likely to have greater emissions. In contrast, using the number of vessels allows for a straightforward interpretation by quantifying the effect of an average ship. Hence, we show both. All results include county-by-year, day-of-week, holiday, and monitor-port fixed effects.

The results in Table 2 show a significant effect of both vessel tonnage and the number of vessels on pollution concentrations for CO, NO_2, $PM_{2.5}$, and SO_2 in the US port areas.[33] Looking across the columns, we find that a 100,000 Mt increase in vessel tonnage in a port in a day results in an increase of 23.19 ppb for CO (4.6%), 1.17 ppb for NO_2 (8.6%), and 1.2 $\mu g/m^3$ for $PM_{2.5}$ (11.3%) within a 25-mile radius of the port. The results in Panel B can help to contextualize the results better and indicate that one additional vessel in a port in a day results in a 10.65 ppb increase in CO (2.1%), a 0.54 ppb increase in NO_2 (4%), and a 0.53 $\mu g/m^3$ increase in $PM_{2.5}$ (about 5%). The estimates associated with SO_2 are not significant, largely due to the international policy restricting marine fuel sulfur content that started in 2005. When using a subsample of earlier years, the estimate for SO_2 becomes significant, as shown in Table A.12.

We also estimate the model given in equation (1) using OLS for comparison purposes, as shown in Panel B of Table 2. The estimated coefficients are smaller than those in Panel B, and not all are significant. The smaller values of these coefficients may be the result of bias due to measurement error or other confounding factors (see Schlenker and Walker (2016), Deschênes et al. (2017), and Deryugina et al. (2019) for similar findings).

In contrast to the pollutants in Table 2, O_3 is a secondary pollutant, which is formed through complex chemical reactions with NO_x and volatile organic compounds (VOCs) in the presence of warm temperatures and sunlight.[34] Yet O_3 is well-known to negatively affect human health (Auffhammer and Kellogg, 2011). We thus conduct the same analysis for O_3 in Table A.13 to more deeply understand how port traffic influences important air

[33]Table A.11 presents the corresponding results using the subset of California ports, since we restrict our analysis of health effects of pollution to the California port areas due to data availability.

[34]NO_x is a generic term for chemical compounds of oxygen and nitrogen (i.e., mainly NO and NO_2) that are related to the formation of smog, acid rain, and ozone. Similarly, SO_x are chemical compounds of oxygen and sulfur, such as SO_2.

pollutants. The estimates are negative but insignificant. This may be driven by increases in NO_x from port traffic (shown in Table 2), which can also interact with existing O_3 in the air and in some cases actually reduce the total O_3 concentrations (Sillman, 1999; Seinfeld and Pandis, 2016; He et al., 2020).[35] In the remainder of the paper, we focus on the four criteria air pollutants (CO, NO_2, $PM_{2.5}$, and SO_2), noting that they can all affect human health via channels separate from O_3.

The increase in pollution from added port traffic can be interpreted as the combined effect from the direct emissions from the additional vessels in port and the indirect emissions due to the complementary activities associated with handling goods from the ship. For example, cargo handling equipment and short-haul trucks are often powered with diesel fuel and can be expected to add to the emissions from the ship itself. While there are no other estimates exactly like ours in the literature, the US Environmental Protection Agency estimates that emissions associated with marine traffic account for 7–61% of NO_x and SO_x in certain port areas (EPA, 2003). In a rough calculation, our estimates suggest that marine shipping in the 27 major ports in the United States contributes 36% of NO_2 within a 25-mile radius (see Appendix C.1).

5.2 Racial Disparities in the Effects of Air Pollution on Health

We now turn to the effects of air pollution on health outcomes—and how they differ by race. We estimate the model given in equation (3) separately for the overall population, Blacks, and whites using two-stage least squares, where we instrument for air pollution using the fitted vessel tonnage and local wind conditions.[36] We perform this estimation using the data from California to leverage our hospital admissions data. The pollutant concentrations are standardized by their sample mean and standard deviation. The standard errors for the health analysis are clustered by zip code-port and day.

Table 3 presents the results of the second stage of the instrumental variables estimation, showing the effect of increased air pollutant concentrations on hospital visits per million residents for respiratory, heart, and psychiatric problems. Panel A shows the results for the overall population within 25 miles of port facilities, while Panels B and C show the results for Blacks and whites, respectively.[37] Each estimate represents an individual regression.

[35]This finding is different from Moretti and Neidell (2011), where port traffic results in an increase in O_3 concentrations in the port areas of Los Angeles. This discrepancy may be due to different studied locations. Auffhammer and Kellogg (2011) show that southern California, including Los Angeles, tends to be VOC-limited for O_3 formation (the opposite is NO_x-limited), where the NO_x concentrations are relatively high, and increases in NO_x emissions may not change O_3 concentrations. Our study covers a larger set of port locations that likely consists of both NO_x-limited and VOC-limited areas.

[36]We obtain fitted vessel tonnage from equation (5) using all 27 US ports from 2001 to 2016.

[37]Tables A.14–A.16 also present more details behind the compiled Table 3, including adjusted R^2 and the

The results in Panel A show significant effects of all four pollutants we are studying on hospital visits for the overall population. For example, a one standard deviation increase in CO leads to an additional 10.46 visits for all respiratory illnesses, 3.16 visits for all heart-related diseases, and 1.87 visits related to all psychiatric conditions (per million residents per day). The effects of a one standard deviation increase in SO_2 are the largest. There are apparent effects of NO_2 and $PM_{2.5}$ as well, but they are an order of magnitude smaller than SO_2. The results for psychiatric disorders are especially notable as there are no similar causal estimates in the literature. For respiratory and heart ailments, we find that our results are roughly in line with the literature, although somewhat smaller than some estimates and larger than others, depending on the exact health effect and pollutant (see Appendix C.1). This may not be surprising because we are focusing on the area around ports, which may be different than other areas.[38]

The results in Panels B and C of Table 3 show striking differences in hospital visits between Blacks and whites. The rate of hospital visits per million residents is more than double for Blacks than for whites in nearly all categories of pollutants we study. For instance, there are only 9.0 visits related to respiratory illnesses per million residents due to a one standard deviation increase in SO_2 exposure for whites, and 39.1 for Blacks. The rate of heart ailments is also higher for Blacks. While we showed an economically and statistically significant effect of air pollution on psychiatric-related hospital visits for the overall population nearby ports, the effects are not significant when using only the Black subsample, possibly due to the smaller sample size. On the white subsample, we observe significant results (at the 5–10% levels) similar to those in the overall results for the all psychiatric category.[39]

Because Blacks and whites may have differences in baseline health, we estimate the elasticities of the effect of pollution on hospital visits, where hospital visit rates and

numbers of observations. Importantly, the test statistics show that we again have a strong first stage. For the pooled estimation, the first-stage F-statistics range from 28 to 79. The first stage is also strong when we split the sample by race (Tables A.15 and A.16). In addition, the p-values from the Anderson-Rubin and Stock-Wright tests help us further rule out the presence of weak instruments. Because there are in total 35 variables (including interaction terms) in the first-stage estimation, we do no show the estimated coefficients in tables. Instead, Figure B.8 presents the adjusted predictions of pollutant concentrations with respect to wind direction and wind speed based on the first-stage regressions of equation (4). The results show that as wind speed increases, pollutant concentrations decrease for most wind directions. At each wind speed level, the wind direction categories [0, 45) and [45, 90) seem to have larger effects (either positive or negative) on pollutant concentrations.

[38] Table A.17 presents the OLS estimates for the same specifications. Some OLS estimates are insignificant, and nearly all OLS estimates have a smaller magnitude than their corresponding instrumented estimates.

[39] Figure C.1 presents results using the recentered influence function approach pioneered by Firpo et al. (2009) and used recently by Currie et al. (2020). Appendix C.2 provides more details on this approach. We find that most air pollutants have a much larger impact on Blacks than whites at the upper quantiles of the distribution of hospital visit rate, providing deeper insight into our primary results.

pollution measures are scaled by the inverse hyperbolic sine (IHS) transformation. The IHS transformation has a similar interpretation as a logarithmic transformation, but zeros are defined. The estimates can be interpreted as percentage changes in the hospital visit rate due to a one percent increase in pollutant concentrations. Table A.18 shows that most elasticities associated with respiratory and heart illnesses are statistically significant and most estimates are greater for Blacks than whites, especially for upper respiratory ailments.

A natural question is whether there is a statistically significant difference between Blacks and whites. We perform a statistical test to examine the equality of the estimates across Blacks and whites.[40] The test results in Table A.19 show that the differences between Blacks and whites are positive for all ailments and significant for respiratory ailments, indicating that respiratory issues are the underlying driver of the racial disparities. We also estimate (3) using differences in hospital visit rates between Blacks and whites as the dependent variable, restricting the data to zip codes with hospital visits for both Blacks and whites (Table A.20). We again observe that the differences in respiratory issues are positive and significant.

While the focus of this paper is the racial gap between Blacks and whites, we also estimate the effects of air pollution on hospital visits for Hispanics, which are shown in Table A.21. When compared to the results in Table 3, Hispanics have higher hospital visit rates associated with respiratory ailments than whites but lower rates than Blacks. We also observe significant estimates associated with psychiatric illnesses for Hispanics.[41]

When interpreting these estimates, it is also important to keep in mind several crucial points. The estimated health effects may not be entirely attributable to a single pollutant since some pollutants may be co-emitted with others. In an extension, we also estimate the joint effects of certain pollutants on hospital visit rates, presented in the next subsection. Another crucial point is that some people who are ill may choose not to visit hospitals due to restricted access to medical resources or the opportunity costs of spending time in a hospital. Some hospital visits may also be pre-scheduled. These are common caveats in the literature using hospital visit data.

Another important point is that these estimates of health effects focus on the contemporaneous effects of air pollution on health. There may also be longer-term effects, including cumulative effects or symptoms that arise a few days later. Thus, we estimate our model using different time windows up to 28 days following a pollution exposure for

[40]The approach uses the following Z test: $Z = \frac{\beta_b - \beta_w}{\sqrt{SE\beta_b^2 + SE\beta_w^2}}$, where β_b and β_w are point estimates for Blacks and whites, and $SE\beta_b$ and $SE\beta_w$ are the associated standard errors.

[41]We also explore heterogeneous effects of air pollution by age and sex. Table A.22 shows that there are larger effects on children for respiratory illnesses and larger effects on the elderly for psychiatric and heart maladies. Table A.23 shows little difference in the effect between males and females.

the overall population, Blacks, and whites.[42] Figures B.9–B.11 illustrate that the estimates gradually increase with the length of the time window for respiratory illnesses, suggesting cumulative health effects of air pollution. For psychiatric and heart illnesses, the effect of air pollution appears to be flat and even decreasing for Blacks and whites after 21 days.

To provide further context, we calculate the effects of one additional average-tonnage vessel in a port over a year on air pollution-induced annual hospital visits and hospital medical costs, as shown in Table 4.[43] Panel A shows the results of annual hospital visits for residents living within 25 miles of a major port facility. For Blacks, one additional vessel in port results in 2,500 respiratory hospital visits, 520 heart-related visits, and 98 psychiatric visits (per million residents in a year in California). This amounts to 3.1 additional hospital visits per thousand Black residents in a year. For whites, one additional vessel in port results in 570 respiratory hospital visits, 300 heart-related visits, and 210 psychiatric visits (per million residents in a year). This adds up to 1.1 additional hospital visits per thousand white residents in a year, only about one-third of the visits for Black residents.

Panel B of Table 4 calculates the cost of these additional hospital visits. For this calculation, we use the 2017 inpatient discharge data from the Centers for Medicare and Medicaid Services (CMS).[44] The results of the calculation show that one more average-tonnage vessel in port over a year leads to $28 in medical costs per capita for Black residents and $10 for white residents.

5.3 Evidence on the Mechanisms Behind the Racial Disparities

These findings show clear racial disparities in the health effects of air pollution in port areas. A natural question that arises is whether these disparities are due to Blacks living in more polluted areas or Blacks having greater vulnerability to air pollution exposure (Hsiang et al., 2019). The evidence presented in Section 3.7 clearly shows that the Black population tends to have greater exposure to pollution than the white population. In the

[42] These estimations include the commensurate number of leading weather controls.

[43] We calculate the results in the following steps: (1) calculate pollution concentration changes for the studied pollutants due to one more vessel in ports (i.e., a 589,000 Mt increase in vessel tonnage) based on the estimates in Panel A of Table 2; (2) calculate changes in annual hospital visits due to the changes in standardized concentrations of CO, NO_2, $PM_{2.5}$, and SO_2 based on the estimates in Table 3; (3) select the largest values across the air pollutants for each illness category. We also estimate the reduced form results for the relationship between vessel tonnage and health outcomes in Section C.3.

[44] The Medicare data provide national average inpatient payments and total discharges for each diagnosis, which is categorized by the MS-DRG code (see https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Medicare-Provider-Charge-Data/Inpatient2017). We use the web service (http://icd10cmcode.com) based on CMS's ICD-10 MS-DRG Conversion Project to convert the ICD-10 diagnosis codes to the MS-DRG codes. The mapped MS-DRG codes for the studied primary illness groups are presented in Table A.2. We calculate the average medical costs for each of the illness groups, weighted by the total number of discharges.

population of hospital patients, Blacks are from zip codes that also face higher pollution exposure. This underscores that differences in exposure are at least part of the story.

To explore whether Blacks have higher marginal damages in response to the same pollutant exposures than whites (i.e., are more vulnerable to exposure), we group zip codes surrounding the California ports by their average daily $PM_{2.5}$ pollution levels. Specifically, we focus on the zip codes with available hospital visit data for Blacks and whites and divide them into eight groups by pollution percentile. We assume that zip codes in each percentile group have similar pollution exposure levels. We cannot entirely rule out differences of exposure to air pollution *within* zip code groups, but we see households of different races well distributed across zip codes around ports and zip codes are fairly small areas in cities, so we expect that differences in pollutant concentrations within zip code groups to be small. The intuition for this analysis is that given the same pollution exposures, different causal effects of pollution on hospital visit rates across racial groups suggest that factors other than pollution play a role.

We estimate equations (3)–(5) for each group of zip codes. Figure 5 illustrates that the four pollutants have larger effects on hospital visit rates (related to respiratory, heart, and psychiatric) for Blacks than whites across percentiles. These results suggest that Blacks face higher damages from air pollution exposure than whites even if exposure is held roughly constant, i.e., Blacks are more vulnerable to pollution exposure than whites.

The difference in vulnerability may depend on a wide range of determinants that differ across races, such as baseline health, income, avoidance behavior, defensive investments, or other socioeconomic characteristics. We explore this by collecting health and economic characteristics data for areas surrounding the major ports in California and compare them for Blacks and whites. Figure C.2(a) shows that Blacks have worse health conditions (e.g., smoking rate, obesity rate, no exercising rate, and poor or fair general health rate) than whites, implying reduced baseline health for Blacks. In addition, Figure C.2(b) indicates that Blacks also have worse socioeconomic status than whites, with higher poverty rates, reduced health insurance coverage, lower income per capita, and lower levels of education, which may make them more vulnerable to health risks from pollution exposure. Figure C.2(c) further shows that the selected economic characteristics are correlated with the Black-white health gap in port areas. The detailed analysis and data sources are presented in Section C.4. While these results on the differences in vulnerablility are illuminating, we should be cautious about interpreting the differences in socioeconomic status and behavioral patterns as causal drivers for the racial health disparities in the causal effects of air pollution that we clearly observe in our setting.

5.4 Placebo Tests, Extensions, and Robustness Checks

In this section, we conduct two placebo tests and a set of extensions and robustness checks to support our identification and highlight the channels driving our results.

Placebo Tests. In the first placebo test, we consider the possibility that lagged distant tropical cyclones might affect air pollution through channels other than port traffic that still have effects days later. Should this be the case, it would imply that our instrument directly affects air pollution through a channel outside of port traffic. To test this possibility, we examine air pollutant concentrations in areas far from ports (e.g., 75–100 miles) but similarly distant from the tropical cyclones as the ports. We regress air pollution concentrations in these "control" areas far from the ports on the lagged distant tropical cyclone instrument. Table 5 shows that the coefficients from this estimation are quite small relative to their sample means and are not significant for any of the pollutants, in clear contrast to our results in Table 2. This finding supports our argument that lagged distant tropical cyclones are unlikely to have a lingering effect on weather patterns and air pollution through channels other than port traffic.

In our second placebo test, we consider the possibility that some other factor relating to port traffic may be influencing hospital admissions besides air pollution. If this were the case, one would expect hospital admissions for other illnesses that are clearly unrelated to pollution exposure also to increase with port traffic. For example, arterial embolisms and appendicitis are all maladies that are highly unlikely to relate to air pollution exposure. Table A.24 estimates the same specifications for the overall population as in Panel A of Table 3 for these prognoses. All of the coefficients are small and not significant at even the 5% level. This result supports our contention that air pollution is actually the cause of the health impacts we estimate.

Extensions and Robustness Checks. Table A.25 presents a set of robustness checks that use slightly different model specifications of the effect of vessels in port on pollutant concentrations. Panels A–C show that temporal fixed effects and weather controls are important for identification. Panel D shows that the results with fewer weather controls are reasonably close to the primary specification, suggesting that the results are not very sensitive to the exact specification of weather controls. Panel E presents the results of pollution monitors within 12.5 miles of the major ports rather than 25 miles. The results are reasonably close to the baseline estimates.

We also run robustness checks relating to the exact definition of our lagged distant tropical cyclone instrument. In the primary specification presented above, we used a dummy variable for the existence seven days prior of tropical cyclones that are at least 500 miles away from ports (and we exclude any observations where a cyclone is within 200 miles within a two-day window). Table A.26 presents a variety of the robustness checks relating to the instrument. These include using an 800-mile threshold to exclude cyclone observations to further reduce the likelihood of tropical cyclones influencing air pollution directly, using different numbers of days for the lag instead of seven days, using multiple lags as instruments, using limited information maximum likelihood (LIML) to address any chance of a weak instrument, and using the count of cyclones rather than a dummy for the existence of tropical cyclones. The results are reasonably close to the primary results in Table 2 for all specifications.[45]

We construct pollution measures in our primary analysis by taking inverse distance weight averages of monitor level data. There are not monitors in every zip code, so one concern might be measurement error in pollution exposures due to the interpolated pollution measures. There is no obvious reason why this would be a problem for racial disparities, but for good measure, we conduct a robustness check by replacing the monitor data with zip code-level satellite-based measures for $PM_{2.5}$ concentrations from Reid et al. (2021). Table A.28 shows that the results are close to the primary results shown in Table 3.[46] We also conduct a robustness check for Figure 5 using the satellite-based pollution measures. The estimates, presented in Figure B.12, are again close to the primary results.

Another important analysis, which also sheds light on the drivers of our results, is to examine the *joint* effects of air pollutants on health outcomes. Our primary specifications examine each air pollutant separately, as is common in the literature. However, air pollutants may be co-emitted and co-transported, so some of the coefficients for individual pollutants may include the effects of multiple pollutants. Identifying joint effects is often more challenging due to the need to instrument for more than one variable, but it is possible. Local wind can impact the spatial dispersion of pollutants differently, and higher wind speeds may even influence the need for ship engine thrust and the rate of pollutant emissions. Thus, wind direction and wind speed continue to be useful instruments, providing a sufficient number of instruments. We focus on the joint effects of CO, NO_2, and SO_2 that are directly emitted from engine combustion in ports. Because NO_2 and SO_2 are

[45]In addition, we run two specifications including all of the removed observations due to the tropical cyclones being close (e.g., within a 200-mile radius) to the ports and excluding 21 days of observations after cyclones near ports. The second specification reduces the concern about the lingering effects of severe storms striking port areas. Table A.27 shows that the estimates remain significant and are quite similar to our primary results.

[46]We conduct another analysis by stratifying zip codes with similar distances to their nearest pollution monitors. We then run the baseline regressions. Figure B.13 shows clear racial disparities across the zip code groups.

precursors to $PM_{2.5}$ with an conversion rate of several percent per hour (Luria et al., 2001; Lin and Cheng, 2007), it is difficult to differentiate the effects between $PM_{2.5}$, NO_2, and SO_2 (Deryugina et al., 2019). We use the sample of zip code-port-days where measurements for CO, NO_2, and SO_2 are all available.

Table A.29 presents the results of the joint estimations.[47] For the joint effects of CO and NO_2 on respiratory ailments (column (1)), the estimates associated with CO are significantly positive, and the estimates associated with NO_2 are negative and insignificant for the overall population. The negative sign is consistent with findings on near-source atmospheric chemistry, indicating that an increase in NO_2 may decrease O_3 concentrations in certain settings (Sillman, 1999; Seinfeld and Pandis, 2016). It is also consistent with results in Schlenker and Walker (2016). The coefficients for whites mirror those for the entire population, while for Blacks we find a positive coefficient.

The coefficients on CO in column (2) of Table A.29 are significant for the overall population and the white subsample. For Blacks, SO_2 appears to be the driver for health outcomes. Blacks tend to live closer to ports and thus are more likely to be exposed to emissions from fossil fuels with high sulfur content (Wan et al., 2016). We see similar results when examining the combination of CO, NO_2, and SO_2 in column (3), with SO_2 having the strongest effect of increasing hospital visits, and with NO_2 having a negative coefficient for all three groups (at the 1% significance level for the overall population, 10% significance level for whites, and insignificant for Blacks). The remaining columns show fewer significant results, but the explanations are likely similar. These results underscore the complexity of joint estimation of co-pollutants.[48]

In another robustness check, we explore whether additional road congestion due to more port activity may be causing some of our health effects findings rather than air pollution. When there are more vessels in ports and greater tonnage being transferred, one would expect there to be more truck traffic. Our primary findings include the effect of additional air pollution from increased truck traffic. Still, one might be concerned that some of the estimates—such as those relating to mental health—could be influenced by additional road congestion. Thus, we bring in vehicle detection data from the California Department of Transportation Performance Measurement System, which contains daily

[47] While some first-stage F statistics (i.e., the cluster-robust Kleibergen-Paap Wald F statistics) are below the threshold of ten, the Anderson-Rubin and Stock-Wright LM S statistics suggest that weak instruments should not be a concern. The standard Cragg-Donald Wald F statistics are also larger than ten (not reported). For joint estimations, we only report the results for the overall categories of respiratory, heart, and psychiatric illnesses.

[48] We also jointly estimate the model only using zip codes closer to ports, finding mostly larger estimates (see columns (1)–(3) in Table A.30).

highway traffic data at the 'vehicle detection station' level for 2010–2016.[49] For each hour of the day, these data include average daily delays (measured in vehicle hours spent to pass a freeway segment) at various threshold speeds (i.e., 35, 40, 45, 50, 55, and 60 miles per hour) for each station.

Our analysis selects all of the stations located within 10 miles of the six major ports in California, and we include the station-days with at least 40% of observations. We then regress traffic delay measures at the various threshold speeds on the fitted vessel tonnage or the fitted vessel count. Table A.31 presents these results, which show no significant coefficients across panels and columns, despite very large samples. We take this as suggestive evidence that our instrument—vessels in ports predicted by distant and lagged cyclones—is unlikely to substantially influence road congestion, indicating that air pollution is much more likely to be the channel through which our results occur.

We also consider whether wind may affect hospital visits through factors other than air pollution. Strong winds may lead to fewer outdoor activities, thus reducing exposure to air pollutants. We run a robustness check excluding days with wind speeds greater than 3.3 meters per second, with this threshold chosen because it is the upper end of the "light breeze" designation under the Beaufort Wind Scale. The results are reasonably robust to the exclusion of intense windy days (see Table A.32).

One minor concern is that our racial disparity findings are due to greater direct exposure to pollution at ports by Blacks if a higher percentage of dock workers are Black. However, the total number of workers in ports is small relative to the population living in the neighborhoods surrounding ports. For example, there are 12,938 employees in port and harbor operations in the US in 2021, which is only about 0.03% of the total 39 million population residing in port areas.[50] Moreover, 71% of port workers are men, while we find effects on women as well (Table A.33).[51]

For additional reference, Table A.34 shows the effect of air pollution on total hospital visits from any cause for the overall population, Blacks, and whites. These include the illnesses examined in this study and all others recorded in the hospital visit data set. We see that all estimates are statistically significant and larger than those in Table 3. While respiratory and cardiovascular hospital visits are known to be the main ailments caused by air pollution, this robustness check suggests that other, non-standard health outcomes are also likely to increase with pollution exposure.

[49]The data are obtained from http://pems.dot.ca.gov.

[50]See https://www.ibisworld.com/industry-statistics/employment/port-harbor-operations-united-states/.

[51]See https://www.bls.gov/cps/cpsaat18.htm.

Finally, we run a set of further robustness checks. We calculate hospital visit rates based only on principal diagnoses rather than the combination of principal and secondary diagnoses. The results (Table A.35) are similar to our baseline results, although the effects are a bit smaller. We estimate the model separately for each of the three hospital visit data sets we pool for our health results. Tables A.36–A.38 illustrate that we still find significant health effects (and racial disparities) from air pollution, and emergency room visits logged in the Emergency Department Data seem the main driver, although again the effects are smaller, as would be expected. We run our primary specification using LIML instead of two-stage least squares (Table A.39) and again find very similar results.

