Air Pollution, Health, and Racial Disparities: Evidence from Ports

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Abstract

This study examines the uneven effects of air pollution on physical and mental health across racial groups surrounding maritime ports. We exploit quasi-random variation from oceanic weather events far out in the ocean to estimate how vessel tonnage in ports influences air pollution and human health. We find that one additional vessel in a port over a year leads to 2.9 hospital visits per thousand nearby Black residents and only 1.0 per thousand for whites. We assess a port-related environmental policy and show that the policy reduces pollution and alleviates 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 for causing human health problems, such as 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; Davis, 2011; Colmer et al., 2020; Currie et al., 2020) and worse health outcomes (e.g., Chay and Greenstone, 2003b; Currie and Walker, 2011; Alexander and Currie, 2017; Deschênes et al., 2017). There are also 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 involves 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]

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, the city of 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 lower-grade fossil fuels, such as bunker fuel and diesel fuel. Yet port emissions tend to be poorly regulated.

This paper estimates 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 in port to identify the causal impact of vessel tonnage on air pollution. The intuition for our identification strategy is that distant storms out in the ocean several days prior 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 the ports themselves.

In the second step, we estimate the causal effect of daily pollution concentrations on hospitalizations 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 results indicate that the health impact on the non-Hispanic Black population is nearly three times than the impact on the non-Hispanic white population. We finally use a regression discontinuity design (RDD) and a simulation model to analyze a port-related environmental

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

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

policy 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 a one percent increase in vessel tonnage in port increases pollution concentrations for major air pollutants by 0.3–0.4% within a 25-mile radius of the 27 largest ports in the United States. Second, we show that air pollution is responsible for hospitalizations 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 2.9 hospital visits per thousand Black residents within 25 miles of a major port in California, and only 1.0 hospital visits per thousand whites. Our results also 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 9.3 avoided hospital visits per thousand Black residents per year, and 3.2 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 and power plants (e.g., Currie, 2011; Davis, 2011). In addition, an emerging body of economic literature provides estimates of heterogeneous marginal damages of pollution exposure, suggesting that disproportionate pollution exposure may translate into inequitable health and well-being in various locations (e.g., Chay and Greenstone, 2003b; Currie and Walker, 2011; Knittel et al., 2016; Schlenker and Walker, 2016; Alexander and Currie, 2017). To our knowledge, our paper is the first to examine environmental inequality due to emissions from port facilities, enriching our knowledge of a driver 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.,

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

2016). For example, Moretti and Neidell (2011) estimate the effect of air pollution on respiratory-related hospitalizations, using variation in local air pollution from moving vessels in the Port of Los Angeles. Our paper differs from theirs 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 and distant storms far out in the ocean as an exogenous source of variation (somewhat similar to how Schlenker and Walker (2016) use weather leading to congestion in distant airports 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 an extensive set of ports and health outcomes, 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 human mental health using patient-level hospital records across racial groups 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. In this sense, 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 about in part due to the impact of air pollution on mental health.

The remainder of the paper is organized 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, including an assessment of a policy in California. Section 7 concludes.

[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.

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 further increase port activities.[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 substantially affect air quality 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 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 it is likely that ports are one contributing factor.

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

[6]See the news article: 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.

2.2 Air Pollution and Health

Air pollution is well known to be detrimental to human health (Dockery et al., 1993). Air pollution 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, an increasing number of studies has been finding links 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 long-term air pollution exposure on human health, using 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) and adult mortality (e.g., Deryugina et al., 2019; Anderson, 2020). Other economic studies have found strong evidence that short-term air pollution exposure adversely cause 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 on 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 tropical storms.

3.1 Port Traffic

We obtain port data from the U.S. 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, 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 seaports in the United States, six of which are in California.[11]

3.2 Air Pollution

We obtain daily air pollution concentration data from U.S. Environmental Protection Agency (EPA) Air Quality System (AQS) for four local air pollutants, carbon monoxide (CO), nitrogen dioxide (NO_2), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_2), for 2001–2016. The data set contains daily maxima and means of pollution concentrations at the pollution monitoring site level.[12]

[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.

[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.

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 a 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 an overnight stays is dropped in the EDD/ASCD and then added to the PDD data set 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 datasets 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 U.S. 2010 Census.[14] We next calculate the daily hospitalization rate at the zip code-level, indicating the number of hospital visits per million residents per day. We focus on hospitalizations of seven categories of illnesses: respiratory (asthma, acute upper respiratory, all respiratory), mental (anxiety, bipolar disorder, all psychiatric), and heart-related. We also include three diseases for placebo checks: arterial embolism, external neck wounds, and appendicitis.[15] Figure B.2 illustrates that this study includes large parts of all of the major 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

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

[14]U.S. 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, which only accounts two percent of the total California population. For the remainder of the paper, we refer simply to 'zip codes' for simplicity.

[15]The administrative data sets adopt what are called 'ICD codes' to record diagnoses. In October 2015, they upgraded from the 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 'MS-DRG' codes for calculating the medical costs of illnesses from the Medicare data.

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 tropical cyclone data from the NOAA National Hurricane Center for 2001–2016. 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) demonstrates all tropical cyclones 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. In our study, we only use data when cyclones that are at least 500 miles away from the 27 major ports to avoid any direct impacts. We chose 500 miles because cyclones tend to have a radius in the range of 207–416 miles.[17] 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 U.S. 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

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

[17] See https://www.usno.navy.mil/JTWC/frequently-asked-questions-1/frequently-asked-questions.

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

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 identification 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 the direction for a monitor relative to 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.

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 and the relative direction 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) similarly, 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; and (5) we calculate the relative wind direction between a zip code and a port to determine whether a zip code is downwind or upwind of the paired port.

Table A.3 contains the summary statistics for the main variables (i.e., port traffic, pollution, and hospitalization rate) in this study. Tables A.4–A.8 present the summary statistics of hospitalization rates for various slices of the data.

[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 (see the examples of papers adopting this distance measure, 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, assuming a spherical Earth.

3.7 Descriptive Statistics on Racial Disparities

Before diving into the empirical modeling, we present descriptive statistics on racial disparities in pollution exposure and hospitalizations near ports in California. Following Currie et al. (2020), we primarily focus on comparing non-Hispanic white and Black populations in this paper because the disparities between these two groups have been well-documented (Boustan, 2012; Boustan et al., 2016). In addition, the Hispanic ethnic identity is found to be 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).

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. Figure 2(b) presents distributions of populations for the two racial groups by decile of mean $PM_{2.5}$ exposure at the zip code level over 2010–2016. We see that the Black population is more likely to be exposed to higher pollution, while the white population is the opposite, implying disproportionate pollution exposure between the two racial groups.

Next, we examine whether the racial gaps in pollution exposure correspond to gaps in health outcomes. Figure 3 plots probability density functions of annual hospitalization 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.[21] In both panels, the distributions of the Black population lie to the right of the distributions for whites. Another observation is that closer to ports, the gaps in hospitalization rates between Blacks and whites become slightly wider. These figures show evidence of clear 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. We model the relationship as follows:

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

[21]The corresponding boxplots are shown in Figure B.3.

where P_{ipt} is the log of local air pollutant concentrations at monitor i that is mapped to port p on day t. The variable V_{pt} is either the log of 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. 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 pollution concentrations for a given day.

There are several potential concerns with directly estimating equation (1) 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), but not all vessels. A second concern is the possibility of omitted variables, such as unobserved economic or weather factors that affect port traffic and local air pollution.

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 in the ocean distant (i.e., at least 500 miles away) from ports on day $t-m$. In our primary specification, we use a seven-day lag ($m = 7$), but we run robustness checks with different lags. 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).[23] A direct threat to the exclusion restriction

[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.

[23] We expect tropical cyclones to reduce the number of vessels and gross tonnage in ports uniformly, so the

would be if the tropical cyclones hit the ports several days later, directly affecting pollution. This should not be a concern, since we remove the observations during the days when cyclones appear within a 300-mile radius of ports (and remove observations two days prior and after the cyclones are within a 300 mile radius). Another concern would be lagged and distant cyclones not only impact vessel tonnage or counts in ports but also dramatically drive the composition of vessels that may affect air pollution in ports. Figure B.4 shows that lagged tropical cyclones distant in the ocean do not shift the composition of vessel types in ports.

A more modest threat could be if lagged tropical cyclones far out in the ocean sufficiently impact meteorologic patterns that they indirectly affect current-day weather in the ports. We conduct a balance check by dividing the sample into month-days when $TC_{t-7} = 1$ and those when it is zero.[24] Figure 4 shows distributions of the six weather variables across the two subsamples. The distributions between the two grouped samples are almost identical, confirming that the weather in the ports themselves is no different when there is a tropical cyclone in the distant ocean seven days prior than when there is not.[25] 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 also perform a placebo test and a set of robustness checks to further support the validity of the instrument.

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:

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

where y_{ipt} is the hospitalization 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,

monotonicity condition should hold.

[24] 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.

[25] To provide further evidence, Table A.9 presents the standardized mean differences, variance ratio, and Kolmogorov-Smirnov statistics for the weather variables. We also create boxplots and empirical quantile-quantile (QQ) plots for the weather variables (see Figures B.5 and B.6). Except for a few outliers, these supplementary figures confirm that the weather is no different.

NO_2, $PM_{2.5}$, and SO_2—that are shown to be detrimental to human health.[26] The remaining variables are similar to those specified in equation (1), where $\mathbf{X}_{it}$ is a set of weather controls; δ_t is the set of temporal fixed effects; μ_{ip} is a zip code-port fixed effect. The coefficient of interest β indicates the effect of a one unit increase in air pollution concentration on daily hospitalization rate associated with an illness.

Again, estimating equation (3) using OLS may lead to a biased estimate of β. One potential concern is that exposure to air pollution is not randomly assigned to residents, and thus sorting of individuals may be present. People with preferences for better air quality may choose to live in cleaner areas or 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. People are also unlikely to be stationary all the time. In addition, there may be omitted variables correlated with both air pollution and health. For example, unobserved macroeconomic factors may affect air pollution levels and bring about changes in income or health care access.

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:

$$\begin{aligned} P_{it} =& \alpha_1 \widehat{V}_{pt} + \alpha_2 WD_{ipt} + \alpha_3 WS_{it} + \alpha_4 \widehat{V}_{pt} \times WD_{ipt} + \alpha_5 \widehat{V}_{pt} \times WS_{it} + \\ & \mathbf{W}_{ipt}\lambda + \epsilon_{ipt}. \end{aligned} \tag{4}$$

In this equation, the variable WD_{ipt} is the relative wind direction, indicating whether a zip code i is downwind or upwind of a paired port p on day t; and the variable WS_{it} represents wind speed. $\mathbf{W}_{ipt}$ includes the same weather controls (except for wind direction and wind speed) and fixed effects as in equation (2). The variable $\widehat{V}_{pt}$ is 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

[26] 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)

cyclones several days prior as our instrument.[27] This approach avoids using any variation in vessel tonnage related to localized economic or other factors that may also influence hospitalization rates. For there to be a remaining identification concern, one must believe that storms in the distant ocean several days prior influence hospitalizations in areas around ports through a channel outside of port traffic. This again seems unlikely.

This specification is also including local weather conditions (e.g., relative wind direction and wind speed) in the set of instruments, a choice that follows much of the literature (Schlenker and Walker, 2016; Knittel et al., 2016; Alexander and Schwandt, 2019). The addition of local weather conditions to the set of instruments adds statistical power because local weather conditions affect 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 exploit variation in local wind as the driver for air pollution (e.g., Moeltner et al., 2013; 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.

In the first stage, we estimate equation (2). We find a strong first-stage relationship (Table A.10), consistent with lagged distant tropical cyclones affecting vessel tonnage and the number of vessels.[28] The point estimates are all significant (with standard errors two-way clustered by monitor-port and day), suggesting that the existence of lagged distant tropical cyclones results in 0.4–0.5% less tonnage (or 0.5 fewer vessels) in ports per day. The first-stage F-statistics range from 26 to 37 in Panel A and from 13 to 23 in Panel B across columns in Table A.10.[29] These are well above standard thresholds for weak instruments

[27] 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.

[28] 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.

[29] 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

to be a concern (e.g., Andrews et al. (2019) suggest that instruments are weak below a threshold of ten). 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 the coefficient of the endogenous variable is equal to 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 1–5% levels.

Estimating the second stage provides our results showing the effect of port traffic on air pollution, which are shown in Table 1. Each column is a separate estimation. Panel A shows the results using vessel tonnage as the covariate of interest, while Panel B 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 telling us the effect of an average ship. Hence, we show both. All results shown include county-by-year, day-of-week, holiday, and monitor-port fixed effects, as well as standard errors are two-way clustered by monitor-port and day.

The results in Table 1 show a significant effect of both vessel tonnage and the number of vessels on pollution concentrations for all of the pollutants examined: CO, NO_2, $PM_{2.5}$, and SO_2. Looking across the columns, we find that a one percent increase in vessel tonnage in a port in a day results in 0.25–0.43% increases in pollution concentrations within a 25-mile radius of the port. The results in Panel B can help to better contextualize the results and indicate that one additional vessel in a port in a day results in 2–4% increases in pollution concentrations within a 25-mile radius of the port. This increase in pollution from added port traffic can be interpreted as the combined effect from the direct emissions from the additional ship 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 like ours in the literature, to our knowledge, the U.S. Environmental Protection Agency estimates that emissions associated with marine vessels account for 7–61% of NO_x and SO_x in certain port areas (EPA, 2003).[30] In a rough calculation, our estimates suggest that marine shipping in the 27 major ports in the United States contributes 40% of air pollution within a 25-mile radius (see Appendix C.1).

assuming i.i.d. errors (not reported in the paper) (Cragg and Donald, 1993).

[30] 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.

We also estimate the model given in equation (1) using OLS for comparison purposes. These results using vessel tonnage as the covariate of interest are shown in Table A.11. The estimated coefficients are much smaller than those in Table 1 and not all are significant. The smaller values of the OLS coefficients may be the result of attenuation bias due to measurement errors, which are exacerbated by our fixed effects setting (see Schlenker and Walker (2016) and Deryugina et al. (2019) for similar findings).