6 Policy Implications

Our results showing racial disparities in the effects of port pollution on health outcomes raise the question of whether policy can help alleviate the disparities. Policy could directly reduce exposures by cutting emissions or address the drivers of the racial gap in the air pollution response functions. However, policy has largely focused on reducing exposures. One example is a regulation in California to reduce emissions from port facilities by reducing fossil-fuel usage in ports, perhaps most importantly by electrifying major port activities. We employ a regression discontinuity design (RDD) to find the causal effect of this policy. Then we use a dynamic simulation to explore whether generating additional electricity to power docked ships produces sufficient emissions to offset the health improvements from reduced ship emissions.

6.1 Brief Background on Port-related Policies

To date, several policies have been implemented to regulate emissions from marine ships. Perhaps the most prominent policy, the MARPOL Annex VI Protocol by International Maritime Organization, adopted in 1997, regulates sulfur content in marine fossil fuels to limit emissions of NO_x, SO_x, PM, and VOCs in the ocean.[52] More recently, attention has turned to replace fossil fuels altogether by electrifying port activities. This could include allowing docked vessels to turn off their auxiliary electricity-generating engines and instead use onshore electricity from the grid. Other port activities could also be electrified.[53]

[52]See http://www.imo.org/en/OurWork/Environment/PollutionPrevention/AirPollution/Pages/Air-Pollution.aspx.

[53]At the national level, United States has implemented several programs to reduce emissions from other port facilities, including the Ports Initiative, EPA's Diesel Emissions Reduction Act (DERA) grant program, Department of Transportation's Transportation Investment Generating Economic Recovery (TIGER) and Congestion Mitigation and Air Quality Improvement (CMAQ) programs, and the Department of Energy's Clean Cities program (EPA, 2016).

California has the strongest regulations on port emissions in the United States. The centerpiece policy is the "Ocean-Going Vessel At-Berth Regulation," which was adopted in December 2007. This regulation limited air pollutant emissions from container ships, passenger ships, and refrigerated cargo ships at the six major California ports.[54] There are two compliance options: use onshore electricity when docked or find an equivalent emission reduction through alternative fuels or emission control equipment. Beginning on January 1, 2010, vessel operators were required to reduce at-berth emissions of NO_x and PM by 10%, and since then the policy has been tightened further.[55] Our analysis focuses on the first phase of the regulation beginning on January 1, 2010.

6.2 Effect of California's Regulation on Air Pollutant Concentrations

Empirical Strategy. Our empirical strategy relies on the sharp discontinuity in how port activities were fueled on January 1, 2010. Onshore electricity and cleaner fossil fuels are more expensive than conventional fuels, and thus there was no incentive for ship operators and port operators to comply before this date (EPA, 2017). It is very likely that some of the at-berth charging infrastructure was already installed prior to this date, but it was not being used until ports were required to comply.

Our regression discontinuity design follows a model specification similar in principle to several recent studies (e.g., Davis, 2008; Auffhammer and Kellogg, 2011; Chen and Whalley, 2012; Anderson, 2014; Bento et al., 2014):

$$P_{ipt} = \rho Policy_t + f(Date_t) + \beta V_{pt} + \mathbf{W}_{it}\theta + \delta_t + \mu_{ip} + e_{ipt}. \tag{6}$$

The dependent variable P_{ipt} is the log of the concentration of a local air pollutant in monitor i that is mapped to port p on day t. $Policy_t$ is a dummy variable that is equal to one when the policy is in effect on day t and zero otherwise. The expression $f(Date_t)$ is a flexible function of the date. The dates are normalized to be zero at the first date of the policy; hence, the coefficient ρ represents the treatment effect of the policy. The variable V_{pt} is the log vessel tonnage in port instrumented using our lagged distant tropical cyclones instrument.[56] We also include the same weather controls ($\mathbf{W}_{it}$) and fixed effects (δ_t and μ_{ip}) as in equation (1).

[54]See https://ww2.arb.ca.gov/resources/documents/berth-faqs.

[55]For instance, beginning on January 1 2014, at least 50% of a fleet's visits must use onshore electricity each quarter of a year and auxiliary engine power generation must be reduced by 50%.

[56]We include the instrumented vessel tonnage because it controls for possible abrupt changes in the number of vessels visiting ports that might occur if there is an avoidance response of vessels to the policy implementation (Klotz and Berazneva, 2021).

The flexible function of the date is crucial for identification, as it controls for potential endogeneity from time as the running variable (Imbens and Lemieux, 2008). We specify $f(Date_t)$ with two terms: $Date_t$ and $Policy_t \times Date_t$. Thus, our final specification is a local linear regression discontinuity design, following Anderson (2014):

$$P_{ipt} = \rho Policy_t + \eta_1 Date_t + \eta_2 Policy_t \times Date_t + \beta V_{pt} + \mathbf{W}_{it}\theta + \delta_t + \mu_{ip} + e_{ipt}. \tag{7}$$

We estimate this equation using an augmented local linear approach to increase the power of estimation, following Hausman and Rapson (2018). The approach consists of two steps. We first use the full data sample to regress pollution measures on the exogenous variables (e.g., weather controls, instrumented log vessel tonnage, and fixed effects). We then regress the residuals obtained from the first step on the local linear terms (i.e., $Policy_t$, $Date_t$, and $Policy_t \times Date_t$) within a narrow bandwidth of dates. We specify a uniform kernel (Imbens and Lemieux, 2008; Anderson, 2014) and choose a bandwidth of 60 days on each side of the policy threshold in the primary specification. We also run robustness checks with different bandwidths. This procedure removes the necessity of using a global polynomial and the associated overfitting concerns (Hausman and Rapson, 2018).

Results. Following the augmented local linear approach, we first obtain the residuals by regressing air pollution measures on all exogenous regressors specified in equation (7) using the full data sample (2001–2016) across the six major California ports. Figure 6 plots daily average residuals for NO_2 with a shorter time window around the first policy date (normalized to be zero). Each point is an average of residuals across all monitor-port pairs. We see clear downward breaks of linear trends occurring at the first date of the California at-berth regulation, suggesting that the regulation results in lower concentrations of NO_2 in port areas (there are similar declines for most other pollutants but without significance).

Table 6 presents the regression results, where each column reports results from a separate regression for a pollutant. The estimates in the first row indicate the effect of the regulation. Consistent with Figure 6, the coefficient for NO_2 is significant at the 5% level, as shown in columns (2). The regulation leads to a decrease in average pollution concentrations by 26% for NO_2. There also appear to be reductions in CO emissions, but the coefficient is not significant at the 5% level.[57]

[57] We conduct bootstrap inference to test the estimates associated with the policy variable, following the fast wild cluster bootstrap algorithm in Roodman et al. (2019). For each regression, we obtain 10,000 bootstrap draws with replacement clustered by monitor-port and day, which is comparable to the primary specification with clustering by monitor-port and day. Figure B.14 presents the bootstrap 95% confidence intervals, which are fairly close to the primary specification results.

We next calculate the avoided annual hospital visits and hospital-related medical costs per capita by race due to the California regulation.[58] Table 7 shows that the regulation avoids 5.5 hospital visits per thousand Black residents per year associated with psychiatric, respiratory, and heart-related illnesses. It also leads to 2.1 avoided hospital visits per thousand white residents per year. The avoided medical costs per capita per year for Black residents come out to $48, which is much larger than the $19 for whites. These results highlight how the policy alleviated the Black-white gaps in air pollution-induced hospital visits around ports.

Simple calculations suggest that the benefits of avoiding adverse health outcomes from this policy outweigh the costs. The California Air Resources Board estimates that the annual regulatory costs for affected businesses and port authorities due to the Ocean-Going Vessel At-Berth Regulation vary from $36 million to $167 million in 2017 USD.[59] Our estimates suggest that the first phase of the policy saves $302 million/year in medical costs.[60]

We also run two placebo tests for the RDD analysis. The first test moves the discontinuity from the actual date of policy implementation to a different date: either January 1, 2009, or January 1, 2011. If seasonal effects drive our results, the coefficients would be similar to our primary results. The second placebo test examines regions further away from the ports to confirm that something else statewide was not affecting air pollution on January 1, 2010. We use the data from air pollution monitors 75–100 miles from the California ports. Table A.40 shows the results of these placebo tests. The coefficients tend to be insignificant and generally close to zero, providing further evidence supporting our identification.

The results from varying the bandwidth are shown in Figure B.15, and indicate that the exact choice of bandwidth makes little difference to our estimates. We also specify a 'donut' model in which a certain number of days are removed on either side of the policy threshold (Barreca et al., 2011). This specification addresses a potential concern about short-term avoidance behaviors by vessels in response to the policy (Hausman and Rapson, 2018). Figure B.16 presents the results with various donut periods, showing that the results do not deviate substantially from our primary estimates.

[58] We calculate the results with the following steps: (1) calculate absolute pollution concentration changes based on the estimates in Table 6; (2) calculate changes in annual hospital visits due to the changes in CO, NO_2, $PM_{2.5}$, and SO_2 concentrations based on the estimates in Table 3; (3) for each illness category, select the largest values across the air pollutants (to avoid double-counting due to the possibility of joint emissions). Note that these results do not account for any increases in emissions from the power sector.

[59] See https://ww3.arb.ca.gov/regact/2007/shorepwr07/tsd.pdf.

[60] Table 7 presents that the California at-berth regulation results in $20 savings per capita for illnesses related to respiratory, heart, and psychiatric illnesses. There are 15.08 million residents living within 25 miles of the major ports in California. The medical costs of $302 million are the multiplication of $20 and 15.08 million.

6.3 Dynamic Simulation

If the California regulation reduced fossil fuel use in ports but increased fossil fuel use from electricity generation, it is possible that the pollution was just shifted from one place to another. To explore this possibility, we use a dynamic simulation of the entire energy system in the United States. Specifically, we implement a reference case scenario based on the US Energy Information Administration (EIA) Annual Energy Outlook and a scenario that gradually shifts at-berth energy consumption from fossil fuel-powered auxiliary engines to electricity across all ports in the United States. Then we examined how electricity generation and emissions change.

To perform this exercise, we use the National Energy Modeling System (NEMS) run on a Yale server.[61] This model is a general equilibrium model that includes all major energy markets and explicitly depicts major energy supply sectors (coal, natural gas, oil), demand sectors (residential, industrial, commercial, and transportation), conversion sectors (electricity and liquid fuels), macroeconomic activities, and international energy markets (EIA, 2009). It has an electricity dispatch model with geographic disaggregation based on the actual fleet of generating plants in the United States. Besides producing well-respected government forecasts, it has been used for decades by researchers to analyze energy markets (e.g., Palmer et al., 2010; Auffhammer and Sanstad, 2011; Wilkerson et al., 2013; Gillingham and Huang, 2019, 2020). It is especially useful for our research question in that it contains a detailed link between energy consumption in ports and electricity generation. Appendix D contains details on the model and the two scenarios.

Figure B.17 presents the simulation modeling results for CO, NO_x, $PM_{2.5}$, and SO_2 emissions from vessels and electricity generation in the United States for the reference case and the policy scenario.[62] Notably, the reduction in emissions from marine vessels is substantial, while the increase in emissions from electricity generation is extremely small. The reason for this result is simple: the power sector uses much cleaner energy sources on average (i.e., natural gas and renewables) and is adopting technologies to mitigate emissions over time. Line losses are modeled and make a negligible impact. While every simulation model should be viewed as an informed approximation and should not be taken as a causal estimate, this finding from the simulation modeling suggests that the localized air pollution benefits in reducing racial disparities from port emission regulations are very likely to outweigh any negative effects of additional air pollution from increased

[61]The model we use is identical to EIA's NEMS with minor configuration adjustments to enable us to run it on a Yale server.

[62]Table A.41 presents the associated fossil fuel and electricity consumptions by marine vessels across the scenarios.

electricity generation. The result is likely to be even stronger in California, which has an especially clean electricity grid.

7 Conclusions

This paper establishes a set of causal relationships from port traffic to air pollution and racial disparities in health outcomes across racial groups. We use a quasi-experiment, where port traffic is influenced by lagged distant tropical cyclones, to ascertain the effect of port traffic on local air pollution and hospital visits. To the best of our knowledge, we are the first to investigate how a highly emitting point source—port facilities—can influence racial disparities in health and how policy can improve distributional outcomes.

Our results show that adding another vessel or increasing the overall vessel tonnage in ports will increase air pollution concentrations in the areas surrounding the ports. This leads to increased hospital visits for respiratory, heart-related, and psychiatric ailments that disproportionately affect Black residents. One additional vessel in port over a year leads to 3.1 additional hospital visits per thousand Black residents per year and 1.1 visits per thousand whites. We provide new evidence on mechanisms: the two racial groups are not only receiving different pollution exposures, but appear to have differing responses to exposure. Policy to reduce emissions from ships at berth may help reduce the disparities, and we show that a major California regulation disproportionately benefits Black residents. This California regulation reduces hospital visits by 5.5 per thousand Blacks per year and 2.1 per thousand whites.

The findings of this study lay the groundwork for further research uncovering racial disparities in air pollution in a variety of settings with highly polluting point sources, informing discussions about environmental justice, and providing guidance to policymakers aiming to improve public health and reduce inequality.

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Tables and Figures

Table 1: Summary statistics of main variables

	Within 25 Miles of US Ports				Within 25 Miles of CA Ports			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Port								
Tonnage (100,000 Mt)	4.25	4.00	0.00	49.30	5.89	4.83	0.00	26.07
Vessel Counts	14.84	14.12	0.00	157.00	10.23	7.59	0.00	43.00
Panel B: Pollution								
CO Mean (ppb)	499.42	398.92	0.00	45666.67	408.82	217.71	0.00	14840.56
NO_2 Mean (ppb)	13.64	10.21	0.00	99.12	14.88	8.49	0.29	56.77
$PM_{2.5}$ Mean ($\mu g/m^3$)	10.66	6.94	0.00	239.20	10.33	5.35	0.00	60.70
SO_2 Mean (ppb)	2.12	3.20	0.00	121.48	0.63	0.48	0.00	8.22
Panel C: Hospital visits per million residents – Overall population								
Asthma	.	.	.	.	67.85	64.69	0.00	3572.04
Upper Respiratory	.	.	.	.	42.71	50.36	0.00	3912.23
All Respiratory	.	.	.	.	227.03	147.87	0.00	12791.29
All Heart	.	.	.	.	140.05	92.80	0.00	1339.42
Anxiety	.	.	.	.	45.28	47.06	0.00	743.83
All Psychiatric	.	.	.	.	137.57	107.62	0.00	2231.48
Panel D: Hospital visits per million residents – Black								
Asthma	.	.	.	.	203.80	292.77	0.00	5771.08
Upper Respiratory	.	.	.	.	94.15	201.07	0.00	4488.62
All Respiratory	.	.	.	.	527.54	549.55	0.00	16992.63
All Heart	.	.	.	.	240.74	316.69	0.00	4664.18
Anxiety	.	.	.	.	65.60	165.94	0.00	2991.03
All Psychiatric	.	.	.	.	273.04	398.59	0.00	6511.63
Panel E: Hospital visits per million residents – White								
Asthma	.	.	.	.	81.04	139.02	0.00	4248.09
Upper Respiratory	.	.	.	.	34.86	94.74	0.00	3992.02
All Respiratory	.	.	.	.	294.03	324.38	0.00	9398.50
All Heart	.	.	.	.	231.28	244.23	0.00	4436.56
Anxiety	.	.	.	.	74.68	129.58	0.00	2851.71
All Psychiatric	.	.	.	.	247.73	316.29	0.00	8458.65

Notes: This table presents summary statistics of the main variables, including mean, standard deviation, minimum, and maximum. The variables are split into three panels, i.e., port, pollution, and health. The data are obtained from the US Army Corps of Engineers, the US EPA Air Quality System, and the Office of Statewide Health Planning and Development of California.

Table 2: Effect of vessels in ports on air pollutant concentrations in the United States

	Dependent variable: pollutant concentration							
	CO	NO_2	$PM_{2.5}$	SO_2	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: IV estimates								
Vessel Tonnage	23.19*	1.17***	1.20**	0.15				
	(13.58)	(0.34)	(0.55)	(0.12)				
Vessel Counts					10.65*	0.54***	0.53**	0.07
					(6.44)	(0.17)	(0.26)	(0.06)
1st-Stage F Stat.	26.79	35.27	21.95	25.52	17.18	21.37	13.13	15.22
Adjusted R^2	0.53	0.72	0.31	0.43	0.53	0.70	0.29	0.43
Observations	524,197	604,632	428,220	484,745	524,197	604,632	428,220	484,745
Panel B: OLS estimates								
Vessel Tonnage	−1.01	0.05***	0.05***	−0.002				
	(0.71)	(0.02)	(0.02)	(0.01)				
Vessel Counts					−0.08	0.01**	0.03***	−0.001
					(0.28)	(0.01)	(0.01)	(0.003)
Adjusted R^2	0.55	0.76	0.40	0.44	0.55	0.76	0.40	0.44
Observations	524,197	604,632	428,220	484,745	524,197	604,632	428,220	484,745

Notes: Panel A presents the IV estimates of the effect of port traffic on pollutant concentrations within a 25-mile radius of ports in the United States, while Panel B presents the corresponding OLS estimates. Each entry presents an individual regression on a local air pollutant. In Panel A, the endogenous variables, vessel tonnage and vessel counts, are instrumented by an indicator of seven-day lagged cyclones at least 500-mile distant from ports. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port fixed effects. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 3: Effect of air pollution on hospitalization rates in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
CO (ppb)	2.79***	3.09***	10.46***	3.16***	0.69**	1.87***
	(0.41)	(0.64)	(1.74)	(0.63)	(0.27)	(0.65)
NO_2 (ppb)	2.39***	2.91***	8.79***	3.09***	0.71***	1.94***
	(0.38)	(0.61)	(1.61)	(0.58)	(0.25)	(0.61)
$PM_{2.5}$ ($\mu g/m^3$)	1.84***	2.21***	6.73***	2.19***	0.50**	1.33***
	(0.32)	(0.51)	(1.37)	(0.49)	(0.21)	(0.50)
SO_2 (ppb)	3.28***	4.68***	13.13***	4.40***	1.19***	3.08***
	(0.63)	(0.97)	(2.57)	(0.93)	(0.40)	(0.96)
Panel B: Black						
CO (ppb)	7.81***	5.38***	20.44***	5.74***	0.92	−0.04
	(1.63)	(1.43)	(4.04)	(1.79)	(0.81)	(1.88)
NO_2 (ppb)	7.18***	8.77***	23.32***	5.95***	1.23	0.66
	(1.68)	(1.48)	(4.23)	(1.85)	(0.85)	(1.96)
$PM_{2.5}$ ($\mu g/m^3$)	5.66***	6.28***	18.00***	3.77***	0.38	−0.53
	(1.28)	(1.13)	(3.29)	(1.41)	(0.60)	(1.45)
SO_2 (ppb)	10.87***	16.35***	39.10***	8.23***	1.93	1.54
	(2.54)	(2.41)	(6.65)	(2.88)	(1.35)	(3.07)
Panel C: White						
CO (ppb)	2.41***	2.10***	9.55***	4.02***	0.11	2.38*
	(0.51)	(0.41)	(1.56)	(1.16)	(0.54)	(1.25)
NO_2 (ppb)	1.78***	1.80***	6.84***	3.51***	0.22	2.32**
	(0.46)	(0.40)	(1.42)	(1.01)	(0.48)	(1.12)
$PM_{2.5}$ ($\mu g/m^3$)	1.53***	1.51***	5.55***	2.78***	0.16	1.82*
	(0.41)	(0.35)	(1.29)	(0.91)	(0.43)	(0.99)
SO_2 (ppb)	2.05***	2.63***	8.98***	4.64***	0.35	3.35**
	(0.69)	(0.58)	(2.10)	(1.49)	(0.70)	(1.63)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on contemporaneous hospital visit rate for the overall population, Blacks, and whites. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. The first-stage F statistics range from 28 to 79 for Panel A, from 21 to 61 for Panel B, and from 27 to 83 for Panel C. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 4: Effect of one additional vessel in a port over an entire year on hospital visits and medical costs in California

	All Respiratory (1)	All Heart (2)	All Psychiatric (3)
Panel A: Hospital visits per million residents			
Black	2,500	520	98
White	570	300	210
Overall Population	840	280	200
Panel B: Medical costs per capita (2017 USD)			
Black	22	5	1
White	5	3	2
Overall Population	7	3	2

Notes: Panel A presents the back-of-the-envelope calculations of the effect of one additional vessel in port on annual hospital visits, based on the instrumental variable estimates in Tables 2 and 3. Panel B presents the medical costs associated with the hospital visits in Panel A based on the payment data from the Centers for Medicare and Medicaid Services. The average medical costs are $8,917 for psychiatric illnesses, $8,715 for respiratory illnesses, and $9,679 for heart-related illnesses. Based on the US 2010 Decennial Census, the total population residing in the zip codes within 25 miles of California's major ports is 15.08 million, where 1.12 million are Black, and 5.07 million are white. All numbers are rounded to two significant figures.

Table 5: Placebo test on the effect of the cyclone instrument on air pollutant concentrations in distant areas

	Dependent variable: pollutant concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Tropical Cyclone	15.67	0.01	−0.19	0.004
	(10.28)	(0.06)	(0.12)	(0.03)
Adjusted R^2	0.54	0.72	0.33	0.48
Observations	82,278	135,801	98,568	70,950

Notes: This table presents the placebo test on regressing the instrumental variable of seven-day lagged cyclones that are at least 500-mile distant from ports on air pollutant concentrations in certain areas that are far from ports (i.e., 75–100 miles from major US ports). Each column presents an individual regression on a local air pollutant. All regressions include weather controls, such as quadratics of maximum, minimum, and dew point temperatures, precipitation, wind speed, and wind direction. All regressions also include county-by-year, month, day-of-week, holiday, and pollution monitor fixed effects. An observation is a monitor-day. Standard errors are clustered by pollution monitor and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 6: Effect of California Ocean-Going Vessel At-Berth Regulation on air pollution, RDD estimation

	Dependent variable: residual of log pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
CA Regulation × Date	-0.01^{**}	-0.004	-0.01^{**}	-0.005
	(0.003)	(0.002)	(0.004)	(0.01)
CA Regulation	-0.13^{*}	-0.26^{**}	0.14	-0.23
	(0.07)	(0.11)	(0.11)	(0.21)
Date	0.005^{**}	0.01^{**}	0.003	0.01^{**}
	(0.002)	(0.002)	(0.003)	(0.004)
Pre-policy Mean	620.35	18.40	14.70	1.83
Observations	4,677	5,082	2,698	2,934

Notes: This table presents the second-stage augmented local linear RDD estimation of the effect of the California at-berth regulation on air pollutant concentrations. The second-stage RDD dependent variable is taken from the residuals by regressing log pollution concentrations on weather controls (i.e., the quadratics of maximum, minimum, and dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair), fixed effects (i.e., county-by-year, month, day-of-week, holiday, and port-monitor pair), and log vessel tonnage (instrumented by seven-day lagged and 500-mile distant cyclones from ports). The local linear bandwidth is specified as 60 days on both sides of the policy threshold. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and normalized day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 7: Effect of California Ocean-Going Vessel At-Berth Regulation on annual hospital visits and medical costs

	All Respiratory (1)	All Heart (2)	All Psychiatric (3)
Panel A: Hospital visits per million residents			
Black	-4,300	-980	-170
White	-1,100	-580	-380
Overall Population	-1,400	-510	-340
Panel B: Medical costs per capita (2017 USD)			
Black	-37	-9	-2
White	-10	-6	-3
Overall Population	-12	-5	-3

Notes: Panel A presents the back-of-the-envelope calculations of the effect of the California at-berth regulation on annual hospital visits based on the estimates in Tables 3 and 6. Panel B presents the medical costs associated with the hospital visits in Panel A based on the payment data from Centers for Medicare and Medicaid Services. The average medical costs are $8,917 for psychiatric illnesses, $8,715 for respiratory illnesses, and $9,679 for heart-related illnesses. Based on the US 2010 Decennial Census, total population residing in the zip codes within 25 miles of the major ports in California is 15.08 million, in which 1.12 million are Black and 5.07 million are white. All numbers are rounded to two significant figures.