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) using two-stage least squares, where we instrument for air pollution using the fitted port traffic and local wind conditions. We perform this estimation using the data from California in order to leverage our hospital admissions data. As before, we have a strong first-stage. Table A.12 shows that most point estimates for the instruments are significant and the first-stage F-statistics are quite large (ranging from 60 to 195). In addition, the p-values from the Anderson-Rubin and Stock-Wright tests help us further rule out the presence of weak instruments. The first stage is also strong when we split the sample by race (Tables A.13 and A.14).

Table 2 presents the second-stage results, 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.[31]

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 part per billion (ppb) increase in CO leads to an additional 0.05 visits for all respiratory illnesses, 0.02 visits for all heart-related illnesses, and 0.01 visits related all psychiatric illnesses (per million residents per day). The effects on one unit increase in SO_2 are substantial. There are clear 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 estimates in the literature.[32] We can put the respiratory and heart ailment results in the context of estimates in the literature, and find that our results are roughly in line with other papers, 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

[31] Table A.15 presents a more detailed table for Panel A of Table 2, including adjusted R^2 and the numbers of observations.

[32] Table A.16 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.

we are focusing on the area around ports, which may be different than other areas.

The results in Panels B and C of Table 2 show striking differences in hospital visits between Blacks and whites.[33] The rate of hospital visits per million residents is more than double for Blacks than for whites in nearly all categories of pollutant we study. For instance, there are only 16.3 visits related to respiratory illnesses per million residents due to SO_2 exposure for whites, and 83.3 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. On the white subsample, we observe significant results (at the 5% level) for NO_2 and SO_2 that are similar to those in the overall results.[34]

When interpreting these estimates, it is also important to keep in mind several crucial points. One is that the estimated health effects may not be entirely attributable to a single pollutant, since some pollutants may be co-emitted with others. We present the estimation results by jointly estimating the effects of multiple pollutants in Section 5.3. Similarly, 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. These are common caveats in the literature.

Another crucial point for interpretation 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 few days later. We also estimate our model using different time windows up to 28 days following a pollution exposure, following Deryugina et al. (2019), for the overall population, Blacks and whites.[35] Figures B.7–B.9 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 after 21 days.

To provide further context, we calculate the effects of one additional average-tonnage

[33]Table A.17 presents the estimation results using differences in hospitalization rates between Blacks and whites as the dependent variable. All estimates associated with respiratory ailments are positive and statistically significant. We do not observe significant estimates for heart and psychiatric illnesses.

[34]While the focus of this paper is the racial gap between Blacks and whites, we also estimate the effects of air pollution on hospitalizations for Hispanics, which are shown in Figure A.18. Comparing to Table 2, Hispanics have higher hospitalization rates associated with respiratory ailments than whites, but lower than Blacks. Hispanics also have lower hospitalization rates associated with heart diseases than Blacks and whites. We also see more significant estimates associated with psychiatric illnesses. We also estimate heterogeneous effects of air pollution by age and sex. Table A.19 shows that there are larger effects on children for respiratory illnesses and larger effects on the elderly for psychiatric and heart maladies. Table A.20 shows little difference in the effect between males and females.

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

vessel in a port over a year on air pollution-induced annual hospitalizations and hospital medical costs, as shown in Table 3.[36] Panel A shows the results of annual hospitalizations for residents living within 25 miles of a major port facility. For Blacks, one additional vessel in port results in 2,400 respiratory hospital visits, 420 heart-related visits, and 81 psychiatric visits (per million residents in a year). This amounts to 2.9 additional hospital visits per thousand Black residents in a year. For whites, one additional vessel in port results in 460 respiratory hospital visits, 300 heart-related visits, and 220 psychiatric visits (per million residents in a year). This adds up to 1.0 additional hospital visits per thousand white residents in a year, nearly one third of the visits for Black residents.

Panel B of Table 3 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).[37] The results of the calculation show that one more average-tonnage vessel in port over a year leads to $26 in medical costs per capita for Black residents and $9 for white residents.[38]

These findings show clear racial disparities in the health consequences of air pollution in port areas. A natural question that arises is whether these disparities are due to differences in baseline pollution exposures or baseline health across the racial group rather than heterogeneity in the dose-response function. Figure 5 presents the estimated coefficients, from which we regress log of pollution concentrations on an indicator for whether a patient living within a 25-mile radius of ports is Black, sperately by pollutant.[39] Similarly, Figure 6 presents the estimates separately by year, where we regress zip code-level hospitalization rates on an indicator for whether a hospitalization rate is Black-specific.[40] The figures

[36]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 12.6 percent increase in vessel tonnage) based on the estimates in Panel A of Table 1; (2) calculate changes in annual hospital visits due to the changes in concentrations of CO, NO_2, $PM_{2.5}$, and SO_2 based on the estimates in Table 2; (3) select the largest values across the air pollutants for each illness category.

[37]The Medicare data provide national average inpatient payments and total discharges for each diagnosis, which is categorized by the Medicare Severity Diagnosis Related Group (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.

[38]We also calculate the effects of a one standard deviation increase in pollution concentrations on annual hospitalizations and medical costs. The results are presented in Table A.21.

[39]Specifically, we assign zip code-level pollution to all patients associated with respiratory, heart, and psychiatric illnesses in our data who live within a 25-mile radius of a major California port based on their residence zip codes. The regressions control for the weather variables defined in equation (1) and year, month, day of week, and holiday fixed effects.

[40]The regressions are conditional on zip-code level weather variables defined in equation (3) and zip code, month, day of week, and holiday fixed effects.

clearly illustrate that Black patients from areas surrounding major port facilities have higher pollution exposure and hospitalization rates than whites from the same areas. This may be because Blacks are located even closer to port facilities or other industrial facilities than whites. This result sheds some light on the explanation for the disparities, but we cannot rule out the case that the dose-response function also playing an important role.[41]

5.3 Placebo Tests and Robustness Checks

In this section, we conduct a set of placebo tests and robustness checks to support our identification and highlight the channels driving our results. We begin with two placebo tests and then turn to additional robustness checks.

Placebo Tests. In the first placebo test, we consider the possibility that lagged and 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 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 (seven days in the primary specification) tropical cyclone instrument. Table 4 shows that the coefficients from this estimation close to zero and are not significant for any of the pollutants, in clear contrast to our results in Table 1. This finding supports our argument that lagged and 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 (i.e., stuck blood clots), external neck wounds, and appendicitis are all maladies that are highly unlikely to relate to air pollution exposure. Table A.22 estimates the same specifications for the overall population as in Panel A of Table 2 for these prognoses. All of the coefficients are small and not statistically significant. This result supports our contention that air pollution is actually the cause of the health impacts we estimate.

[41] Figures B.10 presents additional evidence of the unconditional Black-white gap in pollution exposure in port areas, where we calculate annual average of pollution exposure for patients admitted to a hospital by race over time in our data. In addition, Figure B.11 presents the estimates corresponding to Figure 5, separately by year.

Robustness Checks. Since air pollutants may be co-emitted and co-transported, it is useful to examine the joint effects of air pollutants on health outcomes. While this task is often an empirical challenge, our identification design provides a possible way to separately instrument for each pollutant. Local wind can impact spatial dispersions of pollutants differently. In addition, higher wind speed can provide additional power or resistance for vessels maneuvering into ports, depending on wind direction, which affects engine thrust and then the rate of pollutant emissions. Moreover, instead of using relative wind direction between a paired port and zip code, we use an indicator of wind direction in each zip code times the cosine of the direction as the instrument for joint estimations.[42] The use of local wind direction provides variation in other sources of pollution located in various places in addition to ports.[43] Here 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 precursors to $PM_{2.5}$ with an order of several percent per hour (Luria et al., 2001; Lin and Cheng, 2007), it is difficult to differentiate the effects between $PM_{2.5}$ and NO_2 and SO_2. We therefore do not include $PM_{2.5}$ in our joint estimations.

Table A.23 presents the joint effects of CO, NO_2 and SO_2 using fitted vessel tonnage, wind speed, wind direction, and their interactons as the instruments. While some first-stage F statistics (i.e., the cluster-robust Kleibergen-Paap Wald F statistics) are relatively small, the Stock-Wright LM S statistics suggest that weak instruments should not be a concern.[44] For respiratory ailments (columns (1)–(3)), CO have significant effects on the overall population and whites when paired with other pollutants, while SO_2 has large and significant effects on Blacks. The magnitude of the estimates are still are still comparable to the results in column (3) of Table 2. Most estimates for NO_2 are insignificant and negative, similar to the findings in (Schlenker and Walker, 2016). This is probably because of near-source atmospheric chemistry between NO_x and ozone. An increase in NO_2 may decrease ozone concentrations that also have health effects (Sillman, 1999; Seinfeld and Pandis, 2016). For heart (columns (4)–(6)) and psychiatric (columns (7)–(9)) illnesses, most estimates are statistically insignificant.

Table A.24 presents a first 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

42 The wind direction variable is an indicator, which is equal to one if the daily wind direction in a zip code falls in a 45-degree interval. Hence, in total, there are eight wind direction intervals. The cosine of the wind direction is simply to take the cosine of the wind direction in degrees.

43 We conduct a robustness check using zip code-level wind directions as the instrument for the individual estimations shown in Table 2. The results are very close to the baseline results (not reported).

44 The standard Cragg-Donald Wald F statistics are above ten.

shows that the results with fewer weather controls are reasonably close to the baseline 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. Some point estimates become insignificant, likely due to the reduced sample size, but the results for $PM_{2.5}$ and SO_2 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 results presented above, we used a dummy variable for the existence seven days prior of tropical cyclones in the Atlantic or Pacific ocean that is at least 500 miles away (and we exclude any observations where there is a cyclone is within 300 miles within a two day window). Table A.25 presents a variety of the robustness checks relating to the instrument. These include using an 800-mile threshold to exclude observations to further reduce the likelihood of tropical cyclones influencing air pollution directly, using different number 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 1 for all specifications.[45]

In another robustness check, we explore whether additional road congestion with more port activity may be the cause of some of our findings on health effects 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, but one might be concerned that some of 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.[46] We regress traffic delay measures with respect to various threshold speeds on the fitted vessel tonnage and counts variables, separately. Here traffic delays measures the amount of additional time that vehicles spend to pass a freeway segment beyond a threshold speed, e.g., 55 miles per hour. Table A.27 presents these results, which show no significant coefficients across panels and columns,

[45] In addition, we run a specification including all of the removed observations due to the tropical cyclones being close to the ports. Table A.26 shows that the estimates remain significant and are quite similar to our primary results.

[46] We obtain the daily highway traffic data at the 'vehicle detection station' level for 2010–2016 (http://pems.dot.ca.gov). This data set calculates average daily delays (measured in vehicle hours) with respect to various threshold speeds (i.e., 35, 40, 45, 50, 55, and 60 miles per hour) at each station from hourly observations. Our baseline analysis selects all the stations located within 10 miles of the six major ports in California. We include the station-days that have at least 40 percent of observations.

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 be substantially influencing road congestion, indicating that air pollution is much more likely to be the channel through which our results occur.

We also considered whether wind may affect hospitalizations 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 Beauford Wind Scale. The results for the overall population, Blacks, and whites are reasonably robust to the exclusion of intense windy days (see Table A.28).

Finally, we run a set of further robustness checks. We calculate hospitalization rates for the overall population, Black residents, and white residents based only on primary diagnoses, rather than the combination of primary and secondary. The results (Table A.29) are similar to our primary results, although the effects are a bit smaller. We estimate the model separately for each of three hospitalization data sets we pool for our health results. Tables A.30–A.32 illustrates that we still find significant heath effects 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 results showing the effects of air pollution on health using LIML instead of two-stage least squares (Table A.33) 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 reduce such disparities. We analyze a major policy in California to reduce emissions from port facilities by reducing dirty fossil fuel usage (e.g., replacing fossil fuels with electricity from the grid). We first employ a regression discontinuity design to find the causal effect of the policy, and then we use a dynamic simulation model 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 (IMO), adopted in 1997, regulates sulfur content in marine fossil fuels to limit emissions of NO_x, SO_x, PM, and volatile organic compounds (VOC) in the ocean.[47] 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.[48]

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.[49] 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.[50] 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. The logic behind our empirical strategy is that the January 1, 2010 date is a sharp discontinuity in how port activities are fueled. 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 likely that some of the at-berth charging infrastructure was already installed prior to this date, but it was not being used. Thus, our approach exploits this discontinuity.

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):

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

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

[48]At the national level, the United States has implemented several programs to reduce emissions from ports, 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).

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

[50]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%.

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. $Policy_t$ 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 with the first date of the policy to be zero; 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.[51] We also include the same weather controls ($\mathbf{W}_{it}$) and fixed effects (δ_t and μ_{ip}) as in equation (1).

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 Imbens and Lemieux (2008):

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

We estimate this equation using an augmented local linear approach to increase the power of estimation (Hausman and Rapson, 2018). The approach consists of two steps. We first use the full data sample to regress log 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 regression discontinuity terms (i.e., $Policy_t$, $Date_t$, and $Policy_t \times Date_t$) within a narrow bandwidth of dates. We choose a bandwidth of 65 days on each side of the policy threshold in the baseline specification and run robustness checks with different bandwidths.

Results. Following the augmented local linear approach, we first obtain the residuals by regressing air pollution concentrations on all exogenous regressors specified in equation (7) using the full data sample (2001–2016) across the six major California ports. Figure 7 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.[52]

[51]We include the instrumented vessel tonnage because it controls for potential abrupt changes in the number of vessels visiting ports that might occur if there is an avoidance response of vessels to the policy implementation. This avoidance response is somewhat unlikely given the evidence in Figure B.12, which shows that the number of vessels visiting the six major California ports seems no drastic changes before and after the policy.

[52]We do not observe significant effects for other air pollutants.

Table 5 contains 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 7, 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 20% for NO_2. There also appear to be reductions in CO emissions, but the coefficient is less statistically significant.

We next calculate the avoided annual hospital visits and hospital-related medical costs per capita by race due to the California regulation.[53] Table 6 shows that the regulation results in 9.3 avoided hospital visits per thousand Black residents per year associated with psychiatric, respiratory, and heart-related illnesses. It also leads to 3.2 avoided hospital visits per thousand white residents per year. The avoided medical costs per capita per year for Black residents come out to $82, which is much larger than the $28 for whites. These results highlight how the policy narrowed the Black-white gaps in air pollution-induced hospitalizations around ports.