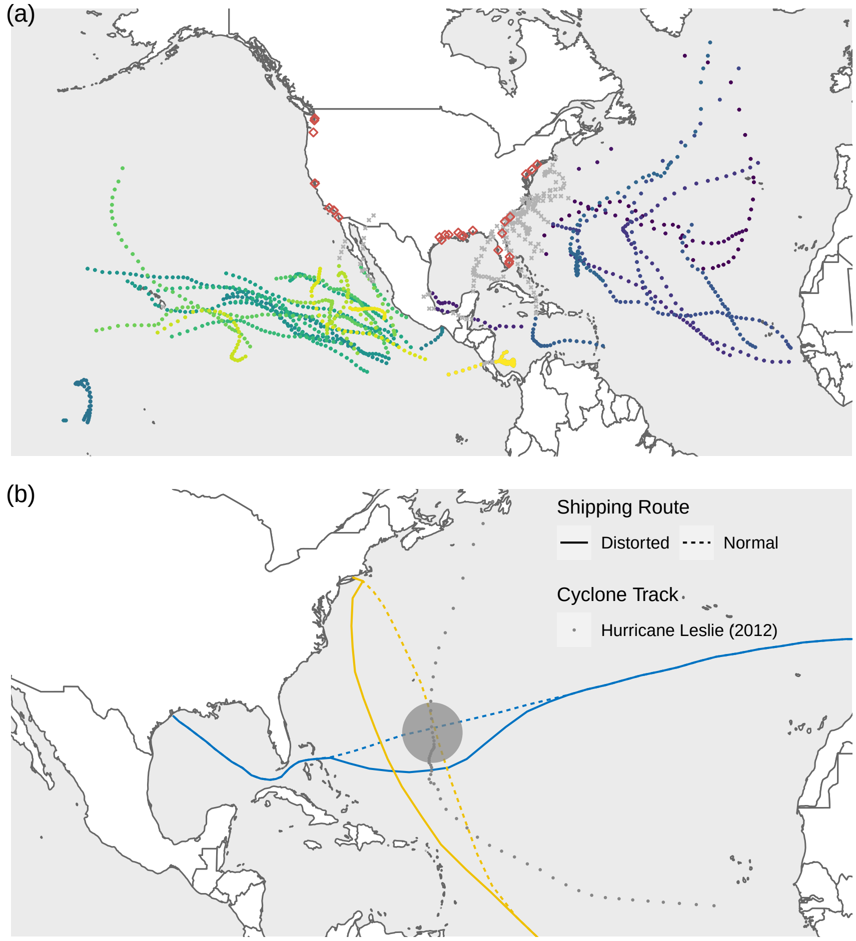

Figure 1: (a) Locations of major ports and tracks of tropical cyclones. (b) Illustrative shipping routes and a tropical cyclone track.

Notes: Panel (a) plots the locations of major ports (red diamonds) in the United States and the tracks of tropical cyclones (colored dots) in the Northeast and North Central Pacific Ocean and the Atlantic Ocean in 2016. The gray × dots indicate the cyclone observations within 500 miles of ports or on land. Panel (b) plots two shipping routes to US ports and the track of Hurricane Leslie in 2012. The solid lines indicate the distorted routes in response to the cyclone, while the dashed lines represent the normal routes. The grey dots and round represent Hurricane Leslie. The hurricane data are obtained from the NOAA National Hurricane Center, and the shipping routes are approximated based on data from the online tool: https://www.shipmap.org.

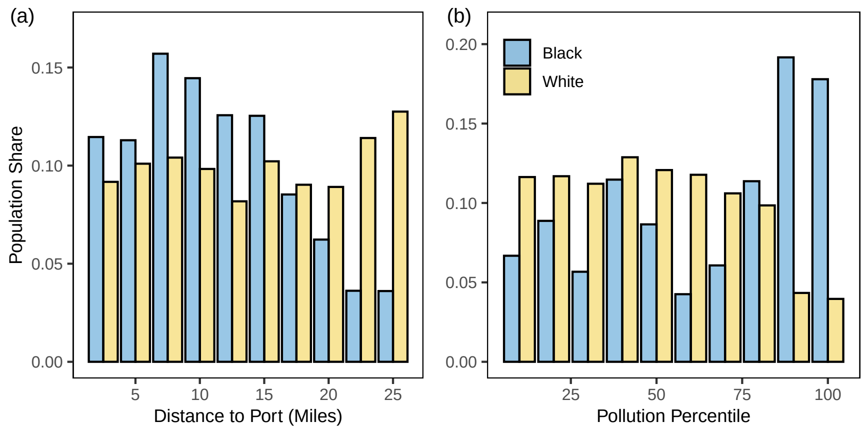

Figure 2: (a) Distribution of population by distance to major California ports. (b) Distribution of the population in California port areas by percentile of $PM_{2.5}$ concentration.

Notes: Panel (a) plots population distribution in the California port areas by the distance between census tract and port, separately for non-Hispanic Black and white populations. We obtain population data at the census tract level and assign a distance between a census tract to its nearest mapped port to all race-specific populations within the census tract. Panel (b) plots population distribution in the California port areas by percentile of $PM_{2.5}$ concentration, separately for non-Hispanic Black and white population. Larger pollution percentiles represent higher pollution exposures. The data are acquired from the US 2010 Decennial Census and US EPA Air Quality System.

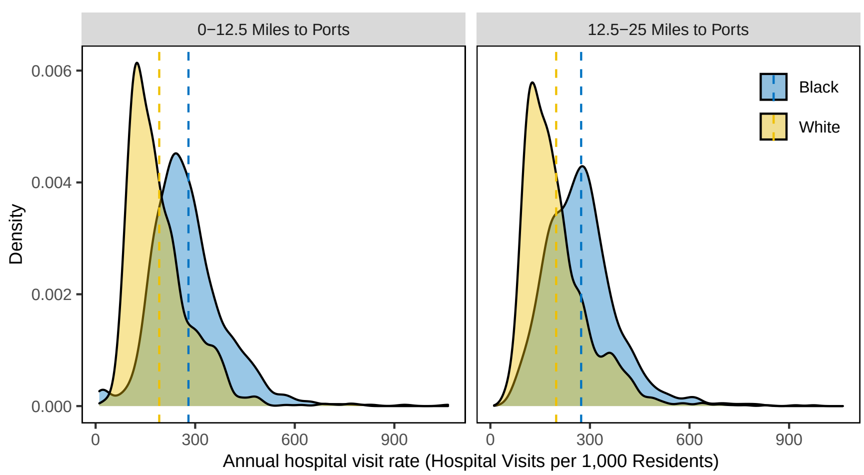

Figure 3: Distribution of annual hospital visit rates in California port areas.

Notes: This figure plots the distribution density of annual hospital visit rates separately for non-Hispanic Black and white population in the areas within 0–12.5 miles from ports and 12.5–25 miles from ports in California. The hospital visit rate is calculated as the annual total hospital visits related to psychiatric, respiratory, and heart-related illnesses in each zip code for 2010–2016. The dashed lines represent sample means. The gap between the dashed lines in the left panel is 88, while the gap in the right panel is 75. We exclude the zip codes having less than 1,000 race-specific populations in our analysis. The data are obtained from the Office of Statewide Health Planning and Development of California.

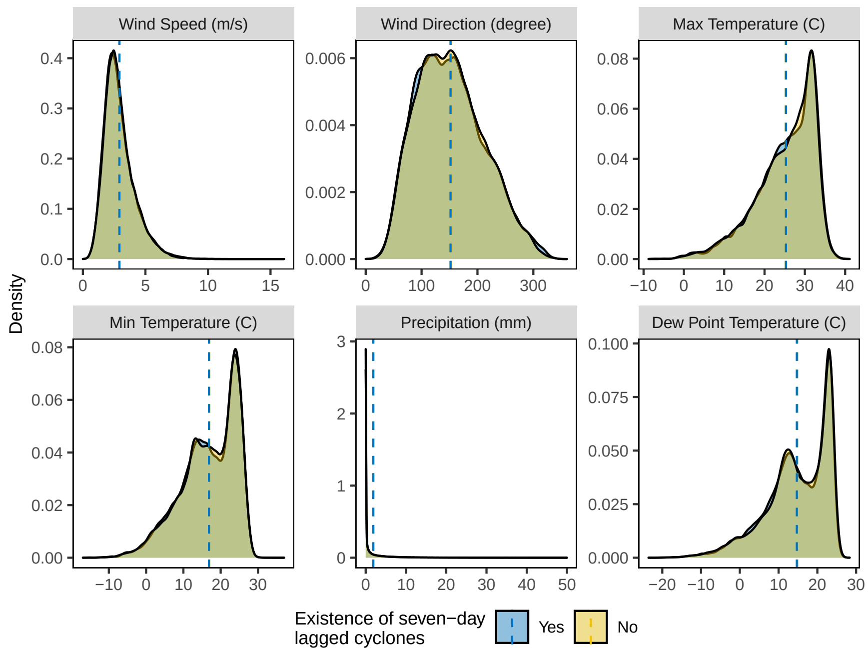

Figure 4: Distribution of local weather in port areas.

Notes: This figure presents the density of weather measures in the US port areas, separately for the month-days when there exist seven-day lagged and 500-mile distant tropical cyclones in the ocean and the same month-days when there are no such cyclones. The dashed lines represent the means of the distributions. We do not plot the observations with precipitation greater than 50. The data are obtained from the NOAA Integrated Surface Database.

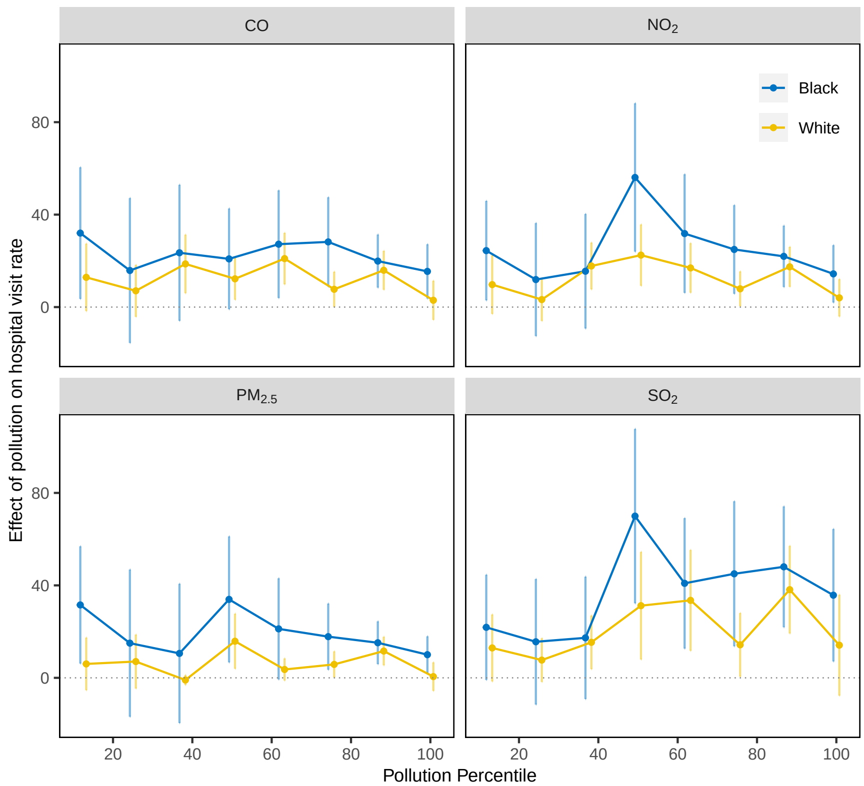

Figure 5: Effects of pollution on hospital visit rates by pollution percentile.

Notes: This figure plots effects of pollution on total hospital visit rates (related to respiratory, heart, and psychiatric illnesses) in eight $PM_{2.5}$ pollution percentile groups. Pollution concentrations in regressions are from the EPA monitoring data, standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. Error bars correspond to 95% confidence intervals, where standard errors from regressions are clustered by port-zip code and day. An observation is a zip code-port-day.

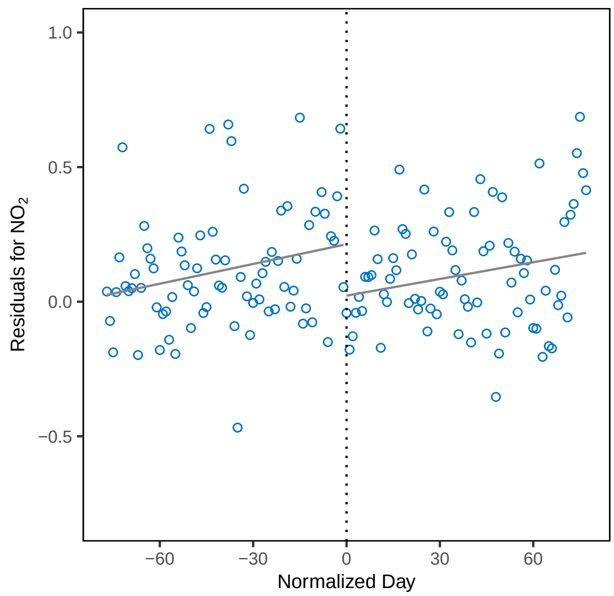

Figure 6: Residuals of NO_2 concentrations for the RDD analysis.

Notes: This figure plots daily average residuals across all monitor-port pairs for NO_2. The grey solid lines are linear fitted lines of the residuals. The policy date is normalized to be zero, indicated by the vertical dotted lines. A few extreme values are not shown in the figure.

A Supplementary Tables (For Online Publication)

Table A.1: Summary statistics of the major ports in United States

	Vessel Tonnage (100,000 Mt)				Vessel Counts			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Houston, TX	12.4	3.4	1.34	35.9	53.9	12.2	8.00	157.0
Long Beach, CA	9.8	3.4	0.00	24.7	18.7	5.8	0.00	55.0
New York, NY and NJ	8.2	2.8	0.41	49.3	21.0	7.2	1.00	142.0
Los Angeles, CA	7.4	3.0	0.00	26.1	15.3	5.6	0.00	49.0
South Louisiana, LA, Port of	7.2	2.7	0.98	17.9	22.7	7.2	4.00	51.0
New Orleans, LA	4.9	1.5	0.29	11.7	19.4	5.7	2.00	46.0
Baltimore, MD	4.9	2.1	0.09	15.6	12.9	4.3	1.00	50.0
Savannah, GA	3.9	1.7	0.00	12.1	10.5	3.5	0.00	29.0
Oakland, CA	3.7	1.9	0.00	23.5	6.9	3.5	0.00	53.0
Seattle, WA	3.5	1.5	0.24	10.6	24.4	5.1	1.00	46.0
Miami, FL	3.5	1.9	0.11	10.7	24.4	7.2	5.00	57.0
Port Everglades, FL	3.3	2.2	0.04	14.4	17.7	4.4	4.00	40.0
Charleston, SC	3.2	1.2	0.00	9.1	8.4	2.9	0.00	26.0
Tacoma, WA	2.9	1.5	0.04	13.7	14.4	4.5	1.00	34.0
Beaumont, TX	2.7	1.2	0.00	7.7	7.3	2.9	0.00	20.0
Mobile, AL	2.7	1.0	0.06	7.2	12.2	3.9	1.00	31.0
Jacksonville, FL	2.2	1.0	0.00	7.6	8.1	3.0	0.00	23.0
Portland, OR	1.8	1.0	0.00	7.0	7.7	3.9	0.00	29.0
Tampa, FL	1.6	0.8	0.00	6.1	7.6	3.3	0.00	30.0
Philadelphia, PA	1.6	1.0	0.00	6.2	3.7	2.1	0.00	21.0
Baton Rouge, LA	1.5	0.8	0.00	6.1	5.3	2.5	0.00	17.0
Galveston, TX	1.5	1.0	0.00	7.1	10.9	4.7	0.00	31.0
Lake Charles, LA	1.4	0.7	0.00	4.3	7.7	3.4	0.00	23.0
San Diego, CA	0.8	0.7	0.00	6.0	4.3	2.4	0.00	15.0
Port Hueneme, CA	0.5	0.4	0.00	2.4	1.7	1.3	0.00	6.0
Palm Beach, FL	0.3	0.2	0.00	3.0	6.2	3.3	0.00	19.0
San Francisco, CA	0.3	0.5	0.00	3.9	0.7	1.1	0.00	11.0

Notes: This table presents the summary statistics of daily vessel tonnage and daily mean vessel counts for the 27 major ports in the United States. The data are obtained from the US Army Corps of Engineers.

Table A.2: ICD-9-CM, ICD-10-CM, and MS-DRG codes

	ICD-9 Code	ICD-10 Code	MS-DRG Code
Panel A: Respiratory			
Asthma	493	J45	202, 203
Upper Respiratory	460-465	J00-J06	011-013, 152, 153
All Respiratory	460-519	J00-J99	011-013, 152-156, 177-182, 186-206, 793, 865, 866, 919-921, 928, 929, 951
Panel B: Heart			
All Heart	410-429	I20-I52	175, 176, 222-227, 280-285, 288-293, 296-298, 302, 303, 306-311, 314-316, 793
Panel C: Psychiatric			
Anxiety	300.0, 300.2	F40, F41	880, 882
All Psychiatric	300.0, 300.2, 296.0, 296.4-296.9, 309.0, 309.2-309.4, 295, 308.9, 309.8, 314.0, 314.2, 314.9, 312.0-312.2, 312.8, 312.9, 313.8, 299.0, 299.8, 312.3, 307.9, 311, 296.2, 296.3, 296.8, 296.9, 298.0, 300.4, 625.4, 301.10, 301.12, 301.13, 301.0, 301.3, 301.4, 301.6-301.9, 301.50, 301.59	F43.2, F43.8, F43.9, F20, F22-F25, F28, F29, F43.0, F43.1, F90, F91, F84.0, F84.5, F84.8, F63, F32, F33, F34.0, F34,1, F60	880-886
Panel D: Placebo			
Arterial Embolism	444	I74	.
Appendicitis	540-543	K35-K38	.

Notes: Table presents the ICD-9-CM, and ICD-10-CM codes for counting hospital visits for the illness groups examined in the paper and the corresponding MS-DRG code for calculating average medical costs for each illness group. The codes include the ranges of themselves and any subcategories. We do not calculate medical costs for the placebo diseases.

Table A.3: Supplementary summary statistics of variables

	Within 25 Miles of US Ports				Within 25 Miles of CA Ports			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Pollution								
CO Max (ppb)	839.9	730.3	0.0	49000.0	921.1	854.2	0.0	49000.0
NO_2 Max (ppb)	25.7	15.9	0.0	417.0	29.1	17.0	0.0	270.0
$PM_{2.5}$ Max ($\mu g/m^3$)	11.7	7.5	0.0	265.9	13.5	8.5	0.0	239.2
SO_2 Max (ppb)	5.5	9.5	0.0	462.1	3.0	3.4	0.0	144.2
O_3 Mean (ppb)	26.6	11.6	0.0	100.7	25.5	11.2	0.0	84.8
O_3 Max (ppb)	37.0	14.5	0.0	144.0	35.7	13.2	0.0	114.0
Panel B: Hospital visits per million residents – Placebo illnesses								
Arterial Embolism	.	.	.	.	0.7	5.2	0.0	297.5
Appendicitis	.	.	.	.	4.0	12.7	0.0	431.8

Notes: This table presents supplementary summary statistics for pollution and placebo illness variables, including mean, standard deviation, minimum, and maximum. The data are obtained from the US EPA Air Quality System and the Office of Statewide Health Planning and Development of California.

Table A.4: Summary statistics of hospital visit rate for Hispanics

	Mean	SD	Min	Max
Asthma	53.5	101.1	0.0	2806.4
Upper Respiratory	51.3	93.0	0.0	3089.1
All Respiratory	184.7	211.2	0.0	8917.6
All Heart	71.1	118.6	0.0	2900.7
Anxiety	36.5	83.2	0.0	1870.9
All Psychiatric	96.6	162.1	0.0	3663.0

Notes: This table presents summary statistics of hospital visit rates (i.e., hospital visits per million residents) for Hispanics, including mean, standard deviation, minimum, and maximum. The data are obtained Office of Statewide Health Planning and Development of California.

Table A.5: Summary statistics of hospital visit rate by age group

	Mean	SD	Min	Max
Panel A: Ages 5 and under				
Asthma	75.4	189.3	0.0	4635.0
Upper Respiratory	251.5	364.6	0.0	5867.6
All Respiratory	491.3	597.6	0.0	11973.7
All Heart	8.0	60.9	0.0	1988.1
Anxiety	0.6	16.8	0.0	983.3
All Psychiatric	5.3	49.7	0.0	2320.2
Panel B: Ages between 5 and 19				
Asthma	58.0	118.7	0.0	4779.8
Upper Respiratory	50.8	110.1	0.0	4490.2
All Respiratory	150.2	223.4	0.0	13035.9
All Heart	4.6	33.3	0.0	1938.0
Anxiety	13.0	56.5	0.0	1938.0
All Psychiatric	53.5	131.0	0.0	3876.0
Panel C: Ages between 20 and 64				
Asthma	59.8	72.8	0.0	3310.1
Upper Respiratory	24.6	43.2	0.0	4280.3
All Respiratory	159.2	144.5	0.0	13640.0
All Heart	70.8	74.1	0.0	1416.4
Anxiety	50.1	60.3	0.0	1045.2
All Psychiatric	147.3	133.3	0.0	2351.7
Panel D: Ages 65 and above				
Asthma	123.2	202.7	0.0	3791.5
Upper Respiratory	18.7	77.2	0.0	2521.0
All Respiratory	577.3	490.6	0.0	11764.7
All Heart	776.8	527.7	0.0	7582.9
Anxiety	94.9	174.5	0.0	3731.3
All Psychiatric	282.9	344.1	0.0	6529.9

Notes: This table presents summary statistics of hospital visit rates (i.e., hospital visits per million residents) by age group, including mean, standard deviation, minimum, and maximum. The data are obtained Office of Statewide Health Planning and Development of California.

Table A.6: Summary statistics of hospital visit rate by sex group

	Mean	SD	Min	Max
Panel A: Female				
Asthma	81.4	92.7	0.0	3621.2
Upper Respiratory	45.1	66.0	0.0	4782.7
All Respiratory	243.3	190.9	0.0	14006.6
All Heart	129.3	112.1	0.0	1642.6
Anxiety	57.6	71.8	0.0	1314.1
All Psychiatric	160.6	147.7	0.0	2956.6
Panel B: Male				
Asthma	54.2	72.3	0.0	3523.3
Upper Respiratory	40.5	61.1	0.0	3252.3
All Respiratory	210.9	168.5	0.0	11518.4
All Heart	151.4	129.0	0.0	2088.6
Anxiety	32.7	53.8	0.0	1135.1
All Psychiatric	113.7	125.4	0.0	2684.0

Notes: This table presents summary statistics of hospital visit rates (i.e., hospital visits per million residents) by sex group, including mean, standard deviation, minimum, and maximum. The data are obtained Office of Statewide Health Planning and Development of California.

Table A.7: Summary statistics of hospital visit rate by data specification

	Overall Population				Black				White			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Panel A: Principal Diagnosis												
All Respiratory	88.6	77.6	0.0	6089.5	200.8	299.9	0.0	8496.3	95.4	161.5	0.0	5639.1
All Heart	32.1	38.5	0.0	729.0	51.5	140.6	0.0	2952.8	51.1	105.1	0.0	3439.4
All Psychiatric	29.4	40.7	0.0	999.3	75.9	191.5	0.0	3787.9	52.0	139.3	0.0	5639.1
Panel B: Patient Discharge Data (PDD)												
All Respiratory	79.6	67.7	0.0	2652.1	160.9	281.1	0.0	5703.4	130.7	205.5	0.0	5988.0
All Heart	77.5	62.0	0.0	1231.4	135.8	232.8	0.0	4296.5	130.0	183.4	0.0	4261.4
All Psychiatric	59.5	61.1	0.0	1142.0	112.8	240.8	0.0	5581.4	118.0	205.9	0.0	6578.9
Panel C: Emergency Department Data (EDD)												
All Respiratory	130.4	115.2	0.0	12519.1	345.4	441.7	0.0	16672.0	137.4	209.6	0.0	7518.8
All Heart	46.2	50.0	0.0	791.5	89.9	187.6	0.0	3738.3	73.6	121.9	0.0	3759.4
All Psychiatric	68.5	71.8	0.0	1190.1	150.7	287.2	0.0	5401.2	112.7	198.7	0.0	6986.0
Panel D: Ambulatory Surgery Center Data (ASCD)												
All Respiratory	17.0	31.1	0.0	785.2	21.2	99.6	0.0	3738.3	25.9	73.5	0.0	2851.7
All Heart	16.4	29.7	0.0	691.9	15.0	77.1	0.0	1994.0	27.7	72.4	0.0	1996.0
All Psychiatric	9.6	23.7	0.0	691.9	9.5	69.3	0.0	2952.8	17.0	61.9	0.0	2991.8

Notes: Table presents summary statistics of hospital visit rate in various data specifications, including mean, standard deviation, minimum, and maximum. Panels A–C show statistics for different OSHPD data sets. Panel D presents the statistics by only counting principal diagnoses (i.e., secondary diagnoses are excluded). The data are obtained Office of Statewide Health Planning and Development of California.

Table A.8: Average pollution exposure weighted by Black and white population in port areas

	Black	White
CO (ppb)	423.12	406.95
NO_2 (ppb)	15.25	13.68
$PM_{2.5}$ ($\mu g/m^3$)	10.55	10.03
SO_2 (ppb)	0.63	0.60

Notes: This table presents average pollution exposure for Blacks and whites for 2010–2016, weighted by the zip code-level Black and white population. The population data are obtained from US 2010 Decennial Census. The pollution data are from the US EPA Air Quality System.