The benefits from avoiding adverse health outcomes outweigh the costs. The California Air Resources Board (CARB) 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.[54] Our estimates suggest that the first phase of the regulation leads to a saving of $483 million medical costs per year.[55]

To support our identification argument, we run two placebo tests for the RDD analysis. The first moves the discontinuity from the actual date of policy implementation to a different date: January 1, 2009 and 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.34 shows the results of these placebo tests. The coefficients tend to be insignificant and generally close to zero, providing evidence supporting our identification.

[53]We calculate the results with the following steps: (1) calculate absolute pollution concentration changes based on the estimates in Table 5; (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 2; (3) for each illness category, select the largest values across the air pollutants. Note that the results do not account for any increases in emissions from the power sector.

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

[55]Table 6 presents that the California at-berth regulation results in $32 savings per capita for illnesses related to respiratory, heart, and psychiatric illnesses. There are 15.08 million of residents living within 25 miles of the major ports in California. Hence, the medical costs of $483 million is the multiplication of $32 and 15.08 million.

The results from varying the bandwidth are shown in Figure B.13, and indicate that the exact choice of bandwidth makes little different 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 alleviates the concerns about short-term avoidance behaviors of vessels corresponding to policy changes (Hausman and Rapson, 2018). Figure B.14 presents the results with various donut periods, showing that the results do not deviate substantially from our primary estimates.

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 model of the entire energy system in the United States. Specifically, we implement a reference case scenario, based on the U.S. 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 changes.

To perform this exercise, we used the National Energy Modeling System (NEMS) run on a Yale server.[56] 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 market transitions and policies (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 more details on the model and the two scenarios.

Figure B.15 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 electrification scenario.[57] Notably, the reduction in emissions from marine vessels

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

[57] Table A.35 presents the associated fossil fuel and electricity consumptions by marine vessels across the

is substantial and notable, 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. This finding from the simulation modeling suggests that the localized air pollution benefits from a policy to reduce emissions from port activities are very likely to outweigh any negative effects of additional air pollution from increased 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. 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 hospitalizations. To the best of our knowledge, we are the first to investigate how a very highly emitting point source—port facilities—can influence racial disparities in health, and how policy can ameliorate these consequences.

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 hospitalizations for respiratory, heart-related, and psychiatric ailments that disproportionately affect Black residents. One additional vessel in port over a year leads to 2.9 additional hospital visits per thousand Black residents per year and 1.0 visits per thousand whites. We provide evidence that differences in baseline exposure and health explain at least some of these racial disparities. 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. The California regulation leads to 9.3 avoided hospital visits per thousand Blacks per year and 3.2 avoided hospital visits 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 high-polluting point sources, informing discussions about environmental justice and providing guidance to policymakers aiming to improve public health and reduce inequality.

scenarios.

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Tables and Figures

Table 1: Effect of vessels in ports on air pollutant concentrations in the United States, IV estimation

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: Vessel tonnage				
Log of Vessel Tonnage	0.37***	0.25**	0.43**	0.43**
	(0.13)	(0.12)	(0.17)	(0.19)
Adjusted R^2	0.50	0.72	0.27	0.47
Observations	502,631	587,833	423,200	431,574
Panel B: Number of vessels				
Number of Vessels	0.030**	0.023**	0.043**	0.042**
	(0.012)	(0.012)	(0.019)	(0.021)
Adjusted R^2	0.54	0.74	0.37	0.48
Observations	502,631	587,833	423,200	431,574

Notes: Panel A presents the IV estimation of the effect of log vessel tonnage on air pollutant concentrations within a 25-mile radius of ports in the United States. Panel B presents the same IV estimation using the number of vessels in ports as the variable of interest. 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. Standard errors are clustered by monitor-port pair and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 2: Effect of air pollution on hospitalizaton rates in California port areas, IV estimation

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall population							
CO (ppb)	0.01***	0.02***	0.05***	0.02***	0.005***	0.002**	0.01***
	(0.003)	(0.004)	(0.01)	(0.004)	(0.002)	(0.001)	(0.004)
NO_2 (ppb)	0.20***	0.32***	0.80***	0.37***	0.10***	0.04**	0.26***
	(0.05)	(0.08)	(0.20)	(0.07)	(0.03)	(0.02)	(0.08)
$PM_{2.5}$ ($\mu g/m^3$)	0.30***	0.51***	1.30***	0.50***	0.13***	0.05*	0.33***
	(0.07)	(0.12)	(0.29)	(0.10)	(0.05)	(0.03)	(0.12)
SO_2 (ppb)	5.40***	7.12***	20.45***	10.18***	2.65***	1.13**	7.21***
	(1.46)	(2.21)	(5.73)	(2.09)	(0.93)	(0.52)	(2.35)
Panel B: Black							
CO (ppb)	0.02**	0.06***	0.11***	0.03***	0.01	0.002	−0.001
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.004)	(0.01)
NO_2 (ppb)	0.56**	1.31***	2.66***	0.60**	0.13	0.06	0.08
	(0.22)	(0.21)	(0.57)	(0.25)	(0.11)	(0.08)	(0.29)
$PM_{2.5}$ ($\mu g/m^3$)	0.86***	1.90***	3.86***	0.77**	0.19	0.07	0.04
	(0.31)	(0.29)	(0.79)	(0.32)	(0.15)	(0.11)	(0.38)
SO_2 (ppb)	18.43***	39.51***	83.28***	15.00**	3.69	1.47	2.87
	(5.90)	(5.62)	(15.61)	(6.62)	(2.96)	(2.15)	(7.50)
Panel C: White							
CO (ppb)	0.01**	0.01***	0.04***	0.02***	0.002	0.004*	0.01*
	(0.003)	(0.003)	(0.01)	(0.01)	(0.003)	(0.002)	(0.01)
NO_2 (ppb)	0.14**	0.23***	0.64***	0.42***	0.05	0.07*	0.30**
	(0.06)	(0.05)	(0.18)	(0.12)	(0.06)	(0.04)	(0.15)
$PM_{2.5}$ ($\mu g/m^3$)	0.20**	0.39***	1.05***	0.63***	0.07	0.07	0.40*
	(0.09)	(0.08)	(0.28)	(0.19)	(0.09)	(0.06)	(0.23)
SO_2 (ppb)	3.98**	5.90***	16.34***	10.62***	1.13	1.71*	7.88**
	(1.59)	(1.32)	(4.71)	(3.27)	(1.55)	(0.96)	(3.82)

Notes: This table presents the IV estimation of the effect of air pollution on contemporaneous hospitalization rate for the overall population, Blacks, and whites. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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 3: Effect of one additional vessel in a port over an entire year on hospitalizations and medical costs in California

	All Respiratory (1)	All Heart (2)	All Psychiatric (3)
Panel A: Hospital visits per million residents			
Black	2,400	420	81
White	460	300	220
Overall Population	580	290	200
Panel B: Medical costs per capita (2017 USD)			
Black	21	4	1
White	4	3	2
Overall Population	5	3	2

Notes: Panel A presents the back-of-the-envelope calculations of the effect of one additional vessel in port on annual hospitalizations, based on the IV estimates in Tables 1 and 2. Panel B presents the medical costs associated with the hospitalizations 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 U.S. 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. Because some ports are near each other (e.g., Ports of Los Angeles and Long Beach), certain zip codes can be impacted by more than one port. The total overlapping population affected by the six major ports in California is 25.81 million, where 2.07 million are Black, and 8.18 million are white. All numbers are rounded to two significant figures.

Table 4: Placebo test on the effect of the cyclone instrument on air pollutant concentrations in distant areas

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Tropical Cyclone	0.01	−0.01	−0.01	−0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Adjusted R^2	0.47	0.77	0.40	0.54
Observations	85,970	141,201	101,324	61,458

Notes: This table presents the placebo test on regressing the IV 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 U.S. 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. Standard errors are clustered by pollution monitor and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 5: 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	-0.12^{*}	-0.20^{**}	0.17	-0.17
	(0.07)	(0.09)	(0.10)	(0.21)
Date	0.005^{***}	0.004^{**}	0.002	0.01^{**}
	(0.002)	(0.002)	(0.002)	(0.004)
CA Regulation × Date	-0.01^{***}	-0.004^{*}	-0.01^{***}	-0.01
	(0.003)	(0.002)	(0.003)	(0.01)
Pre-policy Mean	608.01	18.36	14.54	1.83
Observations	4,710	5,288	2,928	3,171

Notes: This table presents the second-stage augmented local linear 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, 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 65 days on both sides of the policy threshold. Standard errors are clustered by monitor-port pair and normalized day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table 6: Effect of California Ocean-Going Vessel At-Berth Regulation on annual hospitalizations and medical costs

	All Respiratory (1)	All Heart (2)	All Psychiatric (3)
Panel A: Hospital visits per million residents			
Black	-7,600	-1,400	-260
White	-1,500	-970	-720
Overall Population	-1,900	-930	-660
Panel B: Medical costs per capita (2017 USD)			
Black	-66	-14	-2
White	-13	-9	-6
Overall Population	-17	-9	-6

Notes: Panel A presents the back-of-the-envelope calculations of the effect of the California at-berth regulation on annual hospitalizations based on the estimates in Tables 2 and 5. 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.

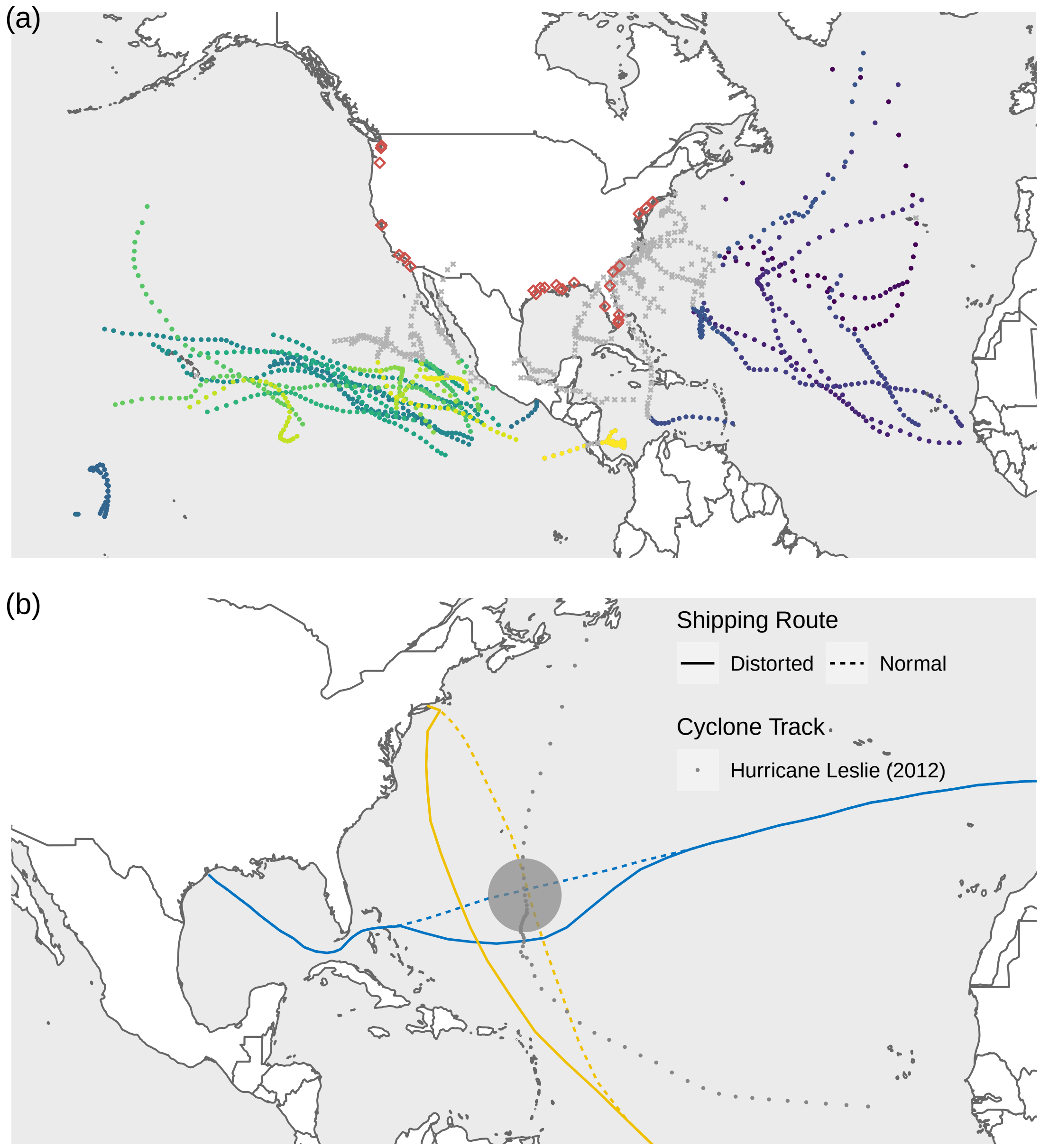

Figure 1: (a) Locations of major ports and tracks of tropical cyclones. (b) Illustrative shipping routes and a tropical cyclone track.

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 U.S. 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 the online tool: https://www.shipmap.org.

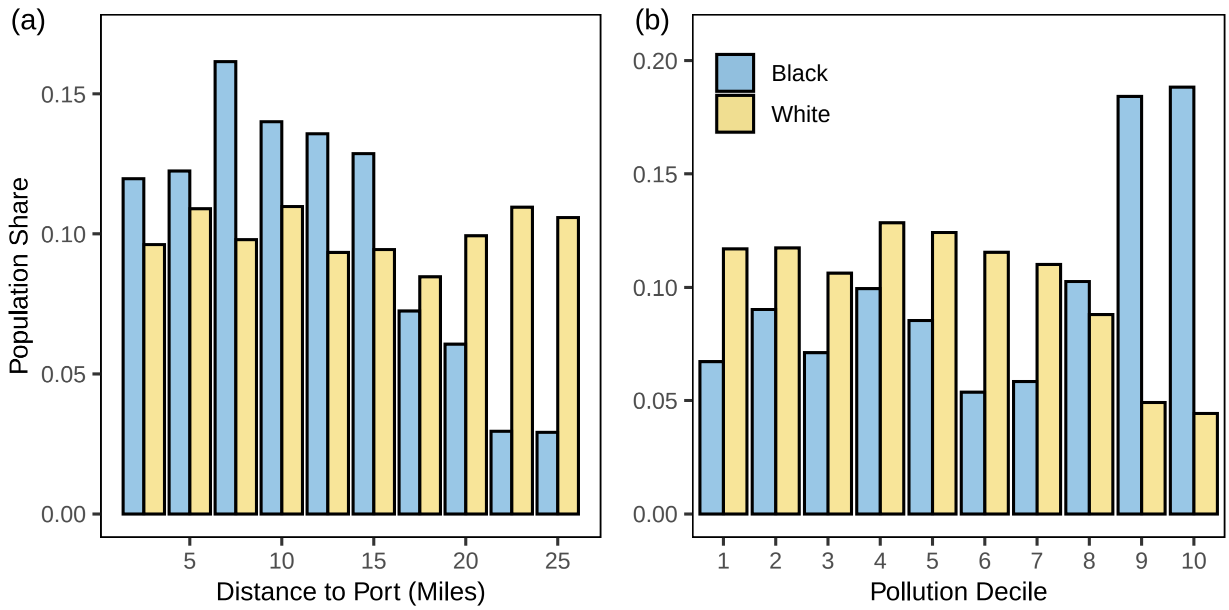

Figure 2: (a) Distribution of population by distance to major California ports. (b) Distribution of population in California port areas by decile of $PM_{2.5}$ concentration.

Notes: Panel (a) plots population distribution in the California port areas by distance between zip code and port, separately for non-Hispanic Black and white population. Panel (b) plots population distribution in the California port areas by decile of $PM_{2.5}$ concentration, separately for non-Hispanic Black and white population. The data are obtained from the U.S. 2010 Decennial Census and U.S. EPA Air Quality System.

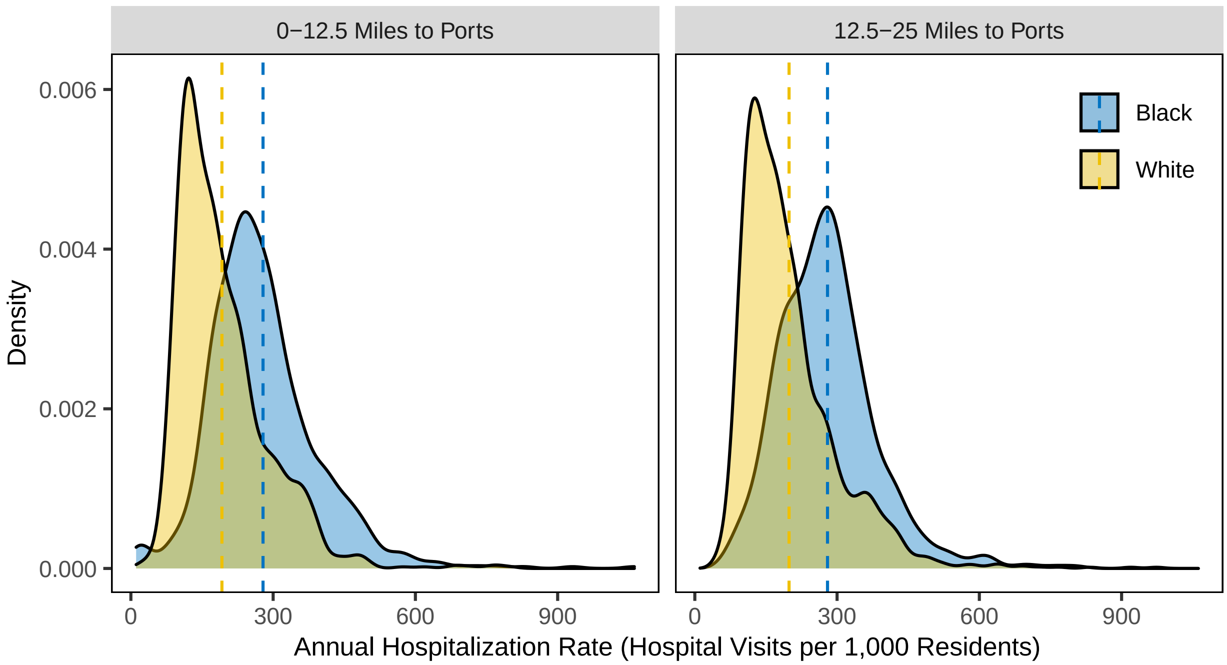

Figure 3: Distribution of annual hospitalizations rates in California port areas.

Notes: This figure plots the density of annual hospitalization 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 hospitalization 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 87, while the gap in the right panel is 81. We exclude the zip codes having less than 1,000 race-specific population in our analysis. The data are obtained from the Office of Statewide Health Planning and Development of California.

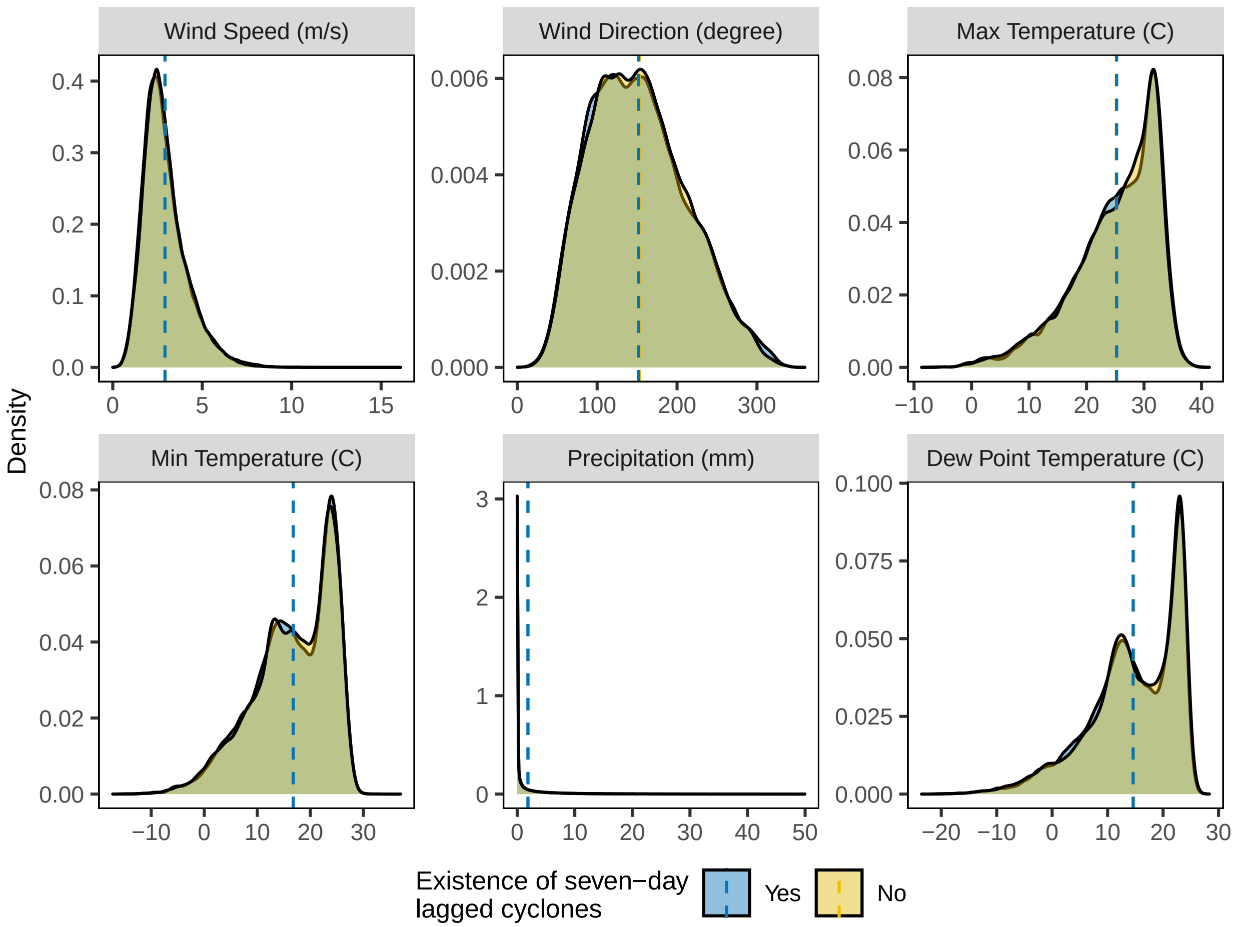

Figure 4: Distribution of local weather in port areas.

Notes: This figure presents the densities of weather measures in the U.S. 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.

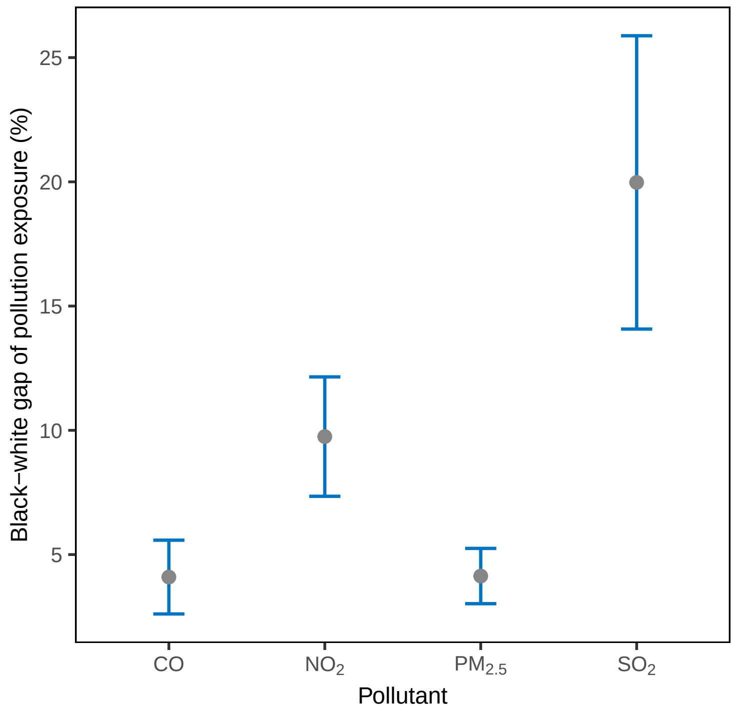

Figure 5: Black-white gap of pollution exposure.

Notes: This figure plots the estimated coefficients, regressing log of pollution concentration on an indicator for whether a patient is Black, controlling for zip code-level weather (defined in equation (1)) and year, month, day of week, and holiday fixed effects. The data are pooled for the years 2010–2016. The patients living within 25 miles from ports in California visit hospitals due to psychiatric, respiratory, and heart-related illnesses. Error bars correspond to 95 percent confidence intervals, where standard errors are clustered by zip code and date. The pollution data are obtained from the U.S. EPA Air Quality System and the hospital visit data are obtained Office of Statewide Health Planning and Development of California.

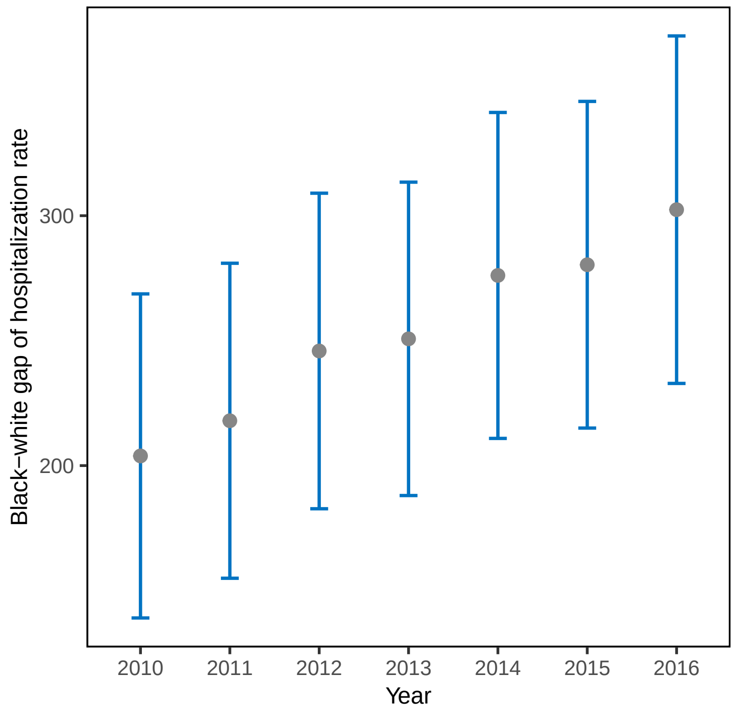

Figure 6: Black-white gap of hospitalization rates separately by year.

Notes: This figure plots the year-specific estimated coefficients, regressing zip code-level daily hospitalization rates (i.e., hospital visits per million residents) on an indicator for whether a hospitalization rate is Black-specific, controlling for weather (defined in equation (3)) and zip code, month, day of week, and holiday fixed effects. The zip codes are located within 25 miles from California ports. The hospitalization rates include all psychiatric, respiratory, and heart-related visits during the years 2010–2016. Ribbons correspond to 95 percent confidence intervals, where standard errors are clustered by zip code and date. The hospital visit data are obtained from Office of Statewide Health Planning and Development of California.

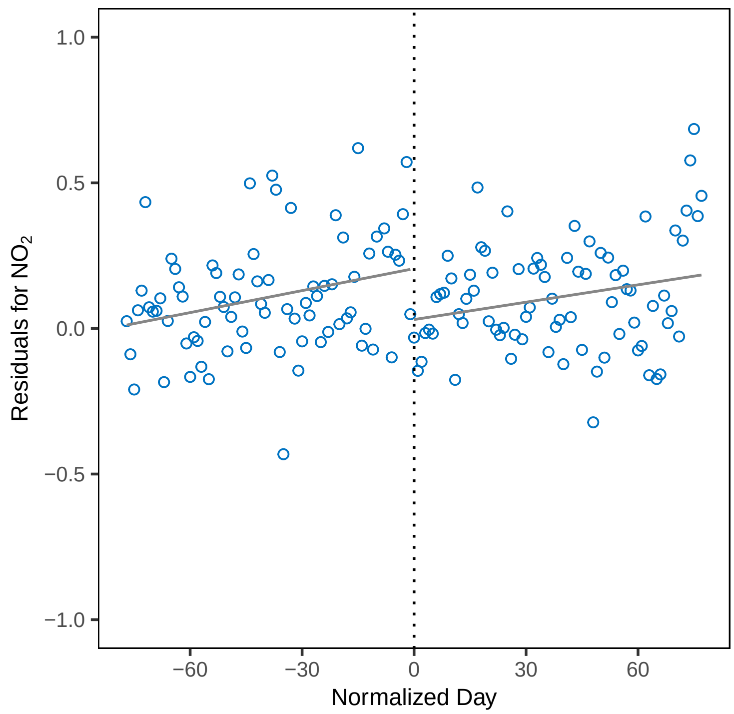

Figure 7: Residuals of NO_2 concentrations for the RDD analysis.