Table A.9: Balance statistics for weather variables in port areas

	Standardized Mean Differences	Variance Ratio	Kolmogorov-Smirnov Statistics
Wind Speed (m/s)	-0.005	1.068	0.016
Wind Direction (degree)	-0.009	1.041	0.013
Max Temperature (C)	0.006	0.989	0.009
Min Temperature (C)	-0.005	1.000	0.008
Precipitation (mm)	-0.011	1.068	0.009
Dew Point Temperature (C)	-0.015	0.991	0.014

Notes: This table presents the balance statistics of weather variables in the US port areas, separately for the month-days when there exist seven-day lagged and 500-mile distant tropical cyclones in the ocean and the same month-days when there are no such cyclones. Balanced sub-samples indicate that standardized mean differences are close to zero, variance ratios are close to one, and Kolmogorov-Smirnov (KS) statistics are close to zero. The data are obtained from the NOAA Integrated Surface Database.

Table A.10: First-stage relationship between tropical cyclones and port traffic

	Dependent variable: port traffic							
	Vessel Tonnage				Vessel Counts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tropical Cyclone	-0.24^{***}	-0.22^{***}	-0.22^{***}	-0.20^{***}	-0.53^{***}	-0.47^{***}	-0.48^{***}	-0.44^{***}
	(0.05)	(0.04)	(0.05)	(0.04)	(0.13)	(0.10)	(0.13)	(0.11)
AR stat. p-val	0.070	0.000	0.019	0.219	0.070	0.000	0.019	0.219
SW S stat. p-val	0.060	0.000	0.017	0.164	0.060	0.000	0.017	0.164
Observations	524,197	604,632	428,220	484,745	524,197	604,632	428,220	484,745

Notes: This table presents the first-stage results for the instrumental variable estimation in Panel A of Table 2. Each entry corresponds to an individual regression. The instrument is an indicator of seven-day lagged and 500-mile distant cyclones in the ocean. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port pair fixed effects. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and day. AR refers to Anderson-Rubin Wald statistic and SW refers to the Stock and Wright LM S statistic. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.11: Effect of vessel tonnage on air pollutant concentrations around California ports

	Dependent variable: pollutant concentration							
	CO	NO_2	$PM_{2.5}$	SO_2	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vessel Tonnage	16.96	1.47**	0.29	−0.02				
	(24.87)	(0.60)	(0.93)	(0.11)				
Vessel Counts					10.25	0.91**	0.19	−0.01
					(15.11)	(0.38)	(0.61)	(0.06)
Adjusted R^2	0.52	0.72	0.42	0.46	0.52	0.71	0.41	0.46
Observations	230,582	247,672	115,797	151,808	230,582	247,672	115,797	151,808

Notes: This table presents the instrumental variable estimates of the effect of vessel tonnage on pollutant concentrations within a 25-mile radius of ports in California. Each entry presents an individual regression on a local air pollutant. The endogenous variable, vessel tonnage, is instrumented by an indicator of seven-day lagged cyclones that are at least 500-mile distant from ports. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port fixed effects. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics range from 12 to 19. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.12: Effect of vessels in ports on air pollutant concentrations in the United States, split by years

	Dependent variable: pollutant concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: 2001–2005				
Vessel Tonnage	31.38*	0.92**	−0.27	0.40**
	(16.92)	(0.37)	(0.73)	(0.18)
Adjusted R^2	0.55	0.74	0.38	0.41
Observations	198,912	191,955	129,683	164,056
Panel B: 2006–2016				
Vessel Tonnage	32.86	1.97***	3.47***	−0.13
	(25.82)	(0.73)	(1.26)	(0.20)
Adjusted R^2	0.39	0.60	-0.62	0.36
Observations	325,285	412,677	298,537	320,689

Notes: Panel A presents the IV estimates of the effect of vessel tonnage on pollutant concentrations within a 25-mile radius of ports in the United States from 2001 to 2005. Panel B presents the corresponding estimates from 2006 to 2016. Each entry presents an individual regression on a local air pollutant. The endogenous variables, vessel tonnage, are instrumented by an indicator of seven-day lagged cyclones at least 500-mile distant from ports. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port fixed effects. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics range from 11 to 21. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.13: 2SLS estimation of the effect of vessels in port on ozone pollution

	Dependent variable: pollutant concentration	
	(1)	(2)
Vessel Tonnage	−1.19	
	(0.78)	
Vessel Counts		−0.55
		(0.38)
1st-Stage F Stat.	36.10	19.60
Adjusted R^2	0.38	0.37
Observations	848,889	848,889

Notes: Panel A presents the OLS estimates of the effect of port traffic on O_3 concentrations within a 25-mile radius of ports in the United States. Panel B presents the IV estimates of the effect of port traffic on O_3 concentrations within a 25-mile radius of ports in the United States. Each entry presents an individual regression on a local air pollutant. The endogenous variables, vessel tonnage and the number of vessels, are instrumented by an indicator of seven-day lagged cyclones that are at least 500-mile distant from ports. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port fixed effects. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics for column (1) is 36 and for column (2) is 20. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.14: Effect of air pollution on hospital visit rates for the overall population in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CO						
CO (ppb)	2.79***	3.09***	10.46***	3.16***	0.69**	1.87***
	(0.41)	(0.64)	(1.74)	(0.63)	(0.27)	(0.65)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.40
1st-Stage F Stat.	56.44	56.44	56.44	56.44	56.44	56.44
AR Stat. P-val	3.99e-10	3.99e-10	3.99e-10	3.99e-10	3.99e-10	3.99e-10
SW S Stat. P-val	5.16e-06	5.16e-06	5.16e-06	5.16e-06	5.16e-06	5.16e-06
Observations	1,776,040	1,776,040	1,776,040	1,776,040	1,776,040	1,776,040
Panel B: NO_2						
NO_2 (ppb)	2.39***	2.91***	8.79***	3.09***	0.71***	1.94***
	(0.38)	(0.61)	(1.61)	(0.58)	(0.25)	(0.61)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.40
1st-Stage F Stat.	78.84	78.84	78.84	78.84	78.84	78.84
AR Stat. P-val	3.02e-09	3.02e-09	3.02e-09	3.02e-09	3.02e-09	3.02e-09
SW S Stat. P-val	1.58e-05	1.58e-05	1.58e-05	1.58e-05	1.58e-05	1.58e-05
Observations	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287
Panel C: $PM_{2.5}$						
$PM_{2.5}$ ($\mu g/m^3$)	1.84***	2.21***	6.73***	2.19***	0.50**	1.33***
	(0.32)	(0.51)	(1.37)	(0.49)	(0.21)	(0.50)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.40
1st-Stage F Stat.	27.67	27.67	27.67	27.67	27.67	27.67
AR Stat. P-val	5.36e-09	5.36e-09	5.36e-09	5.36e-09	5.36e-09	5.36e-09
SW S Stat. P-val	2.07e-05	2.07e-05	2.07e-05	2.07e-05	2.07e-05	2.07e-05
Observations	1,714,554	1,714,554	1,714,554	1,714,554	1,714,554	1,714,554
Panel D: SO_2						
SO_2 (ppb)	3.28***	4.68***	13.13***	4.40***	1.19***	3.08***
	(0.63)	(0.97)	(2.57)	(0.93)	(0.40)	(0.96)
Adjusted R^2	0.39	0.33	0.47	0.35	0.22	0.40
1st-Stage F Stat.	32.73	32.73	32.73	32.73	32.73	32.73
AR Stat. P-val	5.16e-10	5.16e-10	5.16e-10	5.16e-10	5.16e-10	5.16e-10
SW S Stat. P-val	6.40e-06	6.40e-06	6.40e-06	6.40e-06	6.40e-06	6.40e-06
Observations	1,742,012	1,742,012	1,742,012	1,742,012	1,742,012	1,742,012

Notes: This table presents the detailed results of Panel A in Table 3. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.15: Effect of air pollution on hospital visit rates for Blacks in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CO						
CO (ppb)	7.81***	5.38***	20.44***	5.74***	0.92	−0.04
	(1.63)	(1.43)	(4.04)	(1.79)	(0.81)	(1.88)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
1st-Stage F Stat.	46.35	46.35	46.35	46.35	46.35	46.35
AR Stat. P-val	0	0	0	0	0	0
SW S Stat. P-val	0.000361	0.000361	0.000361	0.000361	0.000361	0.000361
Observations	877,072	877,072	877,072	877,072	877,072	877,072
Panel B: NO_2						
NO_2 (ppb)	7.18***	8.77***	23.32***	5.95***	1.23	0.66
	(1.68)	(1.48)	(4.23)	(1.85)	(0.85)	(1.96)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
1st-Stage F Stat.	61.44	61.44	61.44	61.44	61.44	61.44
AR Stat. P-val	0	0	0	0	0	0
SW S Stat. P-val	0.000338	0.000338	0.000338	0.000338	0.000338	0.000338
Observations	887,300	887,300	887,300	887,300	887,300	887,300
Panel C: $PM_{2.5}$						
$PM_{2.5}$ ($\mu g/m^3$)	5.66***	6.28***	18.00***	3.77***	0.38	−0.53
	(1.28)	(1.13)	(3.29)	(1.41)	(0.60)	(1.45)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
1st-Stage F Stat.	23.52	23.52	23.52	23.52	23.52	23.52
AR Stat. P-val	3.32e-10	3.32e-10	3.32e-10	3.32e-10	3.32e-10	3.32e-10
SW S Stat. P-val	0.000549	0.000549	0.000549	0.000549	0.000549	0.000549
Observations	846,980	846,980	846,980	846,980	846,980	846,980
Panel D: SO_2						
SO_2 (ppb)	10.87***	16.35***	39.10***	8.23***	1.93	1.54
	(2.54)	(2.41)	(6.65)	(2.88)	(1.35)	(3.07)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
1st-Stage F Stat.	21.09	21.09	21.09	21.09	21.09	21.09
AR Stat. P-val	0	0	0	0	0	0
SW S Stat. P-val	0.000292	0.000292	0.000292	0.000292	0.000292	0.000292
Observations	871,296	871,296	871,296	871,296	871,296	871,296

Notes: This table presents the detailed results of Panel B in Table 3. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.16: Effect of air pollution on hospital visit rates for whites in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CO						
CO (ppb)	2.41***	2.10***	9.55***	4.02***	0.11	2.38*
	(0.51)	(0.41)	(1.56)	(1.16)	(0.54)	(1.25)
Adjusted R^2	0.17	0.09	0.34	0.28	0.15	0.32
1st-Stage F Stat.	58.31	58.31	58.31	58.31	58.31	58.31
AR Stat. P-val	8.13e-10	8.13e-10	8.13e-10	8.13e-10	8.13e-10	8.13e-10
SW S Stat. P-val	8.72e-06	8.72e-06	8.72e-06	8.72e-06	8.72e-06	8.72e-06
Observations	1,650,747	1,650,747	1,650,747	1,650,747	1,650,747	1,650,747
Panel B: NO_2						
NO_2 (ppb)	1.78***	1.80***	6.84***	3.51***	0.22	2.32**
	(0.46)	(0.40)	(1.42)	(1.01)	(0.48)	(1.12)
Adjusted R^2	0.17	0.09	0.34	0.28	0.15	0.32
1st-Stage F Stat.	83.18	83.18	83.18	83.18	83.18	83.18
AR Stat. P-val	1.84e-08	1.84e-08	1.84e-08	1.84e-08	1.84e-08	1.84e-08
SW S Stat. P-val	2.95e-05	2.95e-05	2.95e-05	2.95e-05	2.95e-05	2.95e-05
Observations	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994
Panel C: $PM_{2.5}$						
$PM_{2.5}$ ($\mu g/m^3$)	1.53***	1.51***	5.55***	2.78***	0.16	1.82*
	(0.41)	(0.35)	(1.29)	(0.91)	(0.43)	(0.99)
Adjusted R^2	0.17	0.09	0.34	0.28	0.15	0.32
1st-Stage F Stat.	27.30	27.30	27.30	27.30	27.30	27.30
AR Stat. P-val	2.31e-08	2.31e-08	2.31e-08	2.31e-08	2.31e-08	2.31e-08
SW S Stat. P-val	4.14e-05	4.14e-05	4.14e-05	4.14e-05	4.14e-05	4.14e-05
Observations	1,598,695	1,598,695	1,598,695	1,598,695	1,598,695	1,598,695
Panel D: SO_2						
SO_2 (ppb)	2.05***	2.63***	8.98***	4.64***	0.35	3.35**
	(0.69)	(0.58)	(2.10)	(1.49)	(0.70)	(1.63)
Adjusted R^2	0.17	0.09	0.33	0.28	0.15	0.32
1st-Stage F Stat.	38.52	38.52	38.52	38.52	38.52	38.52
AR Stat. P-val	9.80e-10	9.80e-10	9.80e-10	9.80e-10	9.80e-10	9.80e-10
SW S Stat. P-val	8.90e-06	8.90e-06	8.90e-06	8.90e-06	8.90e-06	8.90e-06
Observations	1,616,890	1,616,890	1,616,890	1,616,890	1,616,890	1,616,890

Notes: This table presents the detailed results of Panel C in Table 3. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.17: OLS estimates of the effect of air pollution on hospital visit rates in California port areas

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
CO (ppb)	0.63***	0.24	2.06***	1.20***	0.09	0.25
	(0.19)	(0.23)	(0.76)	(0.30)	(0.09)	(0.23)
NO_2 (ppb)	1.36***	−0.11	3.94***	3.18***	0.66***	2.05***
	(0.24)	(0.37)	(0.98)	(0.44)	(0.16)	(0.44)
$PM_{2.5}$ ($\mu g/m^3$)	0.49***	0.32*	1.39***	−0.07	0.06	0.07
	(0.12)	(0.18)	(0.50)	(0.24)	(0.09)	(0.23)
SO_2 (ppb)	0.47***	−0.43***	−0.55	0.35**	0.09	0.27
	(0.13)	(0.16)	(0.45)	(0.17)	(0.08)	(0.19)
Panel B: Black						
CO (ppb)	2.41***	−0.17	5.00***	2.59***	0.58**	1.52**
	(0.70)	(0.54)	(1.72)	(0.74)	(0.28)	(0.74)
NO_2 (ppb)	4.13***	0.65	11.12***	5.06***	1.50***	4.20***
	(1.02)	(0.91)	(2.65)	(1.11)	(0.43)	(1.16)
$PM_{2.5}$ ($\mu g/m^3$)	1.70***	−0.08	2.33*	0.34	0.28	0.01
	(0.54)	(0.45)	(1.35)	(0.59)	(0.22)	(0.58)
SO_2 (ppb)	2.63***	−0.10	2.36	0.81	−0.03	0.64
	(0.70)	(0.56)	(1.64)	(0.59)	(0.26)	(0.67)
Panel C: White						
CO (ppb)	0.74***	−0.08	2.55***	2.17***	0.19	0.64
	(0.23)	(0.13)	(0.77)	(0.50)	(0.17)	(0.43)
NO_2 (ppb)	2.09***	−0.30	6.87***	6.51***	1.50***	4.84***
	(0.29)	(0.23)	(0.90)	(0.72)	(0.28)	(0.73)
$PM_{2.5}$ ($\mu g/m^3$)	0.31**	0.02	0.68	−0.17	0.01	0.14
	(0.15)	(0.11)	(0.44)	(0.38)	(0.16)	(0.38)
SO_2 (ppb)	0.49***	−0.29***	−0.09	0.53*	−0.12	0.02
	(0.15)	(0.10)	(0.38)	(0.31)	(0.15)	(0.33)

Notes: This table presents the OLS estimation of the effect of air pollution on hospital visit rates for the overall population, Blacks, and whites. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a zip code-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.18: Elasticities of the effect of pollution on hospital visit rates for Blacks and whites in California port areas

	Dependent variable: IHS transformation of hospital visit rates					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Black						
CO (ppb)	0.103***	0.224***	0.091***	0.124***	0.068	−0.003
	(0.038)	(0.058)	(0.026)	(0.036)	(0.054)	(0.042)
NO_2 (ppb)	0.016	0.189***	0.038*	0.063**	0.051	0.002
	(0.027)	(0.040)	(0.021)	(0.027)	(0.039)	(0.030)
$PM_{2.5}$ ($\mu g/m^3$)	0.051*	0.174***	0.059***	0.064**	0.032	−0.015
	(0.027)	(0.041)	(0.020)	(0.026)	(0.038)	(0.030)
SO_2 (ppb)	0.185**	0.531***	0.184***	0.248***	0.209*	0.010
	(0.075)	(0.112)	(0.054)	(0.075)	(0.113)	(0.082)
Panel B: White						
CO (ppb)	0.125***	0.141***	0.083***	0.084***	0.005	0.056*
	(0.033)	(0.037)	(0.023)	(0.024)	(0.035)	(0.028)
NO_2 (ppb)	0.037*	0.112***	0.039**	0.049***	0.017	0.034*
	(0.021)	(0.027)	(0.015)	(0.015)	(0.023)	(0.018)
$PM_{2.5}$ ($\mu g/m^3$)	0.056**	0.111***	0.043**	0.058***	0.021	0.044**
	(0.024)	(0.030)	(0.017)	(0.017)	(0.025)	(0.020)
SO_2 (ppb)	0.191***	0.281***	0.145***	0.153***	0.021	0.099*
	(0.063)	(0.074)	(0.045)	(0.044)	(0.065)	(0.052)

Notes: This table presents the instrumental variable estimation of elasticities of the effect of pollution on hospital visit rates for Blacks and whites in California port areas. Each entry presents an individual regression of an air pollutant on an illness category. The dependent variables and pollution measures are IHS transformed. The instruments include fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. The first-stage F statistics range from 20 to 91 for Panel A and from 31 to 103 for Panel B. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.19: Test for differences of hospital visit rates of Blacks and whites in California port areas

	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
CO (ppb)	5.40***	3.29**	10.88**	1.73	0.81	-2.43
	[3.15]	[2.21]	[2.51]	[0.81]	[0.83]	[-1.08]
NO_2 (ppb)	5.41***	6.97***	16.48***	2.44	1.01	-1.66
	[3.10]	[4.55]	[3.69]	[1.16]	[1.04]	[-0.73]
$PM_{2.5}$ ($\mu g/m^3$)	4.13***	4.77***	12.45***	0.98	0.22	-2.35
	[3.08]	[4.04]	[3.52]	[0.58]	[0.29]	[-1.34]
SO_2 (ppb)	8.83***	13.72***	30.12***	3.59	1.58	-1.81
	[3.35]	[5.53]	[4.32]	[1.11]	[1.04]	[-0.52]

Notes: This table presents the statistical tests for the equality of regression coefficients for Blacks and whites in Panels B and C in Table 3. Pollution concentrations are standardized to their means and standard deviations. Each entry presents an individual test. The numbers in square brackets are Z-scores. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.20: Effect of air pollution on differences of hospital visit rates between Blacks and whites in California port areas, instrumental variable estimation

	Dependent variable: hospital visit rate for Blacks – hospital visit rate for whites					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
CO (ppb)	6.75***	5.65***	11.50**	−0.93	−0.26	−6.20
	(2.47)	(1.83)	(5.09)	(3.09)	(1.88)	(4.01)
NO_2 (ppb)	6.62***	9.13***	17.65***	−0.85	−0.52	−5.14
	(2.34)	(1.71)	(4.90)	(2.85)	(1.74)	(3.67)
$PM_{2.5}$ ($\mu g/m^3$)	5.31***	6.76***	14.03***	−1.31	−0.39	−4.62
	(1.93)	(1.45)	(4.13)	(2.29)	(1.40)	(3.08)
SO_2 (ppb)	10.01***	14.72***	29.78***	0.18	−0.55	−5.72
	(3.26)	(2.53)	(7.07)	(4.00)	(2.31)	(4.78)

Notes: This table presents the effects of pollution on the differences of hospital visit rates between Blacks and whites. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum, minimum, and dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 26 to 72. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.21: Effect of air pollution on hospital visit rates for Hispanics in California port areas

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
CO (ppb)	2.21***	3.76***	10.29***	0.79	1.40***	2.71***
	(0.55)	(0.82)	(1.98)	(0.66)	(0.42)	(0.86)
NO_2 (ppb)	2.18***	4.16***	9.92***	0.96	1.15***	2.59***
	(0.50)	(0.78)	(1.82)	(0.60)	(0.38)	(0.78)
$PM_{2.5}$ ($\mu g/m^3$)	1.37***	3.15***	6.97***	0.26	1.05***	1.91***
	(0.41)	(0.65)	(1.52)	(0.48)	(0.31)	(0.65)
SO_2 (ppb)	3.07***	7.00***	15.53***	1.47	1.84***	4.33***
	(0.85)	(1.25)	(2.90)	(0.95)	(0.62)	(1.31)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for the Hispanic population. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 28 to 79. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.22: Effect of air pollution on hospital visit rates in California port areas by age

	Dependent variable: hospital visits/million residents in each age group					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Ages 5 and under						
CO (ppb)	2.97**	13.63***	22.97***	0.46*	0.12	0.92***
	(1.27)	(4.46)	(8.62)	(0.27)	(0.09)	(0.23)
NO_2 (ppb)	3.16***	14.05***	20.00**	0.50*	0.10	0.76***
	(1.21)	(4.20)	(8.07)	(0.27)	(0.08)	(0.21)
$PM_{2.5}$ ($\mu g/m^3$)	2.27**	9.23***	12.52*	0.27	0.08	0.72***
	(0.96)	(3.36)	(6.53)	(0.20)	(0.06)	(0.17)
SO_2 (ppb)	4.13**	21.71***	27.81**	0.72*	0.16	1.07***
	(2.07)	(6.93)	(13.25)	(0.44)	(0.14)	(0.36)
Panel B: Ages between 5 and 19						
CO (ppb)	2.41***	3.59***	7.78***	0.14	−0.10	0.46
	(0.71)	(1.08)	(2.30)	(0.11)	(0.20)	(0.55)
NO_2 (ppb)	2.47***	3.46***	6.67***	0.18*	−0.03	0.82
	(0.67)	(1.03)	(2.17)	(0.11)	(0.19)	(0.52)
$PM_{2.5}$ ($\mu g/m^3$)	1.90***	2.75***	5.37***	0.09	0.05	0.67
	(0.54)	(0.86)	(1.79)	(0.09)	(0.15)	(0.42)
SO_2 (ppb)	3.52***	6.67***	11.35***	0.23	−0.07	1.55*
	(1.13)	(1.67)	(3.51)	(0.18)	(0.31)	(0.85)
Panel C: Ages between 20 and 64						
CO (ppb)	2.42***	1.92***	8.19***	1.42***	0.93***	1.44*
	(0.41)	(0.36)	(1.24)	(0.42)	(0.34)	(0.74)
NO_2 (ppb)	1.94***	2.20***	7.35***	1.26***	0.91***	1.50**
	(0.37)	(0.34)	(1.13)	(0.39)	(0.32)	(0.69)
$PM_{2.5}$ ($\mu g/m^3$)	1.50***	1.75***	5.76***	0.82***	0.66**	0.97*
	(0.31)	(0.29)	(0.98)	(0.32)	(0.26)	(0.57)
SO_2 (ppb)	2.72***	3.72***	11.36***	1.80***	1.49***	2.37**
	(0.61)	(0.56)	(1.87)	(0.61)	(0.50)	(1.10)
Panel D: Ages 65 and above						
CO (ppb)	4.31***	0.50	15.80***	17.87***	0.67	5.90***
	(1.08)	(0.51)	(4.02)	(3.96)	(0.96)	(2.11)
NO_2 (ppb)	4.02***	0.93**	14.51***	17.01***	0.86	5.94***
	(0.99)	(0.45)	(3.57)	(3.57)	(0.86)	(1.89)
$PM_{2.5}$ ($\mu g/m^3$)	2.98***	0.56	11.04***	12.53***	0.40	4.13***
	(0.83)	(0.38)	(3.10)	(3.06)	(0.71)	(1.58)
SO_2 (ppb)	5.86***	1.60**	20.75***	22.63***	1.69	9.33***
	(1.56)	(0.70)	(5.39)	(5.52)	(1.28)	(2.90)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates by age. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 27 to 79. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.23: Effect of air pollution on hospital visit rates in California port areas by sex

	Dependent variable: hospital visits/million residents in each sex group					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Male						
CO (ppb)	2.20***	2.58***	9.09***	2.77***	0.64***	1.72***
	(0.40)	(0.63)	(1.64)	(0.76)	(0.23)	(0.61)
NO_2 (ppb)	1.85***	2.35***	7.56***	2.80***	0.59***	1.85***
	(0.37)	(0.59)	(1.53)	(0.70)	(0.22)	(0.57)
$PM_{2.5}$ ($\mu g/m^3$)	1.43***	1.81***	5.76***	1.78***	0.43**	1.18**
	(0.31)	(0.49)	(1.30)	(0.57)	(0.18)	(0.47)
SO_2 (ppb)	2.36***	3.75***	11.14***	3.66***	1.00***	2.79***
	(0.62)	(0.93)	(2.42)	(1.12)	(0.34)	(0.91)
Panel B: Female						
CO (ppb)	3.37***	3.58***	11.79***	3.52***	0.76*	2.02**
	(0.52)	(0.71)	(1.93)	(0.63)	(0.40)	(0.85)
NO_2 (ppb)	2.91***	3.45***	9.98***	3.37***	0.84**	2.04**
	(0.49)	(0.67)	(1.80)	(0.59)	(0.37)	(0.80)
$PM_{2.5}$ ($\mu g/m^3$)	2.24***	2.59***	7.68***	2.59***	0.58*	1.50**
	(0.40)	(0.56)	(1.52)	(0.50)	(0.30)	(0.65)
SO_2 (ppb)	4.19***	5.59***	15.07***	5.10***	1.39**	3.40***
	(0.80)	(1.09)	(2.89)	(0.95)	(0.59)	(1.26)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates by sex. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 28 to 79. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.24: Effect of air pollution on hospital visit rates of placebo illnesses for the overall population in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents	
	Appendicitis	Arterial Embolism
	(1)	(2)
Panel A: CO		
CO (ppb)	0.09	0.03
	(0.06)	(0.02)
Adjusted R^2	0.01	0.00
Observations	1,776,040	1,776,040
Panel B: NO_2		
NO_2 (ppb)	0.08	0.02
	(0.05)	(0.02)
Adjusted R^2	0.01	0.00
Observations	1,805,287	1,805,287
Panel C: $PM_{2.5}$		
$PM_{2.5}$ ($\mu g/m^3$)	0.07	0.02
	(0.04)	(0.02)
Adjusted R^2	0.01	0.00
Observations	1,714,554	1,714,554
Panel D: SO_2		
SO_2 (ppb)	0.14*	0.03
	(0.08)	(0.03)
Adjusted R^2	0.01	0.00
Observations	1,742,012	1,742,012

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for placebo illnesses. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 28 to 79. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.25: Robustness check for the effect of vessel tonnage in port on air pollution, various model specifications

	Dependent variable: pollutant concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: No weather controls and temporal fixed effects				
Vessel Tonnage	2,358.96	120.54	4.13	37.07
	(3,618.78)	(263.04)	(3.11)	(110.60)
Adjusted R^2	-167.74	-649.67	-1.34	-514.91
Observations	524,197	604,632	428,220	484,745
Panel B: No weather controls				
Vessel Tonnage	16.76	0.57	1.15*	0.17
	(16.01)	(0.43)	(0.66)	(0.13)
Adjusted R^2	0.45	0.61	0.13	0.39
Observations	524,197	604,632	428,220	484,745
Panel C: No temporal fixed effects				
Vessel Tonnage	233.52***	9.84**	8.16***	0.94
	(88.98)	(4.44)	(2.21)	(0.73)
Adjusted R^2	-1.34	-3.79	-5.23	-0.09
Observations	524,197	604,632	428,220	484,745
Panel D: No quadratic weather terms				
Vessel Tonnage	18.06	0.98***	0.93*	0.05
	(13.53)	(0.33)	(0.56)	(0.12)
Adjusted R^2	0.53	0.72	0.29	0.42
Observations	524,197	604,632	428,220	484,745
Panel E: Monitors within 12.5 miles of ports				
Vessel Tonnage	28.21*	1.04***	1.33**	0.23
	(14.67)	(0.39)	(0.57)	(0.17)
Adjusted R^2	0.59	0.73	0.29	0.39
Observations	263,877	282,449	232,277	279,891

Notes: This table presents the robustness check results for Table 2 with various model specifications. Each panel presents regressions using an alternative model specification. Log vessel tonnage is instrumented by an indicator of seven-day lagged and 500-mile distant cyclones from ports. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port pair fixed effects. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics for Panel A is 0.1–3, for Panel B is 21–35, for Panel C is 6–16, for Panel D is 22–36, and for Panel E is 20–25. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.26: Robustness check for the effect of vessel tonnage in port on air pollution, various instrumental variable specifications

	Dependent variable: pollutant concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: Exclude cyclones within 800 miles of ports				
Vessel Tonnage	18.24	0.90***	0.84*	0.06
	(11.80)	(0.31)	(0.51)	(0.12)
Adjusted R^2	0.54	0.73	0.35	0.44
Observations	524,197	604,632	428,220	484,745
Panel B: Six-day lagged cyclones				
Vessel Tonnage	16.90	1.25***	0.97*	0.16
	(13.49)	(0.36)	(0.57)	(0.12)
Adjusted R^2	0.54	0.71	0.34	0.43
Observations	524,197	604,632	428,220	484,745
Panel C: Eight-day lagged cyclones				
Vessel Tonnage	27.75**	0.95***	0.95	0.08
	(13.49)	(0.34)	(0.59)	(0.12)
Adjusted R^2	0.53	0.73	0.34	0.44
Observations	524,197	604,632	428,220	484,745
Panel D: Six-, seven-, and eight-day lagged cyclones (2SLS)				
Vessel Tonnage	22.93*	1.12***	1.07**	0.12
	(12.39)	(0.32)	(0.50)	(0.11)
Adjusted R^2	0.53	0.72	0.33	0.43
Observations	524,197	604,632	428,220	484,745
Panel E: Six-, seven-, and eight-day lagged cyclones (LIML)				
Vessel Tonnage	23.08*	1.13***	1.09**	0.12
	(12.53)	(0.33)	(0.52)	(0.11)
Adjusted R^2	0.53	0.72	0.32	0.43
Observations	524,197	604,632	428,220	484,745
Panel F: Cyclone counts				
Vessel Tonnage	−9.15	0.55**	1.22**	−0.03
	(10.92)	(0.27)	(0.48)	(0.09)
Adjusted R^2	0.55	0.75	0.30	0.44
Observations	524,197	604,632	428,220	484,745

Notes: This table presents the results of robustness check for Table 2 with various instrumental variable specifications. Each panel presents regressions using an alternative instrumental variable specification. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port pair fixed effects. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics for Panel A is 24–31, for Panel B is 21–33, for Panel C is 18–31, for Panel D is 8–12, and for Panel F is 29–41. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.27: Robustness check for the effect of vessel tonnage in port on air pollution, including and excluding different sets of observations where cyclones are close to ports

	Dependent variable: pollutant concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: Including 2 days before and after cyclones near ports				
Vessel Tonnage	20.32	1.11***	1.17**	0.15
	(13.61)	(0.34)	(0.57)	(0.12)
Adjusted R^2	0.54	0.72	0.31	0.43
Observations	529,953	611,553	433,831	491,725
Panel B: Excluding 21 days after cyclones near ports				
Vessel Tonnage	22.62	1.20***	1.54**	0.12
	(13.87)	(0.35)	(0.59)	(0.12)
Adjusted R^2	0.54	0.71	0.25	0.44
Observations	508,766	586,027	412,972	465,777

Notes: Panel A presents the instrumental variable estimation of the effect of vessel tonnage in ports on air pollution, where we include the dates when there exist tropical cyclones near ports (e.g., within the 200-mile radius of ports) and two days before and after the events. Panel B presents the instrumental variable estimation of the effect of vessel tonnage in ports on air pollution, where we exclude 21 days after tropical cyclones near ports (e.g., within the 200-mile radius of ports). Each column presents an individual regression on a local air pollutant. Log of vessel tonnage is instrumented by an indicator of seven-day lagged and 500-mile distant cyclones from ports. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and monitor-port pair fixed effects. Standard errors are clustered by monitor-port pair and day. The first-stage F statistics for Panel A is 21–35 and for Panel B is 21–34. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.28: Effect of air pollution on hospital visit rates in California port areas, satellite-based projected data

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
$PM_{2.5}$ ($\mu g/m^3$)	1.82***	2.41***	7.05***	2.38***	0.51**	1.42***
	(0.32)	(0.51)	(1.38)	(0.50)	(0.22)	(0.52)
Adjusted R^2	0.39	0.33	0.47	0.35	0.22	0.40
Observations	1,799,639	1,799,639	1,799,639	1,799,639	1,799,639	1,799,639
Panel B: Black						
$PM_{2.5}$ ($\mu g/m^3$)	5.45***	5.81***	16.72***	4.33***	0.63	−0.10
	(1.30)	(1.09)	(3.25)	(1.45)	(0.63)	(1.50)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
Observations	884,524	884,524	884,524	884,524	884,524	884,524
Panel C: White						
$PM_{2.5}$ ($\mu g/m^3$)	1.40***	1.53***	5.54***	2.82***	0.10	1.77*
	(0.40)	(0.34)	(1.24)	(0.89)	(0.43)	(0.98)
Adjusted R^2	0.17	0.09	0.33	0.28	0.15	0.32
Observations	1,674,738	1,674,738	1,674,738	1,674,738	1,674,738	1,674,738

Notes: This table presents the instrumental variable estimation of the effect of $PM_{2.5}$ on hospital visit rates for the overall population, Blacks, and whites. $PM_{2.5}$ measures are satellite-based projections, which are standardized by the sample mean and standard deviation. Each entry presents an individual regression of an air pollutant on an illness category. Pollution measures are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 32 to 45. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.29: Effect of air pollution on hospital visit rates in California port areas – joint estimation with zip codes within a 25-mile radius from ports

	Dependent variable: hospital visits/million residents								
	All Respiratory			All Heart			All Psychiatric		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Overall population									
CO (ppb)	15.34***	9.70***	21.16***	0.59	2.05**	−0.17	−0.51	0.31	−0.08
	(5.22)	(3.03)	(5.97)	(1.59)	(1.00)	(1.80)	(1.73)	(1.08)	(1.99)
NO_2 (ppb)	−5.02		−22.14***	2.64*		4.30	2.44		0.75
	(4.97)		(8.49)	(1.51)		(2.84)	(1.70)		(3.23)
SO_2 (ppb)		0.99	18.29**		1.83	−1.53		2.70*	2.11
		(4.37)	(7.27)		(1.40)	(2.59)		(1.55)	(2.91)
1st-Stage F Stat.	23.16	9.46	5.77	23.16	9.46	5.77	23.16	9.46	5.77
AR Stat. P-val	3.99e-10	5.16e-10	5.16e-10	3.99e-10	5.16e-10	5.16e-10	3.99e-10	5.16e-10	5.16e-10
SW S Stat. P-val	5.16e-06	6.40e-06	6.40e-06	5.16e-06	6.40e-06	6.40e-06	5.16e-06	6.40e-06	6.40e-06
Observations	1,776,040	1,742,012	1,742,012	1,776,040	1,742,012	1,742,012	1,776,040	1,742,012	1,742,012
Panel B: Black									
CO (ppb)	−8.67	−1.08	7.69	2.65	3.89	3.26	−4.95	−3.00	−4.53
	(13.01)	(7.08)	(14.61)	(4.95)	(2.89)	(5.31)	(5.61)	(3.16)	(6.33)
NO_2 (ppb)	32.05**		−16.77	3.40		1.19	5.41		2.91
	(13.72)		(21.64)	(5.20)		(8.23)	(5.90)		(10.12)
SO_2 (ppb)		40.46***	52.79***		3.33	2.45		5.33	3.20
		(11.54)	(17.62)		(4.64)	(7.32)		(5.20)	(8.89)
1st-Stage F Stat.	15.41	9.86	5.43	15.41	9.86	5.43	15.41	9.86	5.43
AR Stat. P-val	0	0	0	0	0	0	0	0	0
SW S Stat. P-val	0.000361	0.000292	0.000292	0.000361	0.000292	0.000292	0.000361	0.000292	0.000292
Observations	877,072	871,296	871,296	877,072	871,296	871,296	877,072	871,296	871,296
Panel C: White									
CO (ppb)	17.02***	12.49***	20.30***	3.03	3.27*	1.40	0.23	0.86	−0.11
	(4.35)	(2.69)	(5.16)	(2.76)	(1.83)	(3.41)	(2.94)	(1.91)	(3.70)
NO_2 (ppb)	−7.48*		−14.74*	0.99		3.54	2.15		1.84
	(4.03)		(7.83)	(2.49)		(5.53)	(2.74)		(6.07)
SO_2 (ppb)		−4.59	6.20		1.09	−1.50		2.42	1.07
		(3.39)	(6.39)		(2.21)	(4.71)		(2.33)	(4.98)
1st-Stage F Stat.	24.35	9.62	3.89	24.35	9.62	3.89	24.35	9.62	3.89
AR Stat. P-val	8.13e-10	9.80e-10	9.80e-10	8.13e-10	9.80e-10	9.80e-10	8.13e-10	9.80e-10	9.80e-10
SW S Stat. P-val	8.72e-06	8.90e-06	8.90e-06	8.72e-06	8.90e-06	8.90e-06	8.72e-06	8.90e-06	8.90e-06
Observations	1,650,747	1,616,890	1,616,890	1,650,747	1,616,890	1,616,890	1,650,747	1,616,890	1,616,890

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rate within a 25-mile radius of CA ports, jointly estimated for multiple air pollutants. Each column in a panel presents an individual regression on a set of pollutants. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls and their quadratic terms, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.30: Effect of air pollution on hospital visit rates in California port areas – joint estimation with zip codes within a 15-mile radius from ports

	Dependent variable: hospital visits/million residents								
	All Respiratory			All Heart			All Psychiatric		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Overall population									
CO (ppb)	21.36***	14.32***	24.64***	1.72	2.27**	0.69	−0.83	0.26	−0.63
	(5.42)	(3.31)	(6.14)	(1.53)	(1.03)	(1.81)	(1.68)	(1.17)	(1.89)
NO_2 (ppb)	−10.97**		−23.31**	0.98		3.58	3.78**		2.01
	(5.29)		(9.29)	(1.52)		(3.27)	(1.69)		(3.46)
SO_2 (ppb)		−5.36	12.78*		0.33	−2.45		3.66**	2.09
		(4.25)	(7.20)		(1.30)	(2.76)		(1.45)	(2.93)
Observations	866,835	859,168	859,168	866,835	859,168	859,168	866,835	859,168	859,168
Panel B: Black									
CO (ppb)	9.65	11.09	24.71	1.12	2.41	0.87	−8.60	−5.20	−4.61
	(13.19)	(7.57)	(15.60)	(5.36)	(3.28)	(5.72)	(5.77)	(3.66)	(6.63)
NO_2 (ppb)	17.70		−28.60	3.18		3.23	11.80**		−1.25
	(14.16)		(24.96)	(5.70)		(9.48)	(5.90)		(11.15)
SO_2 (ppb)		24.70**	45.54**		2.48	0.13		12.19**	13.10
		(11.01)	(18.59)		(4.68)	(7.70)		(5.05)	(9.46)
Observations	562,552	557,677	557,677	562,552	557,677	557,677	562,552	557,677	557,677
Panel C: White									
CO (ppb)	23.97***	15.59***	26.54***	6.73**	5.52***	3.29	2.64	3.09	0.13
	(5.08)	(3.32)	(5.77)	(3.06)	(2.13)	(3.69)	(3.27)	(2.27)	(3.82)
NO_2 (ppb)	−14.92***		−23.78***	−3.45		4.83	1.06		6.43
	(4.51)		(9.01)	(2.69)		(6.43)	(3.09)		(6.99)
SO_2 (ppb)		−9.28**	8.92		−3.60	−7.30		0.46	−4.46
		(3.65)	(7.41)		(2.31)	(5.45)		(2.57)	(5.80)
Observations	802,910	795,414	795,414	802,910	795,414	795,414	802,910	795,414	795,414

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rate within a 15-mile radius of CA ports, jointly estimated for multiple air pollutants. Each column in a panel presents an individual regression on a set of pollutants. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls and their quadratic terms, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.31: Effect of fitted vessel tonnage on highway congestion in California port areas

	Dependent variable: traffic delay with respect to threshold speed					
	35 mph	40 mph	45 mph	50 mph	55 mph	60 mph
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Vessel tonnage						
Fitted Vessel Tonnage	7.49	8.78	9.97	10.92	11.69	12.43
	(5.86)	(6.73)	(7.57)	(8.43)	(9.36)	(10.33)
Adjusted R^2	0.33	0.35	0.37	0.39	0.42	0.44
Observations	2,625,756	2,625,756	2,625,756	2,625,756	2,625,756	2,625,756
Panel B: Vessel counts						
Fitted Vessel Counts	4.84	5.67	6.44	7.06	7.55	8.03
	(3.79)	(4.35)	(4.89)	(5.45)	(6.04)	(6.67)
Adjusted R^2	0.33	0.35	0.37	0.39	0.42	0.44
Observations	2,625,756	2,625,756	2,625,756	2,625,756	2,625,756	2,625,756

Notes: This table presents the OLS estimation for the effect of fitted vessel tonnage and counts on highway congestion in California's port areas. The fitted values are obtained from regressing log vessel tonnage or vessel counts on the instrument of seven-day lagged and 500-mile distant cyclones from ports. The dependent variable is measured as average delays to a threshold speed. Each column presents a regression of threshold speed. All regressions include weather controls (i.e., the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, and wind direction) and fixed effects (i.e., county-by-year, month, day-of-week, holiday, freeway, and VDS-port). An observation is a VDS-port-day. Standard errors are clustered by VDS-port and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.32: Effect of air pollution on hospital visit rates in California port areas, excluding strong windy days

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
CO (ppb)	2.56***	2.65***	9.55***	2.95***	0.67**	1.63**
	(0.43)	(0.67)	(1.77)	(0.67)	(0.27)	(0.67)
NO_2 (ppb)	2.56***	2.50***	9.06***	3.13***	0.75***	1.85***
	(0.42)	(0.64)	(1.71)	(0.64)	(0.27)	(0.65)
$PM_{2.5}$ ($\mu g/m^3$)	1.78***	1.90***	6.60***	1.99***	0.50**	1.17**
	(0.31)	(0.48)	(1.31)	(0.50)	(0.20)	(0.49)
SO_2 (ppb)	3.41***	3.67***	12.97***	4.38***	1.27***	2.97***
	(0.65)	(0.96)	(2.58)	(0.97)	(0.41)	(0.98)
Panel B: Black						
CO (ppb)	7.17***	5.62***	20.05***	5.80***	0.64	0.08
	(1.64)	(1.44)	(3.98)	(1.75)	(0.78)	(1.80)
NO_2 (ppb)	7.52***	7.22***	22.56***	6.97***	1.34	1.09
	(1.83)	(1.56)	(4.39)	(1.93)	(0.88)	(1.99)
$PM_{2.5}$ ($\mu g/m^3$)	5.37***	5.09***	16.65***	4.01***	0.33	−0.26
	(1.25)	(1.10)	(3.13)	(1.37)	(0.55)	(1.32)
SO_2 (ppb)	10.08***	11.63***	33.61***	10.04***	2.36*	2.29
	(2.60)	(2.25)	(6.24)	(2.82)	(1.27)	(2.81)
Panel C: White						
CO (ppb)	2.51***	1.54***	9.15***	4.00***	0.39	2.49*
	(0.55)	(0.44)	(1.62)	(1.26)	(0.55)	(1.32)
NO_2 (ppb)	2.41***	1.25***	8.12***	3.89***	0.42	2.51**
	(0.52)	(0.42)	(1.55)	(1.20)	(0.54)	(1.27)
$PM_{2.5}$ ($\mu g/m^3$)	1.77***	1.02***	6.02***	2.83***	0.33	1.87*
	(0.41)	(0.33)	(1.26)	(0.96)	(0.42)	(0.99)
SO_2 (ppb)	2.96***	1.58***	10.15***	5.12***	0.86	3.89**
	(0.74)	(0.57)	(2.17)	(1.67)	(0.75)	(1.78)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rate, where the observations with wind speed greater than 3.3 meters per second are excluded. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 25 to 72. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.33: Effect of air pollution on hospital visit rates for Black and white females in California port areas

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Black female			
CO (ppb)	22.15***	6.68***	0.19
	(4.85)	(1.96)	(2.50)
NO_2 (ppb)	26.06***	6.15***	0.78
	(5.10)	(2.08)	(2.62)
$PM_{2.5}$ ($\mu g/m^3$)	19.67***	4.58***	0.40
	(3.91)	(1.53)	(1.90)
SO_2 (ppb)	44.54***	8.03**	1.89
	(7.88)	(3.20)	(4.21)
Panel B: White female			
CO (ppb)	11.42***	5.27***	2.37
	(1.95)	(1.19)	(1.68)
NO_2 (ppb)	8.10***	4.49***	2.42
	(1.77)	(1.06)	(1.49)
$PM_{2.5}$ ($\mu g/m^3$)	6.66***	3.96***	1.78
	(1.60)	(0.97)	(1.33)
SO_2 (ppb)	10.41***	6.19***	3.48
	(2.64)	(1.58)	(2.21)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for Black and white females. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.34: Effect of air pollution on all-cause total hospital visit rates in California port areas

	Dependent variable: hospital visits/million residents		
	Overall Population	Black	White
	(1)	(2)	(3)
Panel A: CO			
CO (ppb)	19.02***	41.56***	12.29***
	(4.01)	(8.65)	(4.76)
Adjusted R^2	0.69	0.47	0.60
Observations	1,776,040	877,072	1,650,747
Panel B: NO_2			
NO_2 (ppb)	17.31***	41.77***	10.91**
	(3.69)	(8.92)	(4.23)
Adjusted R^2	0.69	0.47	0.60
Observations	1,805,287	887,300	1,679,994
Panel C: $PM_{2.5}$			
$PM_{2.5}$ ($\mu g/m^3$)	13.41***	30.08***	9.02**
	(3.11)	(6.90)	(3.85)
Adjusted R^2	0.69	0.47	0.60
Observations	1,714,554	846,980	1,598,695
Panel D: SO_2			
SO_2 (ppb)	26.07***	57.42***	15.97***
	(5.69)	(13.61)	(6.05)
Adjusted R^2	0.69	0.47	0.60
Observations	1,742,012	871,296	1,616,890

Notes: This table presents the instrumental variable estimation of the effect of air pollution on all-cause total hospital visit rates for the overall population, Blacks, and whites. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.35: Effect of air pollution on hospital visit rates in California port areas, principal diagnoses

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Overall population			
CO (ppb)	6.05***	0.72***	0.32
	(1.24)	(0.22)	(0.20)
NO_2 (ppb)	4.91***	0.63***	0.40**
	(1.16)	(0.20)	(0.18)
$PM_{2.5}$ ($\mu g/m^3$)	3.70***	0.51***	0.27*
	(0.97)	(0.16)	(0.15)
SO_2 (ppb)	7.43***	0.83**	0.64**
	(1.81)	(0.32)	(0.29)
Panel B: Black			
CO (ppb)	10.83***	1.05	−0.40
	(2.47)	(0.69)	(0.81)
NO_2 (ppb)	13.38***	0.84	−0.15
	(2.55)	(0.71)	(0.82)
$PM_{2.5}$ ($\mu g/m^3$)	10.02***	0.84	−0.38
	(1.94)	(0.53)	(0.61)
SO_2 (ppb)	22.65***	0.85	0.29
	(4.05)	(1.10)	(1.24)
Panel C: White			
CO (ppb)	4.72***	0.85*	0.65*
	(0.97)	(0.43)	(0.36)
NO_2 (ppb)	3.19***	0.72*	0.72**
	(0.89)	(0.38)	(0.31)
$PM_{2.5}$ ($\mu g/m^3$)	2.43***	0.66*	0.61**
	(0.80)	(0.34)	(0.28)
SO_2 (ppb)	4.23***	0.89	1.06**
	(1.30)	(0.57)	(0.47)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for the overall population, Blacks, and whites, where hospital visit rates are calculated only using principal diagnoses. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.36: Effect of air pollution on hospital visit rates in California port areas, Patient Discharge Data

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Overall population			
CO (ppb)	2.46***	1.84***	0.98***
	(0.48)	(0.39)	(0.35)
NO_2 (ppb)	2.11***	1.76***	1.13***
	(0.43)	(0.35)	(0.32)
$PM_{2.5}$ ($\mu g/m^3$)	1.80***	1.36***	0.86***
	(0.37)	(0.30)	(0.27)
SO_2 (ppb)	2.90***	2.39***	1.68***
	(0.69)	(0.57)	(0.50)
Panel B: Black			
CO (ppb)	3.49**	2.92**	0.84
	(1.44)	(1.21)	(1.05)
NO_2 (ppb)	3.64**	3.14**	1.46
	(1.48)	(1.23)	(1.09)
$PM_{2.5}$ ($\mu g/m^3$)	3.19***	2.06**	0.85
	(1.16)	(0.94)	(0.80)
SO_2 (ppb)	6.25***	3.88**	2.57
	(2.34)	(1.86)	(1.62)
Panel C: White			
CO (ppb)	3.15***	2.83***	1.36*
	(0.76)	(0.74)	(0.72)
NO_2 (ppb)	2.24***	2.19***	1.56**
	(0.67)	(0.63)	(0.64)
$PM_{2.5}$ ($\mu g/m^3$)	2.10***	1.93***	1.29**
	(0.61)	(0.58)	(0.58)
SO_2 (ppb)	2.41**	2.42**	2.01**
	(0.99)	(0.94)	(0.93)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for the overall population, Blacks, and whites, where hospital visit rates are calculated only using the Patient Discharge Data. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.37: Effect of air pollution on hospital visit rates in California port areas, Emergency Department Data