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 dates are normalized to be zeros, indicated by the vertical dotted lines. A few extreme values are not shown in the figure.

A Supplementary Tables

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

	Vessel Tonnage (100,000 Mt)				Vessel Counts			
	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
Houston, TX	12.38	3.39	1.34	36	53.93	12.24	8.00	157
Long Beach, CA	9.77	3.44	0.00	25	18.75	5.78	0.00	55
New York, NY and NJ	8.23	2.81	0.41	49	21.02	7.21	1.00	142
Los Angeles, CA	7.41	2.99	0.00	26	15.25	5.64	0.00	49
South Louisiana, LA, Port of	7.18	2.75	0.98	18	22.76	7.25	4.00	51
New Orleans, LA	4.89	1.55	0.29	12	19.39	5.68	2.00	46
Baltimore, MD	4.87	2.10	0.09	16	12.91	4.24	1.00	50
Savannah, GA	3.94	1.74	0.00	12	10.51	3.49	0.00	29
Oakland, CA	3.71	1.94	0.00	24	6.92	3.50	0.00	53
Seattle, WA	3.53	1.48	0.24	11	24.43	5.05	1.00	46
Miami, FL	3.51	1.88	0.11	11	24.39	7.17	5.00	57
Port Everglades, FL	3.33	2.24	0.04	14	17.75	4.40	4.00	40
Charleston, SC	3.23	1.19	0.00	9	8.40	2.90	0.00	26
Tacoma, WA	2.85	1.49	0.04	14	14.41	4.46	1.00	34
Beaumont, TX	2.71	1.20	0.00	8	7.27	2.93	0.00	20
Mobile, AL	2.56	1.02	0.06	7	11.69	3.87	1.00	26
Jacksonville, FL	2.20	1.00	0.00	8	8.07	3.03	0.00	23
Portland, OR	1.80	1.00	0.00	7	7.66	3.92	0.00	29
Philadelphia, PA	1.61	1.02	0.00	6	3.76	2.07	0.00	21
Tampa, FL	1.61	0.82	0.00	6	7.56	3.30	0.00	25
Baton Rouge, LA	1.47	0.79	0.00	6	5.27	2.48	0.00	17
Galveston, TX	1.46	1.05	0.00	7	10.92	4.69	0.00	31
Lake Charles, LA	1.43	0.72	0.00	4	7.70	3.35	0.00	23
San Diego, CA	0.83	0.67	0.00	6	4.34	2.37	0.00	15
Port Hueneme, CA	0.46	0.40	0.00	2	1.67	1.28	0.00	6
Palm Beach, FL	0.33	0.22	0.00	3	6.16	3.24	0.00	18
San Francisco, CA	0.30	0.48	0.00	4	0.71	1.07	0.00	11

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.

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
Bipolar Disorder	296.0, 296.4-296.9	F30.2, F30.8, F30.9, F31	885
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	.
Neck Wound	874	S11	.
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: Summary statistics of main variables

	Within 25 Miles of US Ports				Within 25 Miles of CA Ports			
	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
Panel A: Port								
Tonnage (100,000 Mt)	3.64	3.49	0.00	49.30	3.75	4.21	0.00	26.07
Vessel Counts	13.12	11.65	0.00	157.00	7.94	7.77	0.00	55.00
Panel B: Pollution								
CO Max (ppb)	808.17	661.10	0.00	12950.00	900.77	769.08	0.00	12950.00
CO Mean (ppb)	485.97	360.64	0.00	4994.11	525.60	394.61	0.00	4994.11
NO_2 Max (ppb)	25.17	15.48	0.00	268.00	28.11	16.63	0.00	163.00
NO_2 Mean (ppb)	13.27	9.97	0.00	83.43	15.66	10.91	0.00	83.43
$PM_{2.5}$ Max ($\mu g/m^3$)	11.58	7.17	0.00	265.90	13.25	7.93	0.00	112.40
$PM_{2.5}$ Mean ($\mu g/m^3$)	10.67	6.66	0.00	90.30	11.56	7.47	0.00	90.30
SO_2 Max (ppb)	6.01	9.72	0.00	346.65	3.03	3.26	0.00	96.50
SO_2 Mean (ppb)	2.32	3.29	0.00	78.61	1.44	1.48	0.00	20.90
Panel C: Health (hospital visits per million residents)								
Asthma	.	.	.	.	66.05	63.26	0.00	3572.04
Upper Respiratory	.	.	.	.	41.46	49.18	0.00	3912.23
All Respiratory	.	.	.	.	223.40	145.02	0.00	12791.29
All Heart	.	.	.	.	140.76	92.20	0.00	1339.42
Anxiety	.	.	.	.	46.15	47.57	0.00	743.83
Bipolar Disorder	.	.	.	.	17.53	30.30	0.00	743.83
All Psychiatric	.	.	.	.	144.15	114.26	0.00	2380.24
Arterial Embolism	.	.	.	.	0.66	5.11	0.00	297.53
Neck Wound	.	.	.	.	0.23	3.10	0.00	392.62
Appendicitis	.	.	.	.	4.03	12.67	0.00	431.78

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 health data are only available for the state of California.

Table A.4: Summary statistics of hospitalization rate by race group

	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
Panel A: Black							
Mean	199.60	92.43	517.04	236.36	66.67	44.34	289.01
Std. Dev.	291.98	200.84	548.32	317.99	169.14	142.65	432.95
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	5771.08	4488.62	16992.63	4664.18	2991.03	2991.03	6944.44
Panel B: White							
Mean	78.60	33.87	287.05	228.11	74.14	37.79	254.28
Std. Dev.	133.41	90.68	312.36	235.62	125.13	106.86	326.06
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	4248.09	3992.02	9398.50	4436.56	2851.71	5639.10	9398.50

Notes: This table presents summary statistics of hospitalization rates (i.e., hospital visits per million residents) by race group, including mean, standard deviation, minimum, and maximum.

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

	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
Panel A: Ages 5 and under							
Mean	72.62	245.13	479.57	8.18	0.70	0.01	5.44
Std. Dev.	185.63	360.26	589.71	61.67	17.51	2.13	50.32
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	4634.99	5867.56	11973.74	1988.07	983.28	570.45	2320.19
Panel B: Ages between 5 and 19							
Mean	56.06	49.60	146.54	4.70	13.34	7.45	57.47
Std. Dev.	116.36	109.12	220.14	33.65	57.42	44.04	142.83
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	4779.84	4490.15	13035.92	1937.98	1937.98	1937.98	4752.21
Panel C: Ages between 20 and 64							
Mean	58.23	23.89	156.06	70.13	50.88	22.07	154.83
Std. Dev.	71.17	42.14	141.42	73.45	60.83	41.07	142.14
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	3310.12	4280.33	13640.00	1416.43	1045.21	957.67	2489.94
Panel D: Ages 65 and above							
Mean	120.43	18.41	572.51	779.98	96.13	17.23	288.91
Std. Dev.	199.58	76.25	486.42	528.67	175.24	74.85	351.65
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	3791.47	2521.01	11764.71	7582.94	3731.34	2798.51	6529.85

Notes: This table presents summary statistics of hospitalization rates (i.e., hospital visits per million residents) by age group, including mean, standard deviation, minimum, and maximum.

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

	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
Panel A: Male							
Mean	52.53	39.30	207.56	152.43	33.28	15.91	119.79
Std. Dev.	70.63	59.73	165.64	128.42	54.23	39.19	133.66
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	3523.27	3252.25	11518.40	2088.62	1135.07	1418.84	3121.45
Panel B: Female							
Mean	79.46	43.75	239.40	129.74	58.78	19.10	167.77
Std. Dev.	90.87	64.61	187.55	111.53	72.53	42.58	155.56
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	3621.21	4782.73	14006.56	1642.58	1314.06	1578.53	3137.82

Notes: This table presents summary statistics of hospitalization rates (i.e., hospital visits per million residents) by sex group, including mean, standard deviation, minimum, and maximum.

Table A.7: Summary statistics of hospitalization rate by time window following pollution exposure

	All Respiratory	All Heart	All Psychiatric
Panel A: 3-day Time Window			
Mean	670.18	422.38	432.56
Std. Dev.	354.09	197.78	263.68
Min	0.00	0.00	0.00
Max	34903.90	3044.14	4162.42
Panel B: 5-day Time Window			
Mean	1116.89	704.14	721.13
Std. Dev.	555.60	291.90	404.98
Min	0.00	0.00	0.00
Max	49124.00	4566.21	6456.00
Panel C: 9-day Time Window			
Mean	2009.89	1267.67	1298.39
Std. Dev.	954.10	480.63	686.22
Min	0.00	0.00	0.00
Max	66643.99	7549.47	10193.68
Panel D: 14-day Time Window			
Mean	3125.68	1972.27	2020.34
Std. Dev.	1445.29	713.70	1035.55
Min	0.00	0.00	0.00
Max	78278.62	10776.26	15290.52
Panel E: 21-day Time Window			
Mean	4686.89	2958.71	3031.41
Std. Dev.	2124.96	1040.16	1523.94
Min	0.00	0.00	0.00
Max	86205.14	15220.70	22595.99
Panel F: 28-day Time Window			
Mean	6247.17	3945.14	4042.75
Std. Dev.	2797.29	1365.53	2011.19
Min	0.00	0.00	0.00
Max	89607.08	19969.56	28542.30

Notes: This table presents summary statistics of hospitalization rates (i.e., hospital visits per million residents) by time window following pollution exposure, including mean, standard deviation, minimum, and maximum.

Table A.8: Summary statistics of hospitalization rate by data specification

	All Respiratory	All Heart	All Psychiatric
Panel A: Primary Diagnosis			
Mean	86.93	32.25	29.30
Std. Dev.	76.12	38.42	40.31
Min	0.00	0.00	0.00
Max	6089.47	728.97	999.29
Panel B: Patient Discharge Data (PDD)			
Mean	79.15	77.65	62.98
Std. Dev.	66.97	61.70	65.01
Min	0.00	0.00	0.00
Max	2652.14	1231.35	1427.55
Panel C: Emergency Department Data (EDD)			
Mean	127.23	46.52	71.39
Std. Dev.	112.53	49.74	75.93
Min	0.00	0.00	0.00
Max	12519.14	791.48	1636.42
Panel D: Ambulatory Surgery Center Data (ASCD)			
Mean	17.02	16.59	9.78
Std. Dev.	30.98	29.82	23.97
Min	0.00	0.00	0.00
Max	785.24	691.92	691.92

Notes: Table presents summary statistics of hospitalization 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 primary diagnoses (i.e., secondary diagnoses are excluded).

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

	Standardized Mean Differences	Variance Ratio	Kolmogorov-Smirnov Statistics
Wind Speed (m/s)	-0.011	1.072	0.018
Wind Direction (degree)	-0.010	1.040	0.013
Max Temperature (C)	0.008	0.988	0.010
Min Temperature (C)	-0.005	0.999	0.009
Precipitation (mm)	-0.014	1.021	0.008
Dew Point Temperature (C)	-0.015	0.986	0.014

Notes: This table presents the balance statistics of weather variables in the U.S. 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			
	(1)	(2)	(3)	(4)
Panel A: Log of vessel tonnage				
Tropical Cyclone	-0.04^{***}	-0.04^{***}	-0.05^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
First-Stage F Stat.	32.88	37.42	36.52	30.89
Anderson-Rubin Stat. P-val	0.0021	0.0402	0.0080	0.0268
Stock-Wright S Stat. P-val	0.0012	0.0216	0.0066	0.0154
Observations	502,631	587,833	423,200	431,574
Panel B: Number of vessels				
Tropical Cyclone	-0.54^{***}	-0.48^{***}	-0.48^{***}	-0.45^{***}
	(0.13)	(0.10)	(0.13)	(0.12)
First-Stage F Stat.	16.69	20.78	12.96	13.64
Anderson-Rubin Stat. P-val	0.0021	0.0402	0.0080	0.0268
Stock-Wright S Stat. P-val	0.0012	0.0216	0.0066	0.0154
Observations	502,631	587,833	423,200	431,574

Notes: Panel A presents the first-stage results for the IV estimation in Panel A in Table 1, where the port traffic is measured as log of daily vessel tonnage. Panel B presents the the first-stage results for the IV estimation Panel B, using the number of vessels as the variable of interest. Each entry orresponds 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. Standard errors are clustered by monitor-port pair and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.11: OLS estimation of the effect of vessel tonnage in port on air pollution

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Log of Vessel Tonnage	0.001	0.01^{***}	0.01	0.01^{*}
	(0.003)	(0.004)	(0.003)	(0.01)
Adjusted R^2	0.57	0.75	0.46	0.50
Observations	502,631	587,833	423,200	431,574

Notes: This table presents the OLS estimation of the effect of vessel tonnage in port on air pollution. Each column presents an individual regression on a local air pollutant. 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. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.12: First-stage results of the effect of fitted vessel tonnage and local wind conditions on air pollution – overall population