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Overall population			
CO (ppb)	8.05***	1.12***	0.78**
	(1.49)	(0.23)	(0.36)
NO_2 (ppb)	6.86***	1.18***	0.77**
	(1.40)	(0.22)	(0.34)
$PM_{2.5}$ ($\mu g/m^3$)	5.02***	0.74***	0.42
	(1.16)	(0.18)	(0.28)
SO_2 (ppb)	10.57***	1.89***	1.35**
	(2.23)	(0.36)	(0.56)
Panel B: Black			
CO (ppb)	17.27***	2.42**	−0.90
	(3.35)	(0.99)	(1.32)
NO_2 (ppb)	20.20***	2.46**	−0.90
	(3.52)	(1.03)	(1.39)
$PM_{2.5}$ ($\mu g/m^3$)	15.19***	1.42*	−1.38
	(2.69)	(0.76)	(1.04)
SO_2 (ppb)	33.69***	3.86**	−1.12
	(5.55)	(1.64)	(2.25)
Panel C: White			
CO (ppb)	6.67***	1.29***	1.27*
	(1.14)	(0.47)	(0.73)
NO_2 (ppb)	4.89***	1.36***	1.11*
	(1.03)	(0.41)	(0.63)
$PM_{2.5}$ ($\mu g/m^3$)	3.71***	1.00***	0.81
	(0.90)	(0.37)	(0.56)
SO_2 (ppb)	6.81***	2.24***	1.83**
	(1.51)	(0.62)	(0.93)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for the overall population, Blacks, and whites, where hospital visit rates are calculated only using the Emergency Department Data. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.38: Effect of air pollution on hospital visit rates in California port areas, Ambulatory Surgery Center Data

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Overall population			
CO (ppb)	−0.05	0.19	0.11
	(0.28)	(0.26)	(0.19)
NO_2 (ppb)	−0.18	0.15	0.03
	(0.26)	(0.23)	(0.18)
$PM_{2.5}$ ($\mu g/m^3$)	−0.09	0.09	0.05
	(0.21)	(0.19)	(0.14)
SO_2 (ppb)	−0.33	0.12	0.05
	(0.41)	(0.37)	(0.28)
Panel B: Black			
CO (ppb)	−0.32	0.40	0.01
	(0.57)	(0.39)	(0.41)
NO_2 (ppb)	−0.52	0.35	0.10
	(0.58)	(0.42)	(0.39)
$PM_{2.5}$ ($\mu g/m^3$)	−0.38	0.29	−0.003
	(0.42)	(0.30)	(0.31)
SO_2 (ppb)	−0.85	0.50	0.10
	(0.86)	(0.63)	(0.63)
Panel C: White			
CO (ppb)	−0.27	−0.11	−0.25
	(0.44)	(0.50)	(0.37)
NO_2 (ppb)	−0.29	−0.03	−0.35
	(0.40)	(0.44)	(0.33)
$PM_{2.5}$ ($\mu g/m^3$)	−0.26	−0.14	−0.29
	(0.35)	(0.39)	(0.29)
SO_2 (ppb)	−0.24	−0.02	−0.49
	(0.58)	(0.62)	(0.49)

Notes: This table presents the instrumental variable estimation of the effect of air pollution on hospital visit rates for the overall population, Blacks, and whites, where hospital visit rates are calculated only using the Ambulatory Surgery Center Data. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 21 to 83. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.39: LIML estimation of the effect of air pollution on hospital visit rates for the overall population in California port areas

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: CO						
CO (ppb)	2.44***	2.66***	9.09***	3.09***	0.51*	1.81**
	(0.41)	(0.58)	(1.61)	(0.68)	(0.31)	(0.73)
Adjusted R^2	0.33	0.29	0.42	0.31	0.17	0.36
Observations	1,776,040	1,776,040	1,776,040	1,776,040	1,776,040	1,776,040
Panel B: NO_2						
NO_2 (ppb)	1.99***	2.58***	7.50***	3.01***	0.57**	1.94***
	(0.38)	(0.55)	(1.49)	(0.62)	(0.28)	(0.67)
Adjusted R^2	0.33	0.29	0.42	0.31	0.17	0.36
Observations	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287
Panel C: $PM_{2.5}$						
$PM_{2.5}$ ($\mu g/m^3$)	1.49***	1.98***	5.64***	2.11***	0.41*	1.33**
	(0.33)	(0.47)	(1.29)	(0.53)	(0.23)	(0.56)
Adjusted R^2	0.33	0.29	0.42	0.31	0.18	0.36
Observations	1,714,554	1,714,554	1,714,554	1,714,554	1,714,554	1,714,554
Panel D: SO_2						
SO_2 (ppb)	2.45***	4.09***	10.74***	4.10***	0.95**	2.86***
	(0.61)	(0.86)	(2.33)	(0.97)	(0.43)	(1.03)
Adjusted R^2	0.33	0.28	0.42	0.31	0.17	0.36
Observations	1,742,012	1,742,012	1,742,012	1,742,012	1,742,012	1,742,012

Notes: This table presents the LIML instrumental variable estimation of the effect of air pollution on hospital visit rates for the overall population. Each entry presents an individual regression of an air pollutant on an illness category. Pollution concentrations are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. All regressions include weather controls, such as the quadratics of maximum temperature, minimum temperature, dew point temperature, and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are unweighted. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.40: Placebo tests for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollution

	Dependent variable: residual of log pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: One year before the policy				
CA Regulation	0.03	0.02	0.07	−0.005
	(0.08)	(0.08)	(0.13)	(0.13)
Date	0.0001	−0.001	0.002	−0.001
	(0.002)	(0.002)	(0.003)	(0.003)
CA Regulation × Date	0.002	0.001	−0.01**	0.01
	(0.002)	(0.002)	(0.004)	(0.004)
Pre-policy Mean	642.22	18.71	15.01	1.89
Observations	4,745	5,055	1,913	3,129
Panel B: One year after the policy				
CA Regulation	0.15	0.10	0.07	−0.01
	(0.10)	(0.09)	(0.11)	(0.27)
Date	−0.003	0.0003	0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.004)
CA Regulation × Date	0.001	−0.0003	−0.004	−0.002
	(0.002)	(0.003)	(0.003)	(0.01)
Pre-policy Mean	599.15	18.01	14.03	1.74
Observations	4,828	5,166	2,673	3,359
Panel C: Neighboring areas				
CA Regulation	0.27	0.13*	−0.23*	0.15*
	(0.16)	(0.06)	(0.11)	(0.06)
Date	0.001	−0.001	0.004*	0.01
	(0.003)	(0.001)	(0.002)	(0.01)
CA Regulation × Date	−0.01	−0.001	−0.01*	−0.01
	(0.004)	(0.002)	(0.004)	(0.02)
Pre-policy Mean	406.79	11.37	11.28	1.31
Observations	1,591	3,195	1,364	509

Notes: This table presents the placebo tests for RDD estimation of the effect of the California at-berth regulation on local air pollution. The second-stage RDD dependent variable is taken from the residuals by regressing log pollution concentrations on weather controls (i.e., the quadratics of maximum temperature, minimum temperature, dew point temperature, precipitation, wind speed, and relative wind direction between a monitor-port pair), fixed effects (i.e., county-by-year, month, day-of-week, holiday, and port-monitor pair), and log vessel tonnage (instrumented by seven-day lagged and 500-mile distant cyclones from ports). The local linear bandwidth is specified as 60 days on both sides of the policy threshold. Panel A shows the results of specifying placebo policy dates one year before the actual policy date. Panel B shows the results of specifying placebo policy dates one year after the actual policy date. Panel C shows the results by assigning the policy date to neighboring areas located 75 to 100 miles from ports. An observation is a monitor-port-day. Standard errors are clustered by monitor-port pair and normalized day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.41: Projected energy consumption by marine vessels in the United States

	Fossil Fuel		Electricity	
	Reference	Shore Power	Reference	Shore Power
2017	0.78	0.78	0.00	0.00
2020	0.77	0.72	0.01	0.05
2025	0.81	0.64	0.01	0.18
2030	0.85	0.66	0.01	0.19
2035	0.90	0.70	0.01	0.22
2040	0.93	0.72	0.01	0.22
2045	0.97	0.74	0.01	0.24
2050	1.01	0.77	0.01	0.25

Notes: This table presents projected marine vessel energy consumption simulated in Yale-NEMS. The unit is quadrillion Btu. The data include electricity and fossil fuel consumption for the reference case and the shore power scenario.

B Supplementary Figures (For Online Publication)

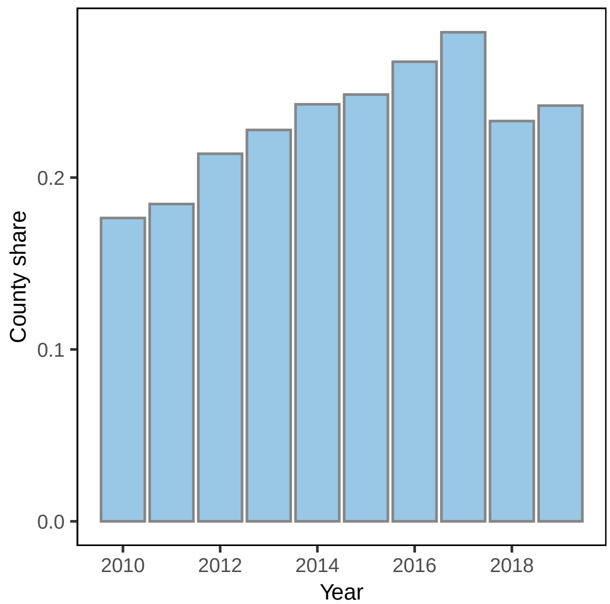

Figure B.1: Share of nonattainment counties adjacent to the major ports in the United States.

Notes: The figure plots the share of nonattainment counties that fail to meet the National Ambient Air Quality Standards and locate within a 50-mile radius of the major ports in the United States. The standards include Carbon Monoxide (1971), Nitrogen Dioxide (1971), 8-Hour Ozone (2008, 2015), PM_{10} (1987), $PM_{2.5}$ (1997, 2006, 2012), Sulfur Dioxide (1971, 2010). The data are obtained from US EPA NAAQS Greenbook.

Figure B.2: Locations of zip codes near the major California ports.

Notes: This figure plots the locations of zip codes that are within 25 miles of the major ports in California, shown in blue areas. According to the US 2010 Decennial Census, around 47 percent of the population in California resides in the blue areas.

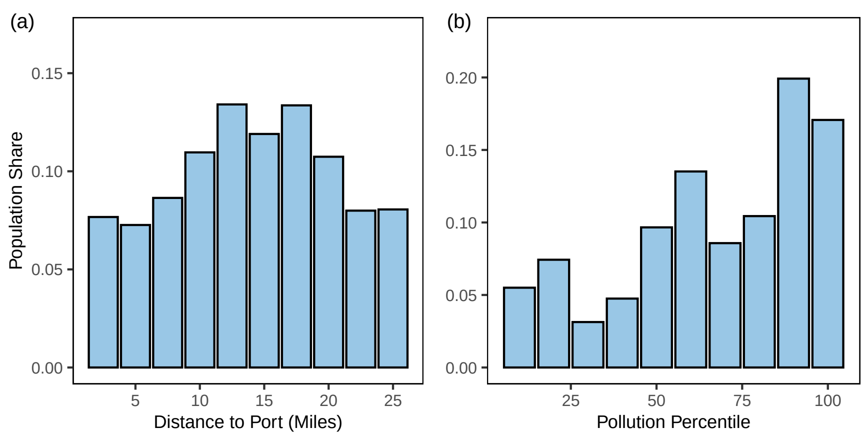

Figure B.3: (a) Distribution of Hispanic population by distance to major California ports. (b) Distribution of the Hispanic population in California port areas by percentile of $PM_{2.5}$ concentration.

Notes: Panel (a) plots population distribution in the California port areas by the distance between census tract and port for the Hispanic population. We obtain the population data at the census tract level and assign a distance between a census tract to its nearest mapped port to the population within the census tract. Panel (b) plots population distribution in the California port areas by percentile of $PM_{2.5}$ concentration. Larger pollution percentiles represent higher pollution exposures. The data are obtained from the US 2010 Decennial Census and US EPA Air Quality System.

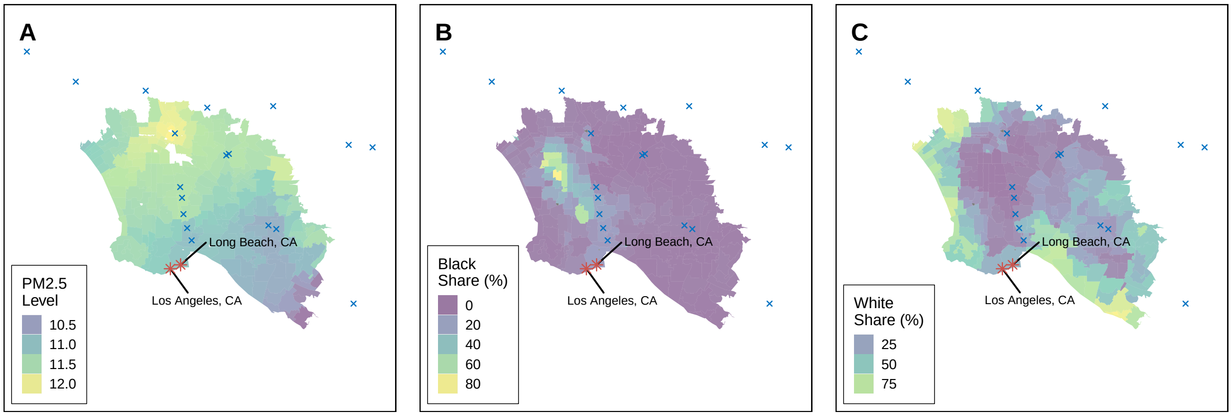

Figure B.4: Average $PM_{2.5}$ concentrations, Black population shares, and white population shares in zip codes near ports in Los Angeles, California.

Notes: Panel A presents the daily average $PM_{2.5}$ concentrations at the zip code level based on the EPA monitoring data within 25 miles from the two major ports near Los Angeles, California. Panel B shows the percentage of Black population in a zip code for the same area, while Panel C shows the percentage of white population. The blue crosses in the panels represent the location of $PM_{2.5}$ monitor sites with available data. The red stars indicate the Ports of Los Angeles and Long Beach. The pollution data are obtained from the US EPA Air Quality System. The population data are acquired from the US 2010 Decennial Census.

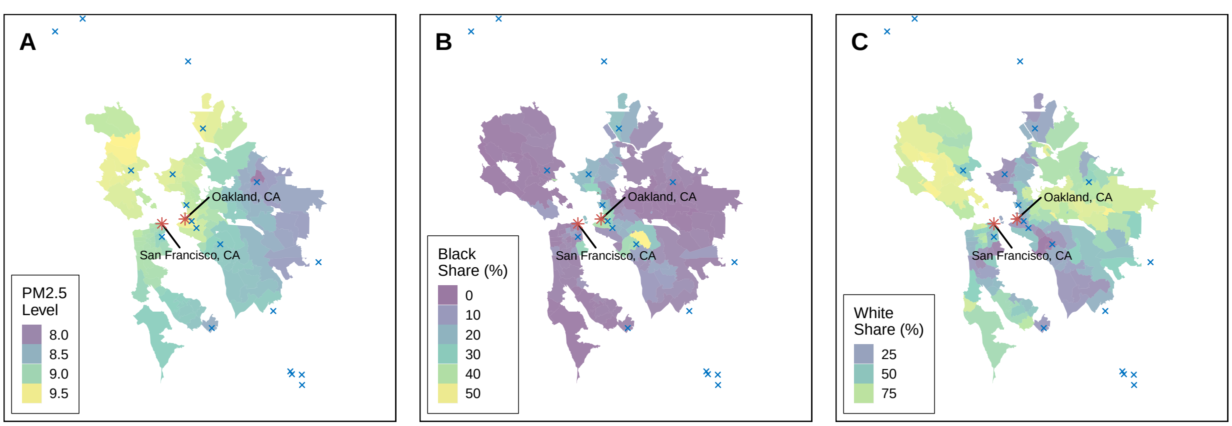

Figure B.5: Average $PM_{2.5}$ concentrations, Black population shares, and white population shares in zip codes near ports in San Francisco, California.

Notes: Panel A presents the daily average $PM_{2.5}$ concentrations at the zip code level based on the EPA monitoring data within 25 miles from the two major ports near San Francisco, California. Panel B shows the percentage of Black population in a zip code for the same area, while Panel C shows the percentage of white population. The blue crosses in the panels represent the location of $PM_{2.5}$ monitor sites with available data. The red stars indicate the Ports of San Francisco and Oakland. The pollution data are obtained from the US EPA Air Quality System. The population data are acquired from the US 2010 Decennial Census.

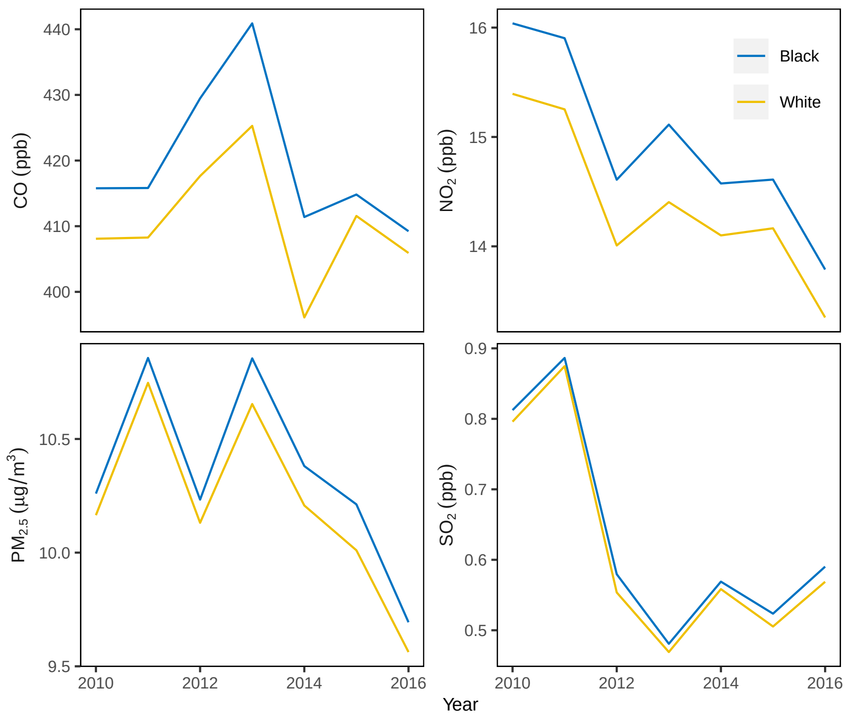

Figure B.6: Annual air pollution exposure for individuals visiting hospitals by race.

Notes: This figure plots the annual averages of baseline pollution exposure separately for non-Hispanic Black and white patients in the areas within 25 miles from ports in California. The patients visit hospitals due to psychiatric, respiratory, and heart-related illnesses during 2010–2016. The pollution data are obtained from the US EPA Air Quality System, and the hospital visit data are obtained Office of Statewide Health Planning and Development of California.

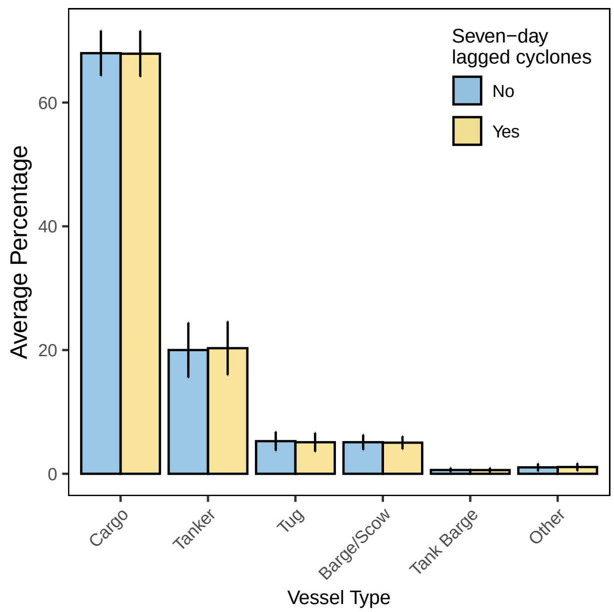

Figure B.7: Average daily share of vessel type in ports.

Notes: This figure presents the average daily share of vessel types in major 27 US ports, separately for the days when there exist seven-day lagged and 500-mile distant tropical cyclones in the ocean and the days when there are no such cyclones. The error bars indicate standard deviations. The data are obtained from the US Army Corps of Engineers.

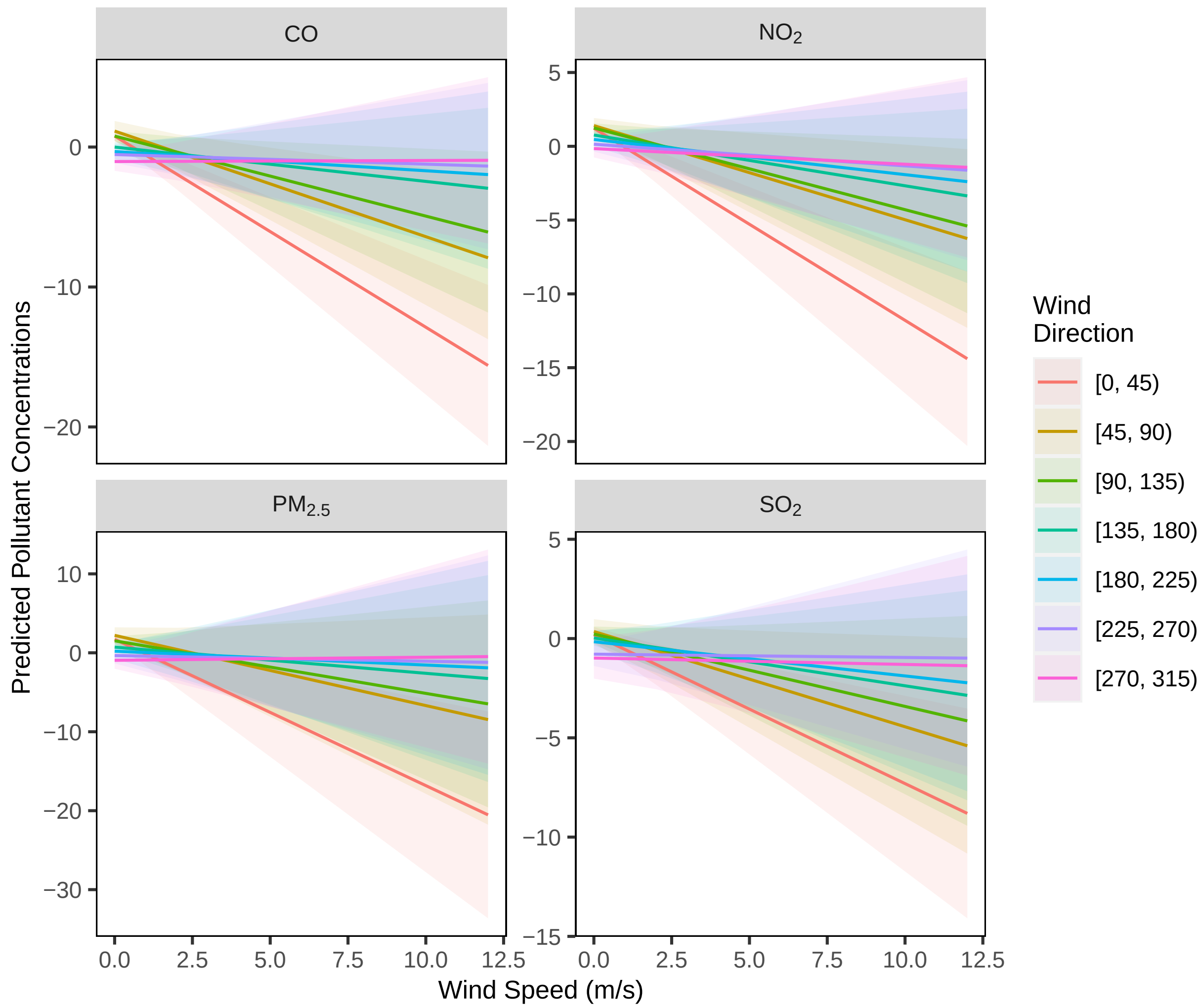

Figure B.8: First-stage results of adjusted predictions of pollutant concentrations with respect to wind direction and wind speed.

Notes: This figure presents the adjusted predictions of pollutant concentrations generated by the first-stage regressions, i.e., equation (4) of 2SLS. We allow the wind direction and wind speed variables to vary, while keeping other non-focal variables constant. Specifically, we evaluate pollutant concentrations at the location of Port of Long Beach and zip code 90062 for the year 2015, with the projected vessel tonnage as 4.56, dew point temperature as 4.56, precipitation as 0.42, maximum temperature as 21.63, minimum temperature as 12.83, month as July, day-of-week as Friday, and non-holiday days. The wind direction blowing north is normalized to zero, and it increases up to 360 degrees clockwise.

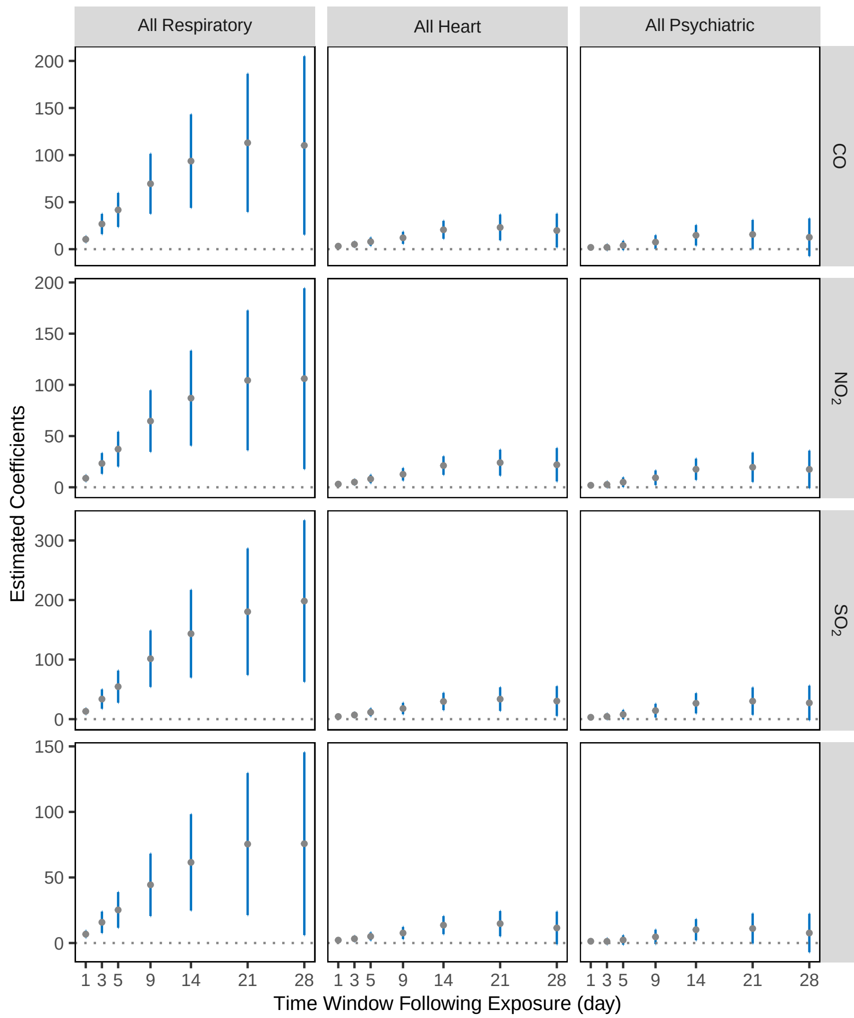

Figure B.9: Effect of air pollution on hospital visit rate for the overall population with different time windows following pollution exposure in California port areas.

Notes: This figure plots IV estimates of equation (3) with different time windows following pollution exposure. Estimates are shown for time windows of one day, three days, five days, nine days, 14 days, 21 days, and 28 days. The dependent variable is the sum of hospital visits over the number of time windows per million residents, indicated on the x-axis. The one-day window estimates are also reported in columns (3), (4), and (7) in Panel A of Table 3. The pollution measures are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and interactions. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, and their leads up to the time window. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by zip code-specific population. The error bars represent 95% confidence intervals.

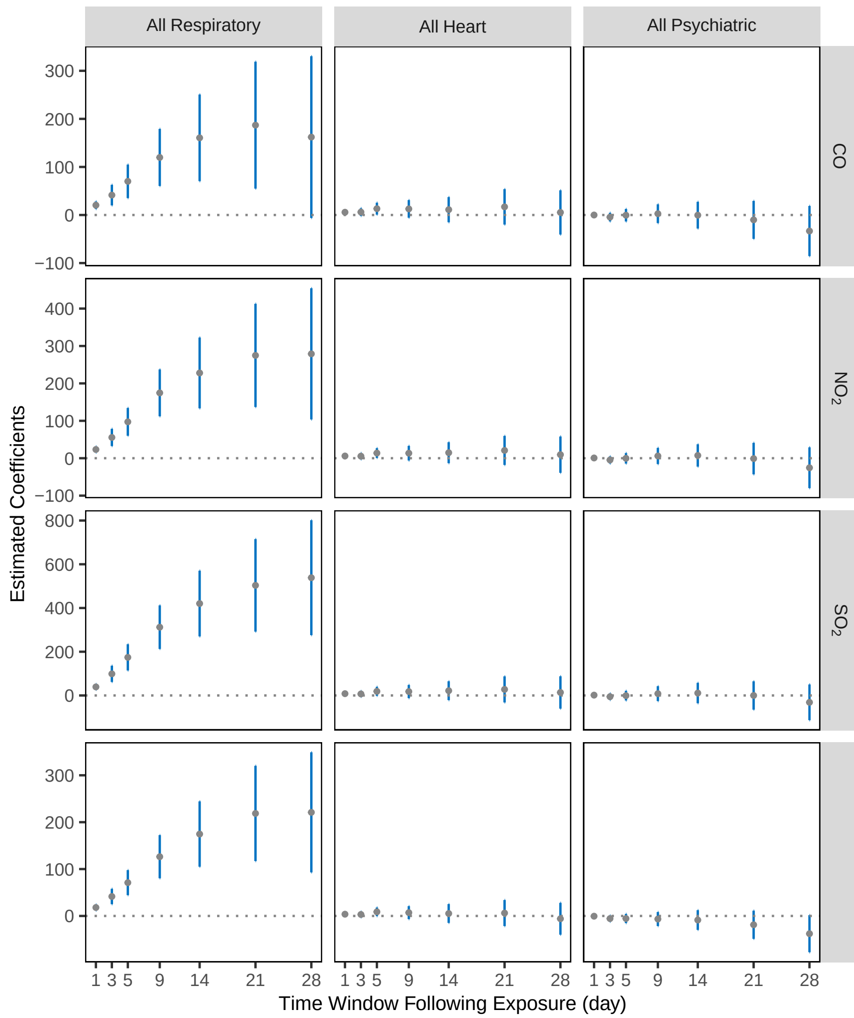

Figure B.10: Effect of air pollution on hospital visit rate for Blacks with different time windows following pollution exposure in California port areas.

Notes: This figure plots IV estimates of equation (3) with different time windows following pollution exposure. Estimates are shown for time windows of one day, three days, five days, nine days, 14 days, 21 days, and 28 days. The dependent variable is the sum of hospital visits over the number of time windows per million residents, indicated on the x-axis. The one-day window estimates are also reported in columns (3), (4), and (7) in Panel B of Table 3. The pollution measures are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and interactions. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, and their leads up to the time window. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by zip code-specific population. The error bars represent 95% confidence intervals.

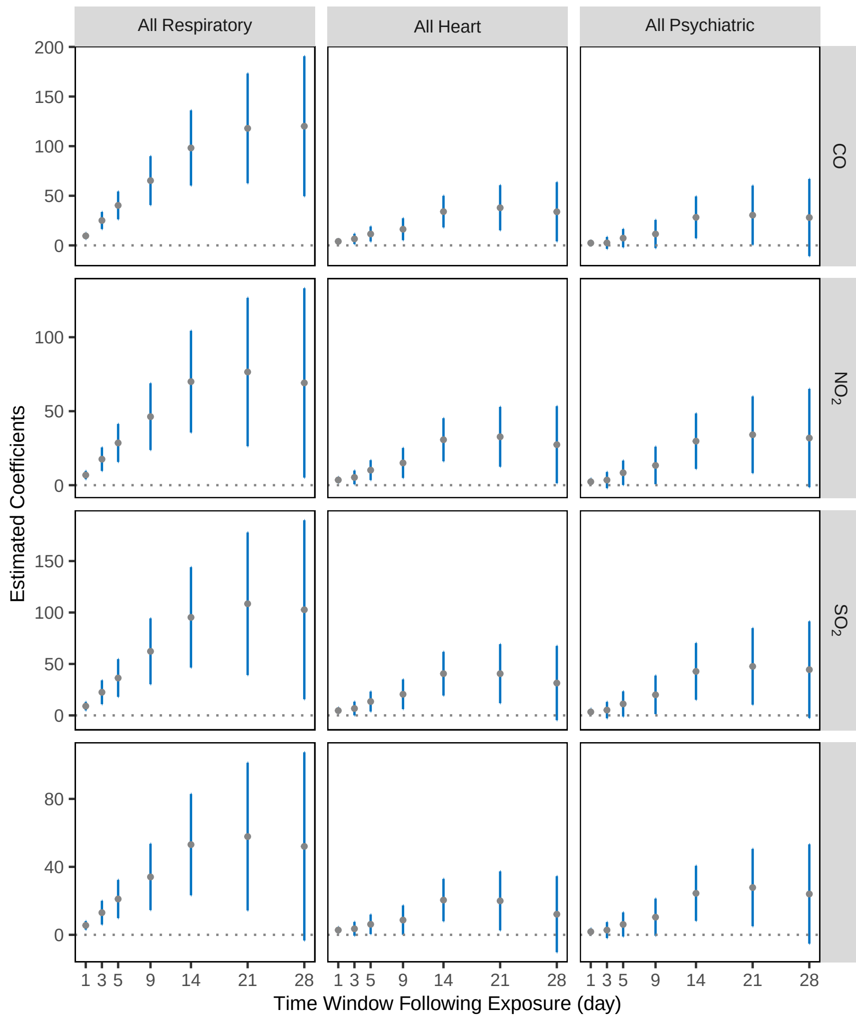

Figure B.11: Effect of air pollution on hospital visit rate for whites with different time windows following pollution exposure in California port areas.

Notes: This figure plots IV estimates of equation (3) with different time windows following pollution exposure. Estimates are shown for time windows of one day, three days, five days, nine days, 14 days, 21 days, and 28 days. The dependent variable is the sum of hospital visits over the number of time windows per million residents, indicated on the x-axis. The one-day window estimates are also reported in columns (3), (4), and (7) in Panel C of Table 3. The pollution measures are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and interactions. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, and their leads up to the time window. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. An observation is a zip code-port-day. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by zip code-specific population. The error bars represent 95% confidence intervals.

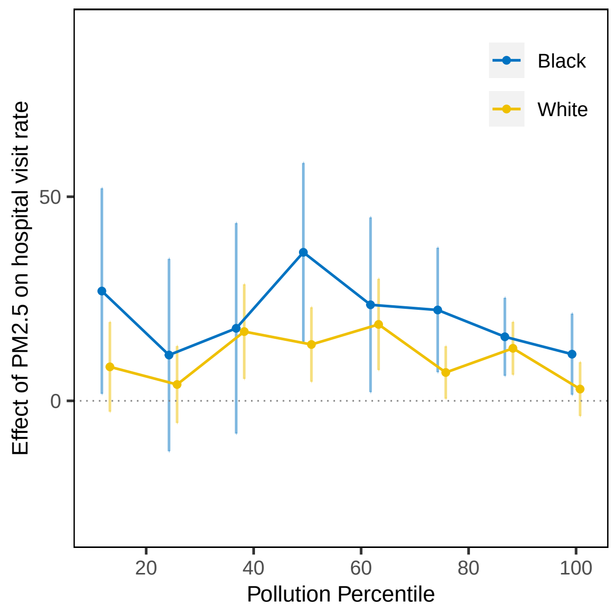

Figure B.12: Effects of $PM_{2.5}$ on hospital visit rates by pollution percentile using satellite-based pollution measures.

Notes: This figure plots the effects of $PM_{2.5}$ pollution on total hospital visit rates (related to respiratory, heart, and psychiatric illnesses) in eight pollution percentile groups. The $PM_{2.5}$ pollution measures are based on satellite-based pollution data. Pollution concentrations in regressions are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. Error bars correspond to 95% confidence intervals, where standard errors from regressions are clustered by port-zip code and day. An observation is a zip code-port-day.

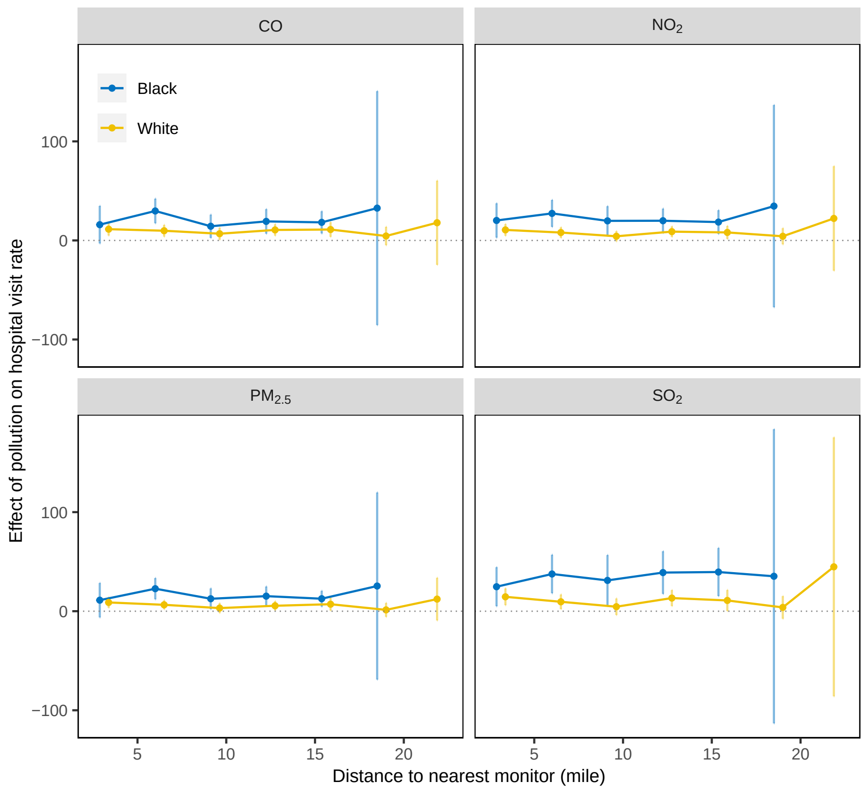

Figure B.13: Effects of pollution on hospital visit rates by distance to nearest pollution monitors.

Notes: This figure plots effects of pollution on total hospital visit rates (related to respiratory, heart, and psychiatric illnesses) for zip codes by distance to nearest pollution monitors. Pollution concentrations in regressions are standardized to their means and standard deviations, and they are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and their interactions. Error bars correspond to 95% confidence intervals, where standard errors from regressions are clustered by port-zip code and day. An observation is a zip code-port-day. Missing values indicate that there are monitors within such distance to zip codes.

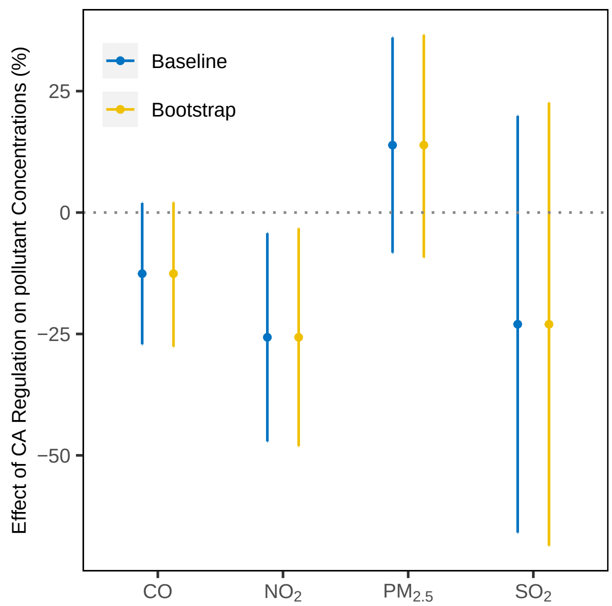

Figure B.14: Cluster bootstrap inference for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollutant concentrations.

Notes: The figure plots the the local linear RDD point estimates and 95% confidence intervals from the baseline regression (shown in Table 6) and a wild cluster bootstrap algorithm.

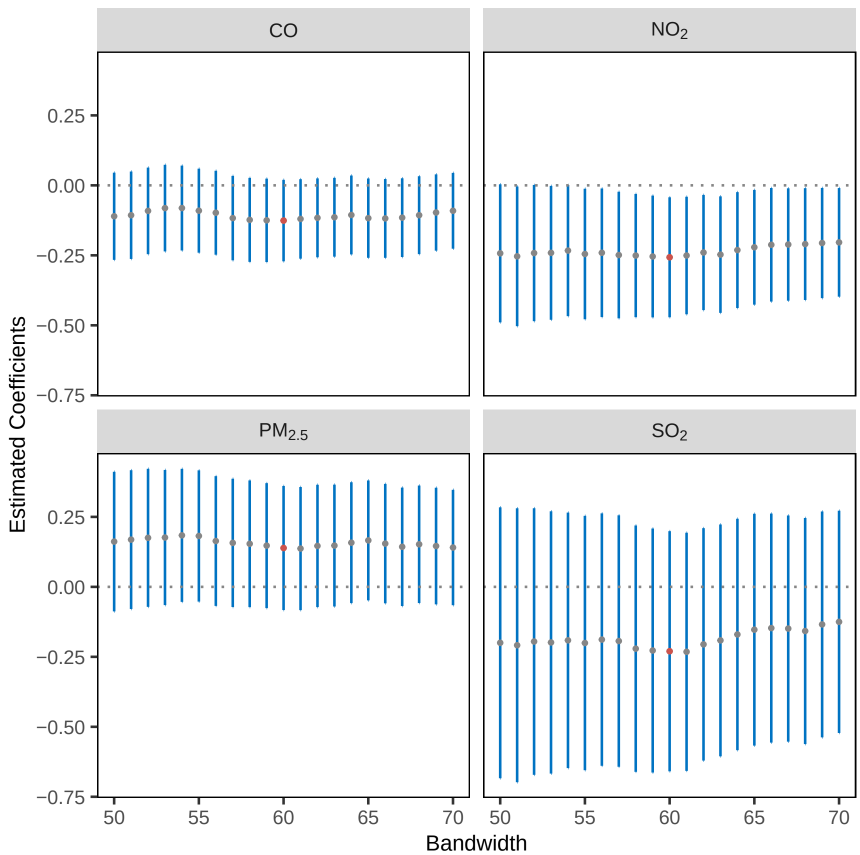

Figure B.15: Robustness check for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollutant concentrations with varying RDD bandwidths.

Notes: The figure plots the local linear RDD point estimates and 95% confidence intervals with varying bandwidths (i.e., 55–75 days on both sides of the policy threshold). The baseline bandwidth is 65 days, as indicated by the red dots.

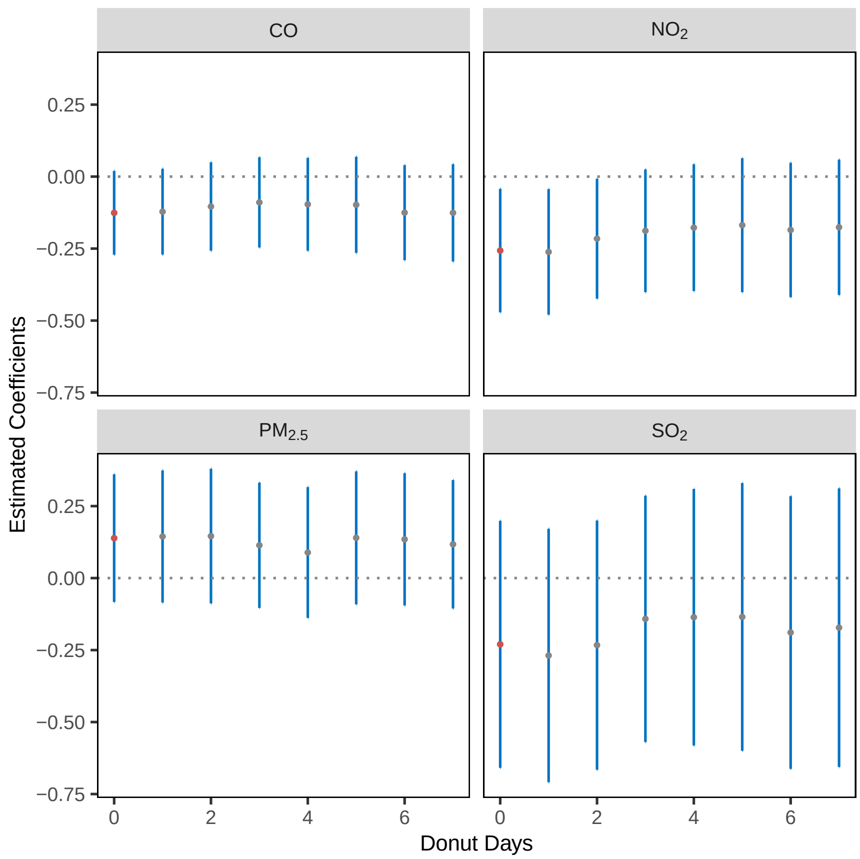

Figure B.16: Robustness check for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollutant concentrations with varying RDD "donut" periods.

Notes: The figure plots the local linear RDD point estimates and 95% confidence intervals with varying "donut" periods (i.e., removing 0–7 days of observations on both sides of the policy threshold). The baseline "donut" period is 0 day, as indicated by the red dots.

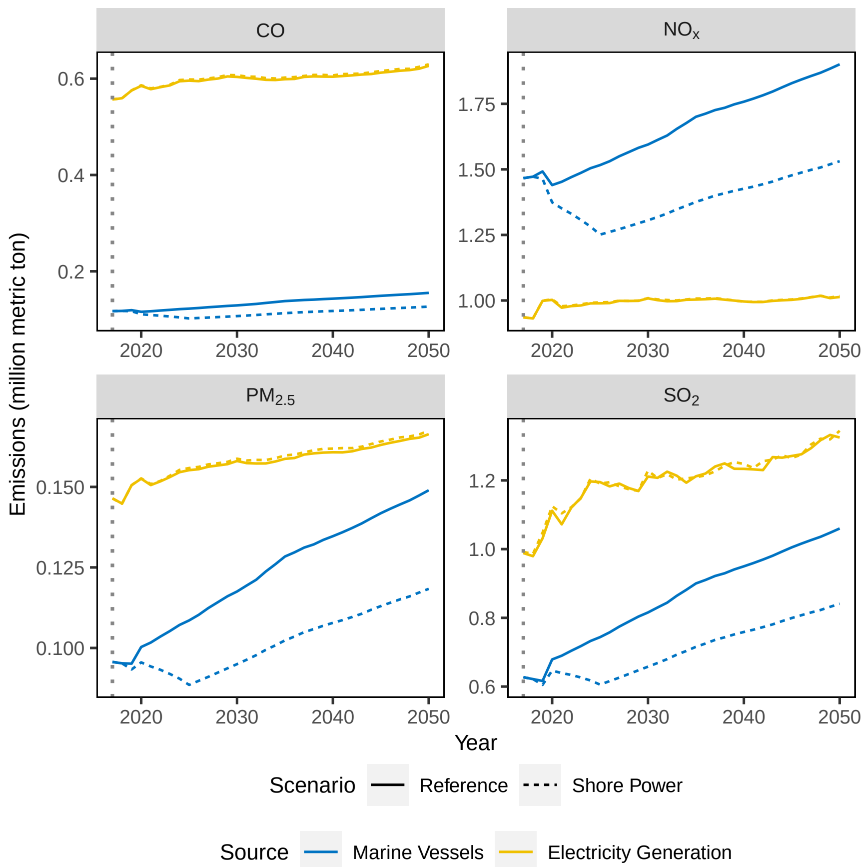

Figure B.17: Projected emissions of local air pollutants from marine vessels and electricity generation in the United States.

Notes: This figure plots local air pollutant emissions from marine vessels and power plants in the United States under the reference and shore power scenarios, projected in Yale-NEMS. The projection starts from 2017 indicated by the gray dotted lines.

C Supplementary Analysis (For Online Publication)

C.1 Results Comparison

This appendix presents supplementary analyses for the main text. We first present comparisons of our baseline estimates to the existing evidence in the literature. We then provide additional evidence on how pollution affects different unconditional quantiles of hospital visit distributions for Blacks and whites. In the third part, we show the estimates of the reduced-form relationship between vessels in ports and human health. Lastly, we present the analysis of the relationship between Black-white health gap and socioeconomic characteristics.

Effect of vessels in ports on air pollution. We first compare our instrumented estimates (focusing on the effects of vessel tonnage) in Table 2 to the existing evidence on the contributions of seaports to local air pollution. We are not aware of any other study that explores this question in the literature; however, some government reports and online articles address the relationship between port and local air pollution. For example, US EPA estimates that ocean-going vessels contribute to 7% of NO_x emissions in Ports of Baton Rouge/New Orleans and up to 61% in the Santa Barbara areas (EPA, 2003). In addition, another evidence states that marine shipping in ports accounts for as much as half SO_x emissions in major port cities, such as Los Angeles.[1]

Our estimates show that a 100,000 Mt vessel tonnage increase in port leads to a 1.17 ppb increase in NO_2 concentrations. The summary statistics in Table 1 show that on average there is 425,000 Mt vessel tonnage in a port in a day. This tonnage results in about a 5 ppb increase in NO_2 concentrations in port areas in the US, a 36% increase of the daily mean concentration. This result is within the range of previously cited sources.