	Dependent variable: pollution measures			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Fitted Log of Vessel Tonnage	24.30***	0.87***	0.71***	0.03**
	(3.71)	(0.14)	(0.14)	(0.01)
Wind Speed	−30.96***	−1.85***	−1.23***	−0.07***
	(2.44)	(0.08)	(0.09)	(0.01)
Downwind	15.93**	0.45*	1.16***	0.04***
	(7.66)	(0.25)	(0.27)	(0.01)
Fitted Log of Vessel Tonnage × Downwind	9.23***	0.37***	0.31***	0.02***
	(1.24)	(0.06)	(0.05)	(0.004)
Fitted Log of Vessel Tonnage × Wind Speed	−14.45***	−0.51***	−0.40***	−0.01**
	(1.41)	(0.05)	(0.05)	(0.004)
Wind Speed × Downwind	−6.56**	−0.46***	−0.35***	−0.03***
	(2.71)	(0.08)	(0.08)	(0.004)
First-stage F Stat.	96.43	195.41	83.07	60.20
Anderson-Rubin Stat. P-val	1.10e-07	1.13e-07	1.34e-07	3.38e-07
Stock-Wright S Stat. P-val	6.27e-07	5.42e-07	5.74e-07	8.28e-07
Observations	1,769,502	1,796,900	1,707,050	1,734,378

Notes: This table presents the first-stage results of the IV estimation for Panel A in Table 2, where each column presents a first-stage regression for a pollutant. The instruments include fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.13: First-stage results of the effect of fitted vessel tonnage and local wind conditions on air pollution – Blacks

	Dependent variable: pollution measures			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Fitted Log of Vessel Tonnage	30.80***	1.29***	1.02***	0.03*
	(5.84)	(0.22)	(0.21)	(0.01)
Wind Speed	−31.04***	−1.79***	−1.31***	−0.08***
	(3.24)	(0.11)	(0.12)	(0.01)
Downwind	−14.23	−0.47	0.19	0.01
	(12.50)	(0.37)	(0.37)	(0.02)
Fitted Log of Vessel Tonnage × Downwind	10.74***	0.20**	0.18*	0.01**
	(2.67)	(0.10)	(0.09)	(0.01)
Fitted Log of Vessel Tonnage × Wind Speed	−17.77***	−0.60***	−0.47***	−0.01
	(2.14)	(0.07)	(0.07)	(0.005)
Wind Speed × Downwind	1.81	−0.07	−0.02	−0.01**
	(4.06)	(0.11)	(0.11)	(0.01)
First-stage F Stat.	50.80	132.99	53.49	56.19
Observations	872,409	880,582	840,787	867,135

Notes: This table presents the first-stage results of the IV estimation for Panel B in Table 2, where each column presents a first-stage regression for a pollutant. The instruments include fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.14: First-stage results of the effect of fitted vessel tonnage and local wind conditions on air pollution – whites

	Dependent variable: pollution measures			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Fitted Log of Vessel Tonnage	13.97***	0.43***	0.44***	0.03***
	(2.96)	(0.12)	(0.11)	(0.01)
Wind Speed	−30.17***	−1.83***	−1.16***	−0.07***
	(2.34)	(0.08)	(0.08)	(0.01)
Downwind	28.18***	0.88***	0.87***	0.04***
	(7.70)	(0.26)	(0.23)	(0.01)
Fitted Log of Vessel Tonnage × Downwind	6.43***	0.34***	0.30***	0.02***
	(1.07)	(0.06)	(0.04)	(0.004)
Fitted Log of Vessel Tonnage × Wind Speed	−9.23***	−0.33***	−0.29***	−0.01***
	(1.24)	(0.04)	(0.04)	(0.004)
Wind Speed × Downwind	−10.82***	−0.63***	−0.33***	−0.03***
	(2.67)	(0.08)	(0.07)	(0.004)
First-stage F Stat.	98.12	196.21	83.08	64.71
Observations	1,644,474	1,671,848	1,591,487	1,609,496

Notes: This table presents the first-stage results of the IV estimation for Panel C in Table 2, where each column presents a first-stage regression for a pollutant. The instruments include fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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 hospitalizaton rates for the overall population in California port areas, IV estimation

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: CO							
CO (ppb)	0.01***	0.02***	0.05***	0.02***	0.005***	0.002**	0.01***
	(0.003)	(0.004)	(0.01)	(0.004)	(0.002)	(0.001)	(0.004)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.18	0.40
Observations	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502
Panel B: NO_2							
NO_2 (ppb)	0.20***	0.32***	0.80***	0.37***	0.10***	0.04**	0.26***
	(0.05)	(0.08)	(0.20)	(0.07)	(0.03)	(0.02)	(0.08)
Adjusted R^2	0.39	0.33	0.47	0.35	0.22	0.17	0.40
Observations	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900
Panel C: $PM_{2.5}$							
$PM_{2.5}$ ($\mu g/m^3$)	0.30***	0.51***	1.30***	0.50***	0.13***	0.05*	0.33***
	(0.07)	(0.12)	(0.29)	(0.10)	(0.05)	(0.03)	(0.12)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.17	0.40
Observations	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050
Panel D: SO_2							
SO_2 (ppb)	5.40***	7.12***	20.45***	10.18***	2.65***	1.13**	7.21***
	(1.46)	(2.21)	(5.73)	(2.09)	(0.93)	(0.52)	(2.35)
Adjusted R^2	0.39	0.33	0.47	0.35	0.22	0.17	0.40
Observations	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378

Notes: This table presents the detailed results of Panel A in Table 2. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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: OLS estimates of the effect of air pollution on hospitalizaton rates in California port areas

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall population							
CO (ppb)	0.005***	0.003	0.02***	0.01***	0.0002	0.0005	0.002
	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)	(0.0003)	(0.002)
NO_2 (ppb)	0.15***	0.003	0.50***	0.38***	0.07***	0.04***	0.25***
	(0.03)	(0.05)	(0.12)	(0.05)	(0.02)	(0.01)	(0.06)
$PM_{2.5}$ ($\mu g/m^3$)	0.08***	0.05	0.23**	−0.03	0.002	0.002	−0.004
	(0.02)	(0.04)	(0.10)	(0.04)	(0.02)	(0.01)	(0.04)
SO_2 (ppb)	1.30***	−0.96**	−0.73	0.92**	0.36*	0.10	1.04**
	(0.29)	(0.38)	(1.06)	(0.39)	(0.18)	(0.11)	(0.48)
Panel B: Black							
CO (ppb)	0.01***	−0.004	0.03**	0.01***	0.002	0.001	0.01
	(0.004)	(0.004)	(0.01)	(0.004)	(0.002)	(0.001)	(0.005)
NO_2 (ppb)	0.45***	0.02	1.22***	0.57***	0.17***	0.11**	0.55***
	(0.12)	(0.11)	(0.32)	(0.14)	(0.05)	(0.04)	(0.15)
$PM_{2.5}$ ($\mu g/m^3$)	0.31***	−0.04	0.37	−0.0001	0.05	0.03	0.03
	(0.10)	(0.09)	(0.26)	(0.11)	(0.04)	(0.03)	(0.12)
SO_2 (ppb)	6.52***	−0.12	6.15	1.27	−0.29	0.40	1.93
	(1.58)	(1.32)	(3.83)	(1.36)	(0.60)	(0.51)	(1.68)
Panel C: White							
CO (ppb)	0.01***	−0.0001	0.02***	0.02***	0.001	0.001	0.005*
	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)	(0.003)
NO_2 (ppb)	0.23***	−0.02	0.84***	0.79***	0.17***	0.08***	0.60***
	(0.04)	(0.03)	(0.11)	(0.09)	(0.03)	(0.02)	(0.09)
$PM_{2.5}$ ($\mu g/m^3$)	0.05	0.005	0.09	−0.05	−0.003	−0.01	−0.003
	(0.03)	(0.02)	(0.08)	(0.07)	(0.03)	(0.01)	(0.07)
SO_2 (ppb)	1.25***	−0.61***	0.28	1.46**	0.25	0.29	1.09
	(0.35)	(0.24)	(0.89)	(0.70)	(0.33)	(0.22)	(0.80)

Notes: This table presents the OLS estimation of the effect of air pollution on hospitalization rates for the overall population, Blacks, and whites. Each entry presents an individual regression of an air pollutant on an illness category. 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. 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: Effect of air pollution on differences of hospitalizaton rates between Blacks and whites in California port areas, IV estimation

	Dependent variable: hospitalization rate for Blacks – hospitalization rate for whites						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CO (ppb)	0.04**	0.06***	0.13***	0.003	−0.003	0.0003	−0.04
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.02)
NO_2 (ppb)	0.79**	1.26***	2.69***	0.07	−0.10	0.01	−0.71
	(0.32)	(0.23)	(0.65)	(0.35)	(0.21)	(0.16)	(0.48)
$PM_{2.5}$ ($\mu g/m^3$)	1.26***	1.90***	4.01***	0.04	−0.03	0.08	−0.95
	(0.46)	(0.34)	(0.95)	(0.50)	(0.30)	(0.22)	(0.68)
SO_2 (ppb)	21.69***	31.88***	71.94***	0.50	−2.21	−0.12	−18.90
	(7.96)	(5.91)	(16.51)	(8.79)	(5.29)	(3.88)	(11.68)

Notes: This table presents the effects of pollution on the differences of hospitalizaton rates between Blacks and whites. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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: Effect of air pollution on hospitalizaton rates for Hispanics in California port areas

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CO (ppb)	0.01***	0.02***	0.05***	0.01***	0.005***	0.001	0.01***
	(0.003)	(0.01)	(0.01)	(0.003)	(0.002)	(0.001)	(0.003)
NO_2 (ppb)	0.26***	0.51***	1.18***	0.22***	0.10***	0.02	0.25***
	(0.05)	(0.11)	(0.24)	(0.05)	(0.03)	(0.02)	(0.07)
$PM_{2.5}$ ($\mu g/m^3$)	0.33***	0.67***	1.57***	0.26***	0.15***	0.02	0.32***
	(0.07)	(0.15)	(0.33)	(0.07)	(0.04)	(0.02)	(0.09)
SO_2 (ppb)	7.89***	16.21***	38.37***	6.58***	3.36***	0.41	7.39***
	(1.80)	(3.65)	(8.05)	(1.79)	(1.09)	(0.50)	(2.26)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for the Hispanic population. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.19: Effect of air pollution on hospitalizaton 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	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Ages 5 and under							
CO (ppb)	0.01	0.08***	0.11**	0.002	0.0003	0.0001**	0.003**
	(0.01)	(0.03)	(0.05)	(0.002)	(0.001)	(0.0001)	(0.001)
NO_2 (ppb)	0.24	1.56***	1.79*	0.05	0.01	0.003**	0.07**
	(0.17)	(0.56)	(1.05)	(0.04)	(0.01)	(0.001)	(0.03)
$PM_{2.5}$ (μg/m^3)	0.39*	2.12***	2.75*	0.07	0.01	0.004**	0.10**
	(0.24)	(0.78)	(1.49)	(0.05)	(0.02)	(0.002)	(0.04)
SO_2 (ppb)	4.55	28.80*	22.39	1.47	0.28	0.07*	2.03**
	(4.88)	(16.03)	(30.29)	(1.04)	(0.33)	(0.04)	(0.85)
Panel B: Ages between 5 and 19							
CO (ppb)	0.01*	0.02***	0.02*	0.001	−0.001	0.002	0.004
	(0.004)	(0.01)	(0.01)	(0.001)	(0.001)	(0.001)	(0.004)
NO_2 (ppb)	0.19**	0.37***	0.47*	0.02	−0.01	0.03	0.12
	(0.09)	(0.13)	(0.27)	(0.01)	(0.03)	(0.02)	(0.07)
$PM_{2.5}$ (μg/m^3)	0.28**	0.55***	0.76**	0.02	−0.003	0.06**	0.18*
	(0.12)	(0.18)	(0.37)	(0.02)	(0.04)	(0.03)	(0.10)
SO_2 (ppb)	4.41*	8.41**	10.09	0.38	−0.37	0.95*	3.56*
	(2.54)	(3.70)	(7.63)	(0.40)	(0.72)	(0.57)	(2.09)
Panel C: Ages between 20 and 64							
CO (ppb)	0.01***	0.02***	0.04***	0.01***	0.01***	0.002*	0.01*
	(0.003)	(0.002)	(0.01)	(0.002)	(0.002)	(0.001)	(0.01)
NO_2 (ppb)	0.15***	0.29***	0.74***	0.14***	0.11***	0.05*	0.19**
	(0.05)	(0.04)	(0.14)	(0.05)	(0.04)	(0.03)	(0.10)
$PM_{2.5}$ (μg/m^3)	0.22***	0.46***	1.16***	0.19***	0.16***	0.05	0.24*
	(0.07)	(0.07)	(0.21)	(0.07)	(0.06)	(0.04)	(0.14)
SO_2 (ppb)	4.81***	8.15***	22.08***	3.62***	2.91**	1.35*	5.44**
	(1.40)	(1.26)	(4.16)	(1.37)	(1.13)	(0.71)	(2.68)
Panel D: Ages 65 and above							
CO (ppb)	0.02***	0.01**	0.08***	0.10***	0.01	0.002	0.04***
	(0.01)	(0.003)	(0.02)	(0.02)	(0.01)	(0.002)	(0.01)
NO_2 (ppb)	0.47***	0.15***	1.62***	1.96***	0.19*	0.05	0.83***
	(0.13)	(0.05)	(0.43)	(0.44)	(0.11)	(0.04)	(0.24)
$PM_{2.5}$ (μg/m^3)	0.66***	0.22***	2.42***	2.75***	0.24	0.05	1.10***
	(0.19)	(0.08)	(0.62)	(0.63)	(0.15)	(0.06)	(0.34)
SO_2 (ppb)	12.58***	3.99***	41.78***	51.46***	5.68*	0.83	22.20***
	(3.67)	(1.49)	(11.78)	(12.08)	(2.89)	(1.07)	(6.54)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates by age. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.20: Effect of air pollution on hospitalizaton 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	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Male							
CO (ppb)	0.01***	0.01***	0.04***	0.02***	0.004***	0.002*	0.01***
	(0.003)	(0.004)	(0.01)	(0.004)	(0.001)	(0.001)	(0.004)
NO_2 (ppb)	0.15***	0.24***	0.70***	0.34***	0.08***	0.04*	0.27***
	(0.05)	(0.08)	(0.19)	(0.09)	(0.03)	(0.02)	(0.08)
$PM_{2.5}$ ($\mu g/m^3$)	0.22***	0.41***	1.14***	0.44***	0.12***	0.05*	0.37***
	(0.07)	(0.11)	(0.28)	(0.12)	(0.04)	(0.03)	(0.11)
SO_2 (ppb)	3.79***	5.01**	17.69***	9.55***	2.02**	1.11*	7.14***
	(1.45)	(2.14)	(5.46)	(2.54)	(0.80)	(0.65)	(2.20)
Panel B: Female							
CO (ppb)	0.01***	0.02***	0.05***	0.02***	0.005**	0.002*	0.01*
	(0.003)	(0.004)	(0.01)	(0.004)	(0.002)	(0.001)	(0.01)
NO_2 (ppb)	0.24***	0.39***	0.90***	0.40***	0.11**	0.04*	0.25**
	(0.07)	(0.09)	(0.23)	(0.08)	(0.05)	(0.02)	(0.11)
$PM_{2.5}$ ($\mu g/m^3$)	0.37***	0.61***	1.45***	0.56***	0.15**	0.05	0.30*
	(0.09)	(0.13)	(0.33)	(0.11)	(0.07)	(0.03)	(0.16)
SO_2 (ppb)	6.98***	9.18***	23.14***	10.80***	3.30**	1.14*	7.35**
	(1.86)	(2.44)	(6.41)	(2.21)	(1.36)	(0.64)	(3.10)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates by sex. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.21: Effect of one standard deviation increase of air pollution on annual hospitalizations and medical costs in California port areas

	All Respiratory (1)	All Heart (2)	All Psychiatric (3)
Panel A: Hospital visits per million residents			
Black	45,000	8,100	1,600
White	8,800	5,700	4,300
Overall Population	11,000	5,500	3,900
Panel B: Medical costs per capita (2017 USD)			
Black	392	78	14
White	77	55	38
Overall Population	96	53	35

Notes: Panel A presents the back-of-the-envelope calculations of the effect of one standard deviation increase of air pollution on daily hospital visits in the port areas of California, based on the IV estimates in Panel A of Table 2. 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 U.S. 2010 Decennial Census, the total population residing in the zip codes within 25 miles of California's major ports is 15.08 million, in which 1.12 million are Black 5.07 million are white. All numbers are rounded to two significant figures.

Table A.22: Effect of air pollution on hospitalizaton rates of placebo illnesses for the overall population in California port areas, IV estimation

	Dependent variable: hospital visits/million residents		
	Arterial Embolism	Neck Wound	Appendicitis
	(1)	(2)	(3)
Panel A: CO			
CO (ppb)	0.0002	−0.0000	0.0004
	(0.0001)	(0.0001)	(0.0003)
Adjusted R^2	0.00	0.00	0.01
Observations	1,769,502	1,769,502	1,769,502
Panel B: NO_2			
NO_2 (ppb)	0.003	0.0003	0.01
	(0.003)	(0.001)	(0.01)
Adjusted R^2	0.00	0.00	0.01
Observations	1,796,900	1,796,900	1,796,900
Panel C: $PM_{2.5}$			
$PM_{2.5}$ ($\mu g/m^3$)	0.004	−0.001	0.01
	(0.003)	(0.002)	(0.01)
Adjusted R^2	0.00	0.00	0.01
Observations	1,707,050	1,707,050	1,707,050
Panel D: SO_2			
SO_2 (ppb)	0.08	0.01	0.29
	(0.07)	(0.04)	(0.18)
Adjusted R^2	0.00	0.00	0.01
Observations	1,734,378	1,734,378	1,734,378

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for placebo illnesses. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.23: Effect of air pollution on hospitalization rates in California port areas – joint estimation

	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)	0.06**	0.04***	0.08***	0.004	0.01*	0.01	−0.01	0.0004	−0.01
	(0.02)	(0.01)	(0.03)	(0.01)	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)
NO_2 (ppb)	−0.27		−1.79*	0.30		0.02	0.44**		0.25
	(0.58)		(0.93)	(0.19)		(0.36)	(0.21)		(0.41)
SO_2 (ppb)		2.87	26.36*		5.68*	5.41		7.05**	3.75
		(9.46)	(15.32)		(2.97)	(5.72)		(3.28)	(6.23)
First-stage F Stat.	16.94	8.84	3.16	16.94	8.84	3.16	16.94	8.84	3.16
Stock-Wright S Stat. P-val	0.000136	0.000126	0.000125	0.000136	0.000126	0.000125	0.000136	0.000126	0.000125
Observations	1,769,495	1,733,603	1,733,596	1,769,495	1,733,603	1,733,596	1,769,495	1,733,603	1,733,596
Panel B: Black									
CO (ppb)	−0.08	−0.01	0.04	0.01	0.02	0.02	−0.03	−0.02	−0.02
	(0.06)	(0.03)	(0.07)	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.04)
NO_2 (ppb)	4.64***		−2.32	0.35		−0.20	0.83		0.003
	(1.66)		(2.85)	(0.64)		(1.13)	(0.75)		(1.49)
SO_2 (ppb)		88.05***	117.01***		7.00	9.55		14.49	14.45
		(23.77)	(40.99)		(9.12)	(16.03)		(10.29)	(20.12)
First-stage F Stat.	13.23	11.08	3.74	13.23	11.08	3.74	13.23	11.08	3.74
Stock-Wright S Stat. P-val	0.00319	0.00251	0.00251	0.00319	0.00251	0.00251	0.00319	0.00251	0.00251
Observations	872,407	866,610	866,608	872,407	866,610	866,608	872,407	866,610	866,608
Panel C: White									
CO (ppb)	0.07***	0.06***	0.08***	0.03*	0.02**	0.03	−0.01	0.002	−0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
NO_2 (ppb)	−0.73		−1.17	−0.08		−0.32	0.46		0.36
	(0.48)		(0.86)	(0.31)		(0.66)	(0.36)		(0.75)
SO_2 (ppb)		−8.26	5.38		1.16	4.86		7.28	3.04
		(7.06)	(12.18)		(4.58)	(9.40)		(5.10)	(10.25)
First-stage F Stat.	17.59	9.83	3.50	17.59	9.83	3.50	17.59	9.83	3.50
Stock-Wright S Stat. P-val	2.08e-05	1.33e-05	1.32e-05	2.08e-05	1.33e-05	1.32e-05	2.08e-05	1.33e-05	1.32e-05
Observations	1,644,468	1,608,746	1,608,740	1,644,468	1,608,746	1,608,740	1,644,468	1,608,746	1,608,740

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rate, jointly estimated for multiple air pollutants. Each column in a panel presents an individual regression on a set of pollutants. The pollution concentrations are instrumented by fitted vessel tonnage in ports, wind speed, wind direction (an eight-direction indicator times cosine of directions) and all possible 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. 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.24: Robustness check for the effect of vessel tonnage in port on air pollution, various model specifications

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: No weather controls and temporal fixed effects				
Log of Vessel Tonnage	10.34	10.66	1.16	19.66
	(8.35)	(6.94)	(0.76)	(22.17)
Adjusted R^2	-62.20	-64.60	-1.44	-87.77
Observations	502,631	587,833	423,200	431,574
Panel B: No weather controls				
Log of Vessel Tonnage	0.35^{**}	0.12	0.45^{*}	0.34
	(0.17)	(0.18)	(0.23)	(0.23)
Adjusted R^2	0.42	0.62	0.02	0.43
Observations	502,631	587,833	423,200	431,574
Panel C: No temporal fixed effects				
Log of Vessel Tonnage	4.65	0.96	3.67^{***}	2.33
	(2.83)	(0.88)	(1.08)	(2.09)
Adjusted R^2	-12.30	0.11	-15.14	-0.99
Observations	502,631	587,833	423,200	431,574
Panel D: No quadratic weather terms				
Log of Vessel Tonnage	0.33^{**}	0.23^{*}	0.34^{*}	0.29
	(0.13)	(0.12)	(0.18)	(0.19)
Adjusted R^2	0.51	0.72	0.28	0.48
Observations	502,631	587,833	423,200	431,574
Panel E: Monitors within 12.5 miles of ports				
Log of Vessel Tonnage	0.23	0.16	0.45^{**}	0.50^{**}
	(0.15)	(0.13)	(0.18)	(0.25)
Adjusted R^2	0.54	0.73	0.23	0.43
Observations	258,799	278,898	229,503	256,711

Notes: This table presents the robustness check results for Table 1 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. 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 IV specifications

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Panel A: Exclude cyclones within 800 miles of ports				
Log of Vessel Tonnage	0.41***	0.28**	0.40**	0.56**
	(0.13)	(0.13)	(0.18)	(0.24)
Adjusted R^2	0.48	0.71	0.30	0.44
Observations	502,631	587,833	423,200	431,574
Panel B: Six-day lagged cyclones				
Log of Vessel Tonnage	0.33***	0.31**	0.40**	0.45**
	(0.12)	(0.12)	(0.18)	(0.19)
Adjusted R^2	0.51	0.70	0.29	0.46
Observations	502,631	587,833	423,200	431,574
Panel C: Eight-day lagged cyclones				
Log of Vessel Tonnage	0.40**	0.18	0.49**	0.36
	(0.16)	(0.14)	(0.23)	(0.27)
Adjusted R^2	0.49	0.74	0.21	0.48
Observations	502,631	587,833	423,200	431,574
Panel D: Six-, seven-, and eight-day lagged cyclones (2SLS)				
Log of Vessel Tonnage	0.35***	0.27**	0.42**	0.44**
	(0.12)	(0.12)	(0.17)	(0.18)
Adjusted R^2	0.51	0.72	0.28	0.47
Observations	502,631	587,833	423,200	431,574
Panel E: Six-, seven-, and eight-day lagged cyclones (LIML)				
Log of Vessel Tonnage	0.35***	0.28**	0.39***	0.42**
	(0.12)	(0.12)	(0.15)	(0.17)
Adjusted R^2	0.51	0.71	0.72	0.28
Observations	502,631	587,833	511,432	423,200
Panel F: Cyclone counts				
Log of Vessel Tonnage	0.34**	0.29**	0.39**	0.35*
	(0.14)	(0.13)	(0.17)	(0.20)
Adjusted R^2	0.51	0.71	0.30	0.48
Observations	502,631	587,833	423,200	431,574

Notes: This table presents the results of robustness check for Table 1 with various IV specifications. Each panel presents regressions using an alternative IV 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. 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, including the observations where cyclones are close to ports

	Dependent variable: log of pollution concentration			
	CO	NO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Log of Vessel Tonnage	0.34**	0.23*	0.40**	0.38*
	(0.13)	(0.12)	(0.17)	(0.20)
First-Stage F Stat.	30.88	36.64	34.19	28.69
Adjusted R^2	0.51	0.72	0.29	0.47
Observations	513,256	600,681	433,377	442,141

Notes: This table presents the IV 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 300-mile radius of ports) and two days before and after the events. 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. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.27: 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	0.17	0.22	0.24	0.15	−0.10	−0.47
	(0.32)	(0.36)	(0.40)	(0.43)	(0.48)	(0.52)
Adjusted R^2	0.33	0.35	0.37	0.39	0.42	0.44
Observations	2,618,707	2,618,707	2,618,707	2,618,707	2,618,707	2,618,707
Panel B: Vessel counts						
Fitted Vessel Counts	−0.04	−0.03	−0.02	−0.03	−0.07	−0.13
	(0.09)	(0.10)	(0.11)	(0.12)	(0.13)	(0.13)
Adjusted R^2	0.33	0.35	0.37	0.39	0.42	0.44
Observations	2,618,707	2,618,707	2,618,707	2,618,707	2,618,707	2,618,707

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 instrumet 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). Standard errors are clustered by VDS-port and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.28: Effect of air pollution on hospitalization 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	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall population							
CO (ppb)	0.01***	0.01***	0.04***	0.02***	0.004***	0.001	0.01***
	(0.002)	(0.003)	(0.01)	(0.003)	(0.001)	(0.001)	(0.004)
NO_2 (ppb)	0.26***	0.25***	0.90***	0.37***	0.10***	0.03	0.26***
	(0.05)	(0.07)	(0.20)	(0.08)	(0.03)	(0.02)	(0.08)
$PM_{2.5}$ ($\mu g/m^3$)	0.34***	0.35***	1.22***	0.44***	0.13***	0.04	0.33***
	(0.06)	(0.09)	(0.25)	(0.09)	(0.04)	(0.02)	(0.10)
SO_2 (ppb)	7.18***	5.72***	23.76***	10.51***	2.86***	0.82	7.40***
	(1.49)	(2.05)	(5.67)	(2.16)	(0.91)	(0.57)	(2.28)
Panel B: Black							
CO (ppb)	0.03***	0.03***	0.09***	0.03***	0.01	0.002	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.004)	(0.003)	(0.01)
NO_2 (ppb)	0.72***	0.87***	2.36***	0.78***	0.18	0.06	0.22
	(0.22)	(0.19)	(0.53)	(0.24)	(0.11)	(0.09)	(0.26)
$PM_{2.5}$ ($\mu g/m^3$)	0.95***	1.11***	3.08***	0.84***	0.19	0.06	0.20
	(0.26)	(0.23)	(0.62)	(0.28)	(0.12)	(0.10)	(0.30)
SO_2 (ppb)	21.53***	25.62***	72.55***	21.08***	4.93*	1.05	6.72
	(5.74)	(5.02)	(14.05)	(6.33)	(2.89)	(2.24)	(6.82)
Panel C: White							
CO (ppb)	0.01***	0.01***	0.04***	0.02***	0.003	0.002	0.02**
	(0.003)	(0.002)	(0.01)	(0.01)	(0.003)	(0.002)	(0.01)
NO_2 (ppb)	0.24***	0.14***	0.83***	0.43***	0.07	0.06	0.35**
	(0.06)	(0.05)	(0.18)	(0.14)	(0.06)	(0.04)	(0.16)
$PM_{2.5}$ ($\mu g/m^3$)	0.32***	0.21***	1.14***	0.57***	0.12	0.06	0.47**
	(0.08)	(0.06)	(0.24)	(0.18)	(0.08)	(0.05)	(0.20)
SO_2 (ppb)	6.80***	3.53***	21.94***	11.84***	1.93	1.57	9.95**
	(1.71)	(1.26)	(4.93)	(3.72)	(1.64)	(1.05)	(4.15)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization 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. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.29: Effect of air pollution on hospitalizaton rates in California port areas, primary diagnoses