We also compare our estimates to the NAAQS to examine whether pollution from ports is likely to lead to nonattainment status.[2] The current one-hour standard for CO is that the pollution concentration cannot exceed 35,000 ppb more than once per year. Our results show that one average-sized vessel (29,000 Mt) in a port results in a 6.64 ppb increase in CO pollution.[3] Combining this 6.64 ppb increase with the average daily maximum of CO (shown in Table A.3), the estimated resulting concentration is 846.54 ppb (6.64 + 839.9), which is far below the EPA standard. Similarly, the resulting pollution concentrations

[1]See https://www.ft.com/content/31d0e224-dde8-11e8-9f04-38d397e6661c.

[2]The details of the standards for pollutants considered harmful to public health and the environment are available at https://www.epa.gov/criteria-air-pollutants/naaqs-table.

[3]The 6.64 ppb increase is calculated from 0.29×23.19 based on the estimates in Table 2 and summary statistics reported in Table 1.

for NO_2 and SO_2 due to average gross vessel tonnage in ports are also below the EPA's one-hour standards.[4]

EPA has established a 24-hour standard for $PM_{2.5}$ at 35 micrograms per cubic meter (μg/m^3). Adding the increase in $PM_{2.5}$ concentrations 0.35 μg/m^3 (0.29×1.20) (owing to an average-sized vessel in a port) to the daily 24-hour average (10.66 μg/m^3) results in a concentration of 11 μg/m^3, which is around 31% of the EPA standard. Note that the calculations presented above are based on the summary averages across all ports. Some areas on certain days may still exceed the EPA standards due to increased vessel counts in ports.

Effect of air pollution on health. Since there is a large body of economics and epidemiological literature examining the effect of air pollution on health, it is natural to compare our estimates in Panel A of Table 3 to the literature. Compared to Schlenker and Walker (2016), our estimates associated with the effect of CO on respiratory and heart hospital visits are relatively larger. For example, we find that a one ppb increase in CO concentration leads to a 0.02% increase in all respiratory hospital visits, while Schlenker and Walker (2016) find a 0.037% increase.[5] The discrepancy in results may be driven by different studied locations. Other epidemiological studies show the effect of a one ppb increase in CO pollution on respiratory hospital visits in a range of 0.001–0.008% (e.g., Hwang and Chan, 2002; Peel et al., 2005; Stieb et al., 2009), which are smaller than our estimates.

For heart-related illness, we find that a one μg/m^3 increase in $PM_{2.5}$ concentration leads to a 0.3% increase of hospital visits, which is higher than the estimates 0.13–0.15% in the epidemiology literature (e.g., Dominici et al., 2006; Bell et al., 2008). Two recent epidemiology studies find evidence that a 0.11% increase in psychiatric hospital visits is attributed to a one μg/m^3 increase in $PM_{2.5}$ concentration, which is fairly close to our estimate, 0.09%.

C.2 RIF-Quantile Effect of Air Pollution on Health

We provide additional evidence on how pollution affects different unconditional quantiles of the hospital visit distributions for Blacks and whites using the unconditional quantile regression method introduced by Firpo et al. (2009). This method involves calculating the re-centered influence function (RIF) for the outcome variable (e.g., hospital visit rates) at a certain quantile and replace the dependent variable in equation (3) with the calculated RIF. The RIF for hospital visit y at the nth quantile q_n is calculated as $\text{RIF}(y, q_n) = q_n + \frac{n - \mathbb{1}\{y \leq q_n\}}{f_y(q_n)}$,

[4]The one-hour standards for NO_2 and SO_2 are 100 parts per billion (ppb) and 75 ppb, respectively.

[5]This calculation requires converting standardized estimates to the level before standardization.

where $f_y(q_n)$ is the density function of y at quantile q_n. In practice, we calculate 19 RIF statistics, starting from the 5th quantile to the 95th quantile of the hospital visit rate distribution for each subsample of Blacks and whites. In total, we fit 38 RIF-quantile regressions for each of the four studied air pollutants. Because pollution is endogenous, we adopt a control-function approach, where we include the residuals from the first-stage regression equation (4) into the regression equation of interest (3). One caveat of this RIF-quantile analysis using the control-function approach is that we should interpret the standard errors carefully because there may exist sampling error in the first-stage residuals.

The regression estimates illustrate how the effect of pollution on hospital visit rates directly transforms to the unconditional distribution of hospital visit rates. Figure C.1 presents the RIF-quantile regression estimates by race and pollutant, suggesting that at the upper quantiles of the hospital visit rate distribution, air pollution has larger impacts on Blacks compared to whites.

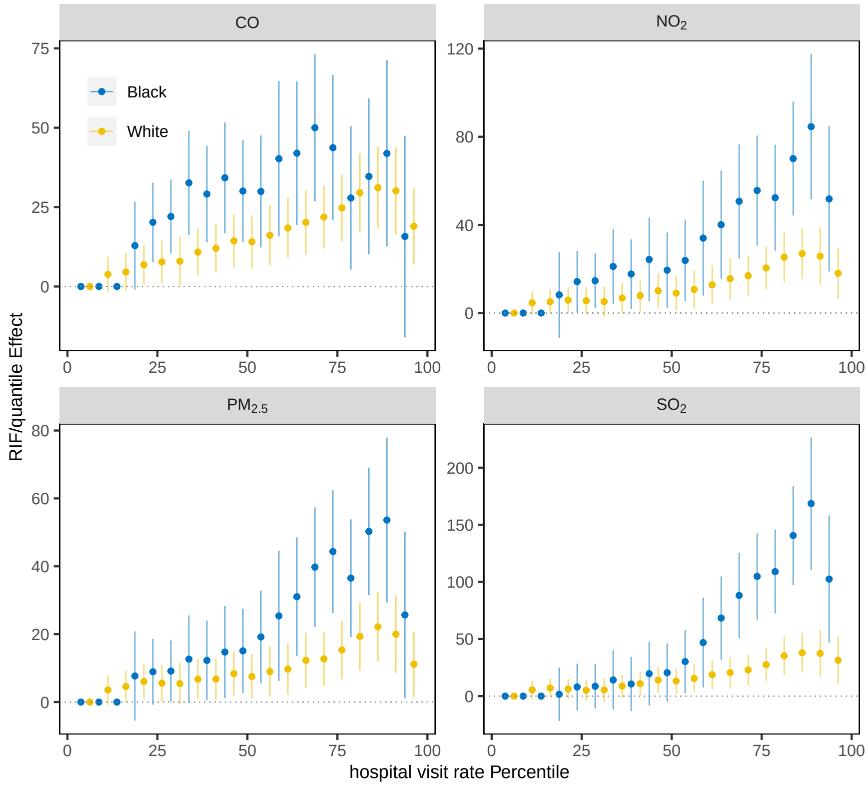

Figure C.1: RIF-quantile effects of pollution on hospital visit rates by race.

Notes: This figure plots the estimates from 38 individual regressions of equation (3) for each air pollutant, with 19 regressions for each race. The dependent variable is the RIF statistics of total hospital visit rate associated with respiratory, heart, and psychiatric ailments for a given quantile. The pollution measures are instrumented by fitted vessel tonnage in ports, wind direction, wind speed, and interactions. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures and precipitation. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by zip code-specific population. The error bars represent 95% confidence intervals.

C.3 Reduced-form Relationship between Vessels in Ports and Health

This section examines the reduced-form relationship between the number of vessels in ports and human health. We estimate the regression model in equations (1) and (2) by specifying the dependent variable as hospital visit rate across illness categories. We use the ten-day lagged cyclones that are 500 miles distant from ports as the instrumental variable in our baseline specification.[6] Since the instrumental variable specification is similar to the one used in the main text, we do not present the results for instrument validity checks.

[6]We use the ten-day lagged cyclones here instead of the seven-day lagged ones in the main text because the ten-day lagged cyclones show a stronger correlation in the first stage.

Table C.1 presents the first-stage relationship between the cyclone instrument and vessel tonnage in ports across samples. The point estimate is statistically significant, suggesting the cyclone instrument leads to a 3–4% reduction in vessel tonnage in ports. The first-stage F statistics are in a range of 22–23, which are above the threshold of ten, suggesting no evidence of weak instruments.

Table C.1: First-stage results of the effect of tropical cyclones on vessel tonnage

	Dependent variable: vessel tonnage		
	Overall	Black	White
	(1)	(2)	(3)
Tropical Cyclone	-0.38^{***}	-0.39^{***}	-0.31^{***}
	(0.08)	(0.08)	(0.07)
First-stage F Stat.	22.04	21.89	22.54
Adjusted R^2	0.74	0.73	0.78
Observations	1,805,287	887,300	1,679,994

Notes: This table presents the first-stage results of the instrumental variable estimation in Table C.2. The instrument is a dummy of ten-day lagged and 500-mile distant cyclones from ports. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, wind speed, and relative wind direction between a zip code-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table C.2 presents the instrumental variable estimation for the effect of vessel tonnage on hospital visits across seven illness categories. Most estimates associated with respiratory illnesses shown in columns (1)–(3) are statistically significant. They show that a 100,000 Mt increase in gross vessel tonnage in a port results in an additional 15.19 hospital visits per million residents related to all respiratory illnesses for the overall population, 35.59 hospital visits per million Black population, and 10.33 hospital visits per million white population. These results provide additional evidence that vessels in ports can contribute to racial disparities in respiratory-related health outcomes. However, the estimates associated with psychiatric and heart illnesses have surprising signs, and they are either statistically significant at the 5–10% level or insignificant. We do not see strong results related to psychiatric and heart illnesses, probably because the composition of air pollutants co-emitted from vessels together may not cause mental and heart illnesses.

Table C.2: Effect of vessel tonnage on contemporaneous hospital visit rate in California port areas, instrumental variable estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
Vessel Tonnage	1.82**	5.41***	15.19***	−0.30	−1.10*	−2.91*
	(0.80)	(1.38)	(3.74)	(1.40)	(0.60)	(1.56)
Adjusted R^2	0.38	0.26	0.40	0.35	0.21	0.39
Observations	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287
Panel B: Black						
Vessel Tonnage	7.08**	9.79***	35.59***	−0.80	−2.07	−9.34**
	(3.51)	(3.02)	(10.97)	(3.41)	(1.40)	(4.10)
Adjusted R^2	0.16	0.08	0.19	0.13	0.05	0.18
Observations	887,300	887,300	887,300	887,300	887,300	887,300
Panel C: White						
Vessel Tonnage	1.24	2.34***	10.33***	−0.61	−1.43	−4.22
	(1.12)	(0.83)	(3.41)	(2.82)	(1.22)	(3.06)
Adjusted R^2	0.17	0.09	0.32	0.28	0.15	0.32
Observations	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994

Notes: This table presents the instrumental variable estimation of the effect of vessel tonnage on the contemporaneous hospital visit rate. Each column presents an individual regression on an illness category. The endogenous variable, log of vessel tonnage, is instrumented by the dummy of ten-day lagged and 500-mile distant cyclones from ports. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, wind speed, and relative wind direction between a zip code-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Tables C.3 shows the OLS estimates for the effect of vessel tonnage on hospital visits. The estimates for respiratory illnesses become insignificant for the Black population. They are also much smaller than the corresponding instrumental variable estimates, suggesting potential bias. The OLS estimates associated with psychiatric and heart illnesses are positive, but they are with small magnitudes.

Table C.3: Effect of vessel tonnage on contemporaneous hospitalizaton rate in California port areas, OLS estimation

	Dependent variable: hospital visits/million residents					
	Respiratory			Heart	Psychiatric	
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall population						
Vessel Tonnage	0.06	0.06	0.38***	0.21***	0.08***	0.19***
	(0.03)	(0.05)	(0.14)	(0.06)	(0.02)	(0.06)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.40
Observations	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287	1,805,287
Panel B: Black						
Vessel Tonnage	0.03	0.18	0.49	0.67***	0.04	0.11
	(0.14)	(0.12)	(0.36)	(0.17)	(0.07)	(0.17)
Adjusted R^2	0.17	0.10	0.23	0.13	0.05	0.19
Observations	887,300	887,300	887,300	887,300	887,300	887,300
Panel C: White						
Vessel Tonnage	0.18***	0.01	0.71***	0.81***	0.31***	0.78***
	(0.05)	(0.03)	(0.14)	(0.12)	(0.05)	(0.13)
Adjusted R^2	0.17	0.09	0.34	0.28	0.15	0.32
Observations	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994	1,679,994

Notes: This table presents the OLS estimation of the effect of vessel tonnage on the contemporaneous hospital visit rate. Each column presents an individual regression on an illness category. All regressions include a set of weather controls, such as the quadratics of maximum, minimum, and dew point temperatures, precipitation, wind speed, and relative wind direction between a zip code-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and zip code-port pair fixed effects. Standard errors are clustered by zip code-port pair and day. Estimates are weighted by the zip code-specific population. The first-stage F statistics range from 22 to 23. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

C.4 Relationship between Racial Health Gap and Health and Economic Characteristics

To explore the correlates of racial health disparities, we collect local public health and economic characteristics by race at the zip code or county level from multiple sources.

Health characteristics The county-level health characteristics are obtained from the Annual Survey Data of the Behavioral Risk Factor Surveillance System (BRFSS) from the

Centers for Disease Control and Prevention.[7] BRFSS is a survey that collects information on chronic health conditions and health behaviors, conducted every year via telephone across the US We collect data for the period 2003–2012, where county-level responses are available. We focus on the counties where the zip codes within 25 miles of the major California ports are located. An observation in the final dataset is county-year.

We calculate the race-specific smoking rate in each county as the share of survey respondents who report smoking "every day" or "some days" to the total number of respondents in the race group. We calculate the poor or fair health status rate as the percent of respondents who report their general health as "poor" or "fair." We also calculate the obesity rate in each county as the share of survey respondents who have a body mass index 30 or above. Lastly, we calculate the no exercise rate in each county as the share of respondents who did not participate in exercises other than regular jobs during the past month. We then plot the distributions of each calculated health characteristic separately for Blacks and whites, as shown in Figure C.2(a). The results demonstrate that Blacks tend to have worse health conditions than whites, implying worse baseline health for Blacks.

Economic characteristics We obtain zip code-level economic characteristics data from the American Community Survey (ACS) 5-Year Data from US Census Bureau for the period 2012–2016.[8] An observation in the final dataset is zip code-year.

The race-specific poverty rate characteristic in each zip code is calculated as the percent of the population who have income in the past 12 months below the poverty level to the total population of the race group. We calculate the no health insurance rate as the share of the population who do not have health insurance coverage. We measure income as per capita inflation-adjusted to the data year dollar. We calculate the bachelor's degree rate as the percent of the population who have a bachelor's degree or above.

Similarly, we plot the distributions of each calculated economic characteristic separately for Blacks and whites. Figure C.2(b) shows that Blacks have worse socioeconomic status than whites, which may make them more vulnerable to deal with health risks from pollution exposure.

We also estimate the correlations between the Black-white health gap and the considered economic characteristics by running the following regression:

$$y_{it} = Xb_{it} + Xw_{it} + e_{it},$$

[7] Data were downloaded from https://www.cdc.gov/brfss/annual_data/annual_data.htm (December 26, 2021).

[8] We use the R package "tidycensus" to get access to the data.

where y_{it} is the difference of average daily hospital visit rate between Blacks and whites for zip code i in year t. Xb_{ip} is an economic characteristic for Blacks, standardized to its mean and standard deviation, while Xw_{ip} is the corresponding standardized economic characteristic for whites. We run the regression separately for each economic characteristic. Figure C.2(c) presents the estimated coefficients and 95% confidence intervals, showing correlations between the Black-white health gap in port areas and the economic characteristics.

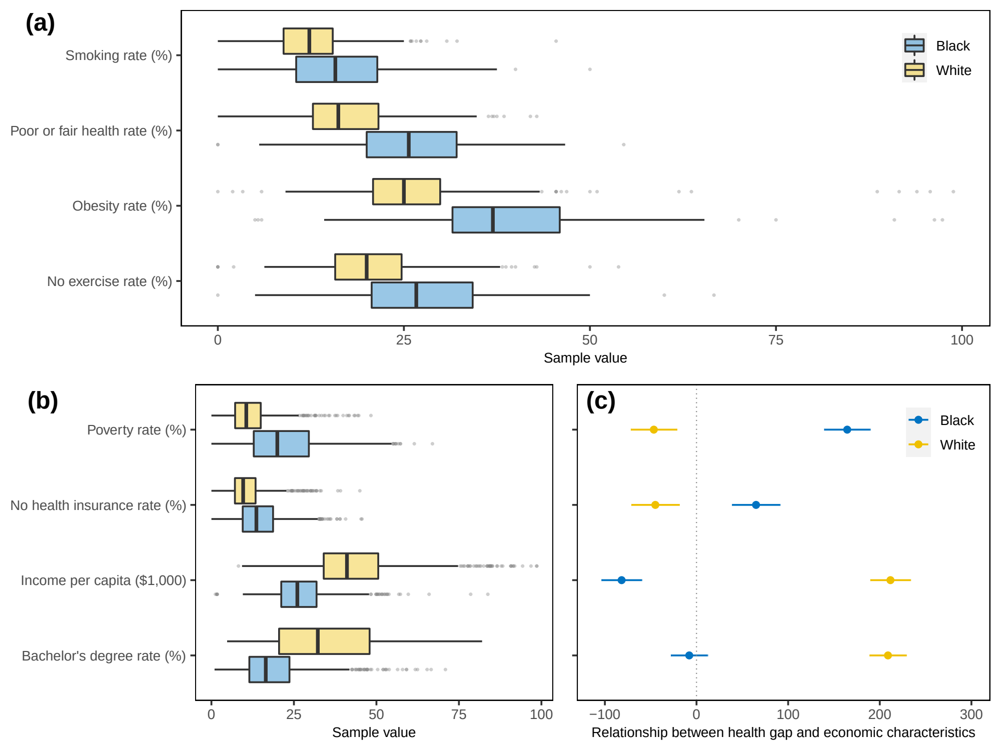

Figure C.2: (a) Distributions of local health characteristics by race. (b) Distributions of local economic characteristics by race. (c) Relationship between Black-white health gap and standardized economic characteristics.

Notes: Panel (a) presents the distributions of county-level health characteristics. Panel (b) shows the distributions of zip code-level economic characteristics. Panel (c) demonstrates the relationship between the Black-white health gap and economic characteristics. The Black-white health gap is measured as the difference of annual average daily hospital visit rates between Blacks and whites. The economic characteristics in Panel (c) are standardized to their means and standard deviations. Error bars in Panel (c) correspond to 95% confidence intervals. The health characteristics data are from the Annual Survey Data of the Behavioral Risk Factor Surveillance System from the Centers for Disease Control and Prevention. The economic characteristics data are obtained from the American Community Survey (ACS) 5-Year Data from US Census Bureau. The hospital visit rates are calculated based on data from the Office of Statewide Health Planning and Development of California.

D National Energy Modeling System (For Online Publication)

The National Energy Modeling System (NEMS) is an integrated energy-economy modeling system developed by EIA. A 2017 version of NEMS is currently hosted on a server at Yale University, and we call it Yale-NEMS at EIA's request. Yale-NEMS comprises 13 modules comprehensively modeling major energy supply sectors, conversion sectors, demand markets, macroeconomics, and international energy markets. The model simulates energy markets out to 2050 subject to a comprehensive set of constraints, such as economics, technological advancement, demographics, resource availability, and behavior assumptions. The model also includes current energy and environmental policies at the state and federal levels, while it does not consider any proposed rule-makings. Model projections include energy consumption, production, trade, prices, and emissions.

Since we are particularly interested in the effects of shore-side energy consumption and its interaction with the power sector, this appendix discusses how Yale-NEMS models marine fuel consumption and electricity generation. The description of other modules is available at EIA (2009). We first introduce the reference case of Yale-NEMS, which we use as the baseline for our analysis.

D.1 Annual Energy Outlook

We take Annual Energy Outlook (AEO) 2017 as the reference case. AEO 2017 is a regular update of the US energy market outlook, released in early 2017 by EIA. The series of AEOs have been widely referenced for decision makings by government agencies, academia, and private sectors for decades. AEO 2017 projects a time path of key US energy market indicators from present to 2050 EIA (2017a). Comparing to previous annual outlooks, AEO 2017 includes two reference projections, one including the Clean Power Plan (CPP) and the other excluding it. Because the CPP is much less stringent than its original form, in this study, we use AEO 2017 without the Clean Power Plan as the reference case.

While AEO 2017 is a few years old, electricity generation in the United States has only become cleaner since 2017. Thus, if our simulation results are biased in any direction, they would be biased towards *overestimating* the air pollution from electricity consumption. This suggests that using AEO 2021 would only strengthen our results that the California port electrification regulation reduced air pollution emissions on net.

D.2 Marine Energy Consumption

In Yale-NEMS, the transportation demand module projects transit and auxiliary fuel consumption by marine vessels, within the US Emission Control Area—the areas within 200 nautical miles of the US coast and outside ECA EIA (2016).

Yale-NEMS models the marine fuel consumption by vessel type (tanker, container, gas (LPG/LNG), roll-on/roll-off, bulk, and general cargo) within the ECA in three steps, as is discussed in great detail in EIA (2016). First, the model estimates the total energy consumption in a base year (2013) based on historical data. From the base year, the model then determines the projections of energy demand in future years by several factors: fleet turnover rate—representing the rate of new vessels entering a fleet moving through ECA, marine fuel efficiency improvement, and industrial output—accounting for economic growth. Third, the model splits total energy consumption into four fuel types, including distillate oil, residual oil, CNG, and LNG, based on fuel price changes using a logit model specification.

EIA's NEMS does not explicitly model port-side electricity consumption and we add this feature to Yale-NEMS. First, we obtain historical data on vessel visits connected to onshore electricity and compare them to the total number of visits, which provides us the approximate percentage of energy consumption from electricity by year and region. For future years, we assume the same proportion of using electricity from 2016. We also incorporate the California Ocean-Going Vessel At-Berth Regulation (see Section 6.1 for details). Second, since we know the total fossil fuel consumption in ECA, we calculate the total electricity consumption based on the calculated percentages, constituting the reference shore-side electricity consumption in the model. Third, we subtract the newly added marine electricity demand from the total commercial electricity demand. Thus the total electricity demand across sectors is still comparable to the AEO 2017 base projections. Fourth, we calculate the reference emissions from vessels by applying the emission factors by engine type (transit and auxiliary) and fuel type to total fuel consumption.

D.3 Electricity Generation

The Electricity Market Module (EMM) in Yale-NEMS explicitly models the US electricity market and its interaction with other energy markets EIA (2017b). The module is at the North American Electric Reliability Corporation (NERC) region level. In each modeling year, other interrelated modules pass critical parameters to the EMM, including electricity demand from the four end-use demand modules (commercial, industrial, residential, and transportation demand), input fuel prices from the fuel supply modules (coal, natural gas, and fuel oils), and macroeconomic expectations from the macroeconomic module. The EMM then makes production decisions by choosing a fuel mix to generate electricity to meet demand cost-efficiently with perfect foresight.

The outputs from the EMM include electricity quantities and prices, input fuel consumption, emissions, and capital investment for additional capacity, which are then all returned to the related modules. Several factors determine the total emissions from generating electricity, including emission factors across energy types and mitigation technologies. The model iterates until market equilibrium achieves. The electricity consumption from ports is linked to EMM. When there is electricity incurred by vessels, the demand is received by the EMM, and then the EMM generates electricity to meet such demand most economically.

Yale-NEMS only reports emissions of SO_2 and NO_x from the power sector. To evaluate $PM_{2.5}$, we use an approximation approach similar to Gillingham and Huang (2019, 2020). First, we calculate the base year (2014) $PM_{2.5}$ emissions from power plants based on the EPA 2014 National Emissions Inventory (NEI) data and obtain the energy consumption from Yale-NEMS in the same year. Second, we extrapolate the emissions after 2014 as a constant proportion of energy consumption.

D.4 Shore Power Scenario

We construct a shore power scenario, in which all US ports implement shore power for auxiliary engines of vessels. Specifically, we allow auxiliary fuels (e.g., distillate oil, residual oil, and natural gas) consumed by vessels to be gradually replaced by electricity generated by power plants from 2020 to 2025, and after 2025 all auxiliary engines are powered by electricity. The fuel switch follows the following linear adjustment:

$$q_{f,t} = \left(1 - \frac{t - 2019}{2025 - 2019}\right) q^0_{f,t},$$
$$q_{e,t} = \frac{t - 2019}{2025 - 2019} \sum_f q^0_{f,t},$$

where $q^0_{f,t}$ represents the consumption of auxiliary fuel f by vessels in ports in year t ($t < 2025$) in the reference case and $q_{f,t}$ is the adjusted fuel consumption in the Shore Power scenario. $q_{e,t}$ is electricity consumption by vessels in ports switched from fossil fuels. From the year 2025 onwards, fossil fuels consumed by auxiliary engines are entirely replaced with electricity, as represented in the following:

$$
\begin{aligned}
q_{f,t} &= 0, \\
q_{e,t} &= \sum_{f} q^{0}_{f,t}.
\end{aligned}
$$

We run the reference case and the Shore Power scenario individually in Yale-NEMS. We then compare the emissions results between the two cases, and the differences indicate the effect of implementing shore power in ports.

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