	Dependent variable: hospital visits/million residents		
	All Respiratory	All Heart	All Psychiatric
	(1)	(2)	(3)
Panel A: Overall population			
CO (ppb)	0.03***	0.005***	0.003***
	(0.01)	(0.001)	(0.001)
NO_2 (ppb)	0.65***	0.08***	0.07***
	(0.16)	(0.03)	(0.02)
$PM_{2.5}$ ($\mu g/m^3$)	0.97***	0.13***	0.09***
	(0.20)	(0.03)	(0.03)
SO_2 (ppb)	14.90***	2.59***	1.90***
	(4.80)	(0.84)	(0.72)
Panel B: Black			
CO (ppb)	0.07***	0.005	−0.001
	(0.02)	(0.004)	(0.01)
NO_2 (ppb)	1.65***	0.08	0.03
	(0.35)	(0.09)	(0.11)
$PM_{2.5}$ ($\mu g/m^3$)	2.35***	0.15	−0.03
	(0.48)	(0.13)	(0.14)
SO_2 (ppb)	51.55***	2.10	1.55
	(9.52)	(2.51)	(2.89)
Panel C: White			
CO (ppb)	0.02***	0.01**	0.004**
	(0.01)	(0.003)	(0.002)
NO_2 (ppb)	0.28**	0.09*	0.08**
	(0.11)	(0.05)	(0.04)
$PM_{2.5}$ ($\mu g/m^3$)	0.52***	0.18**	0.11*
	(0.17)	(0.07)	(0.06)
SO_2 (ppb)	6.67**	2.54**	1.96*
	(2.84)	(1.26)	(1.04)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for the overall population, Blacks, and whites, where hospitalization rates are calculated only using primary diagnoses. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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 hospitalizaton 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)	0.01***	0.01***	0.01***
	(0.002)	(0.002)	(0.002)
NO_2 (ppb)	0.23***	0.20***	0.16***
	(0.05)	(0.04)	(0.04)
$PM_{2.5}$ ($\mu g/m^3$)	0.34***	0.29***	0.20***
	(0.07)	(0.06)	(0.05)
SO_2 (ppb)	5.60***	6.17***	5.11***
	(1.69)	(1.46)	(1.34)
Panel B: Black			
CO (ppb)	0.02**	0.01**	0.01
	(0.01)	(0.01)	(0.01)
NO_2 (ppb)	0.39**	0.28*	0.20
	(0.19)	(0.16)	(0.15)
$PM_{2.5}$ ($\mu g/m^3$)	0.61**	0.41**	0.28
	(0.26)	(0.21)	(0.20)
SO_2 (ppb)	11.25**	7.48*	6.23
	(5.23)	(4.27)	(3.90)
Panel C: White			
CO (ppb)	0.01***	0.01***	0.01**
	(0.004)	(0.004)	(0.005)
NO_2 (ppb)	0.21**	0.24***	0.23***
	(0.08)	(0.08)	(0.08)
$PM_{2.5}$ ($\mu g/m^3$)	0.37***	0.39***	0.33***
	(0.13)	(0.12)	(0.13)
SO_2 (ppb)	4.39**	5.65***	5.74***
	(2.19)	(2.06)	(2.16)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for the overall population, Blacks, and whites, where hospitalization rates are calculated only using the Patient Discharge Data. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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 air pollution on hospitalizaton 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)	0.04***	0.01***	0.01***
	(0.01)	(0.001)	(0.003)
NO_2 (ppb)	0.89***	0.19***	0.17***
	(0.20)	(0.03)	(0.05)
$PM_{2.5}$ ($\mu g/m^3$)	1.28***	0.22***	0.19***
	(0.25)	(0.04)	(0.07)
SO_2 (ppb)	22.52***	5.92***	4.94***
	(6.04)	(1.04)	(1.64)
Panel B: Black			
CO (ppb)	0.10***	0.01**	−0.01
	(0.02)	(0.01)	(0.01)
NO_2 (ppb)	2.33***	0.29**	−0.14
	(0.48)	(0.14)	(0.20)
$PM_{2.5}$ ($\mu g/m^3$)	3.36***	0.33*	−0.27
	(0.66)	(0.18)	(0.27)
SO_2 (ppb)	73.96***	6.85*	−3.73
	(12.92)	(3.73)	(5.40)
Panel C: White			
CO (ppb)	0.03***	0.01***	0.01
	(0.01)	(0.003)	(0.005)
NO_2 (ppb)	0.46***	0.18***	0.12
	(0.12)	(0.05)	(0.09)
$PM_{2.5}$ ($\mu g/m^3$)	0.72***	0.25***	0.15
	(0.19)	(0.08)	(0.13)
SO_2 (ppb)	12.58***	5.22***	3.17
	(3.25)	(1.36)	(2.19)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for the overall population, Blacks, and whites, where hospitalization rates are calculated only using the Emergency Department Data. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.32: Effect of air pollution on hospitalizaton 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)	−0.001	0.001	0.0005
	(0.002)	(0.001)	(0.001)
NO_2 (ppb)	−0.02	0.01	0.01
	(0.04)	(0.03)	(0.03)
$PM_{2.5}$ ($\mu g/m^3$)	−0.02	0.02	0.01
	(0.05)	(0.04)	(0.03)
SO_2 (ppb)	−0.74	0.21	0.45
	(1.14)	(0.95)	(0.77)
Panel B: Black			
CO (ppb)	−0.003	0.002	0.001
	(0.004)	(0.003)	(0.002)
NO_2 (ppb)	−0.06	0.03	0.02
	(0.08)	(0.06)	(0.05)
$PM_{2.5}$ ($\mu g/m^3$)	−0.10	0.03	0.03
	(0.10)	(0.08)	(0.06)
SO_2 (ppb)	−1.99	0.68	0.38
	(1.97)	(1.55)	(1.27)
Panel C: White			
CO (ppb)	−0.002	−0.001	−0.003
	(0.003)	(0.003)	(0.002)
NO_2 (ppb)	−0.03	−0.005	−0.04
	(0.05)	(0.05)	(0.04)
$PM_{2.5}$ ($\mu g/m^3$)	−0.05	−0.01	−0.07
	(0.08)	(0.08)	(0.07)
SO_2 (ppb)	−0.65	−0.25	−1.03
	(1.33)	(1.33)	(1.11)

Notes: This table presents the IV estimation of the effect of air pollution on hospitalization rates for the overall population, Blacks, and whites, where hospitalization rates are calculated only using the Ambulatory Surgery Center Data. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. 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.33: LIML estimation of the effect of air pollution on hospitalizaton rates in California port areas

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: CO							
CO (ppb)	0.01***	0.02***	0.04***	0.02***	0.004**	0.003**	0.01***
	(0.003)	(0.004)	(0.01)	(0.004)	(0.002)	(0.001)	(0.005)
Adjusted R^2	0.33	0.29	0.42	0.31	0.17	0.17	0.36
Observations	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502	1,769,502
Panel B: NO_2							
NO_2 (ppb)	0.15***	0.31***	0.71***	0.37***	0.09**	0.05***	0.28***
	(0.05)	(0.07)	(0.19)	(0.08)	(0.04)	(0.02)	(0.09)
Adjusted R^2	0.33	0.29	0.42	0.31	0.17	0.17	0.36
Observations	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900	1,796,900
Panel C: $PM_{2.5}$							
$PM_{2.5}$ ($\mu g/m^3$)	0.24***	0.51***	1.19***	0.50***	0.12**	0.07**	0.36***
	(0.08)	(0.11)	(0.28)	(0.11)	(0.05)	(0.03)	(0.13)
Adjusted R^2	0.34	0.29	0.42	0.31	0.18	0.17	0.36
Observations	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050	1,707,050
Panel D: SO_2							
SO_2 (ppb)	4.01***	7.21***	17.59***	9.42***	2.37**	1.34**	7.17***
	(1.39)	(1.98)	(5.21)	(2.16)	(0.98)	(0.54)	(2.44)
Adjusted R^2	0.33	0.29	0.42	0.31	0.17	0.17	0.36
Observations	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378	1,734,378

Notes: This table presents the LIML IV estimation of the effect of air pollution on hospitalization rates. Each entry presents an individual regression of an air pollutant on an illness category. The pollution concentrations are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, 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. Standard errors are clustered by zip code-port pair and day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.34: 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	0.06	0.05	0.04	0.04
	(0.08)	(0.08)	(0.11)	(0.13)
Date	−0.001	−0.002	0.001	−0.002
	(0.001)	(0.002)	(0.002)	(0.002)
CA Regulation × Date	0.003	0.003	−0.01***	0.01*
	(0.002)	(0.002)	(0.003)	(0.003)
Pre-policy Mean	630.35	18.70	14.84	1.89
Observations	4,809	5,303	2,076	3,290
Panel B: One year after the policy				
CA Regulation	0.13	0.08	0.07	0.07
	(0.10)	(0.08)	(0.10)	(0.25)
Date	−0.002	−0.0003	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.004)
CA Regulation × Date	0.001	0.0004	−0.01**	−0.003
	(0.002)	(0.003)	(0.002)	(0.01)
Pre-policy Mean	586.64	17.96	13.89	1.74
Observations	4,861	5,368	2,890	3,550
Panel C: Neighboring areas				
CA Regulation	0.43	0.13*	−0.18*	−0.01
	(0.26)	(0.07)	(0.10)	(0.20)
Date	−0.0002	−0.001	0.003	0.01
	(0.004)	(0.001)	(0.002)	(0.01)
CA Regulation × Date	−0.01	−0.0001	−0.01*	−0.003
	(0.01)	(0.002)	(0.004)	(0.02)
Pre-policy Mean	394.78	10.81	12.43	1.17
Observations	1,190	2,500	1,074	538

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 65 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. Standard errors are clustered by monitor-port pair and normalized day. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table A.35: 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

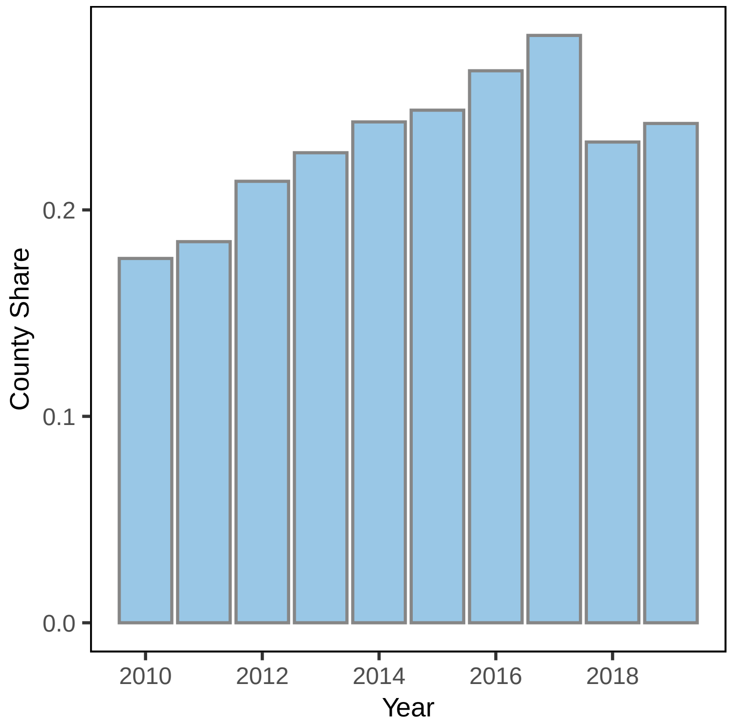

Figure B.1: Share of nonattainment counties adjacent to the major ports in the United States.

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 U.S. EPA NAAQS Greenbook.

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

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

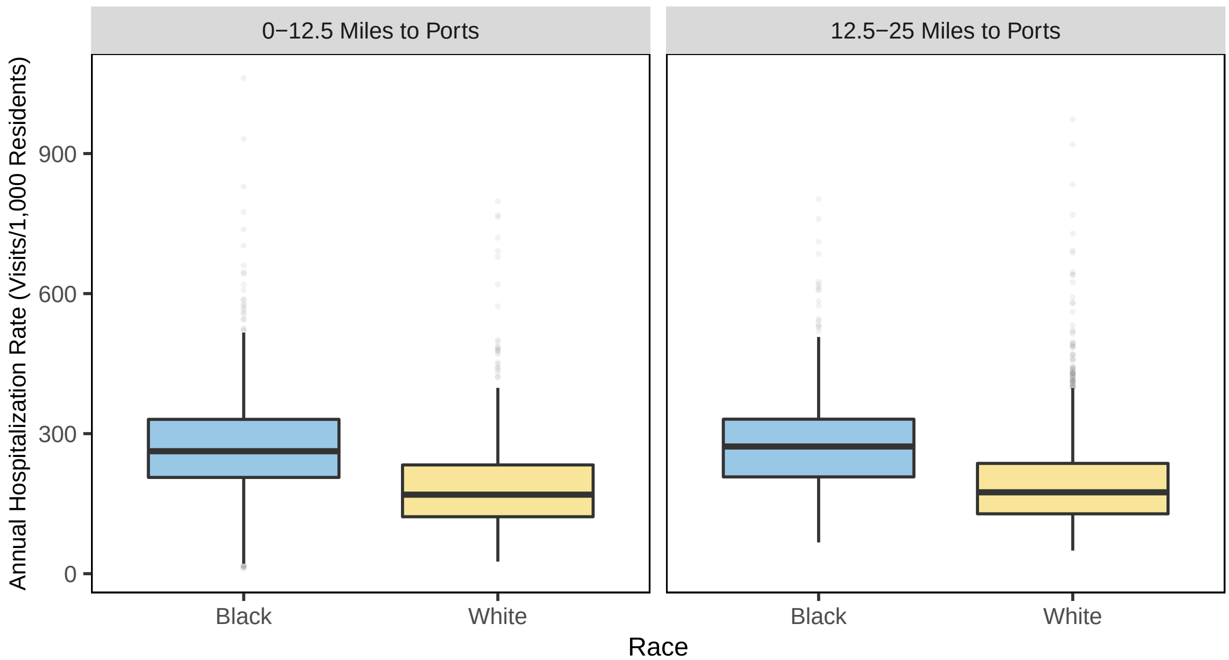

Figure B.3: Boxplots of annual hospitalizations rates in California port areas.

Notes: This figure presents the boxplots of annual hospitalization 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 hospitalization 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 grey dots represent outliers. The difference of sample means in the left panel is 122, while the difference in the right panel is 83. The data are obtained from the Office of Statewide Health Planning and Development of California. We exclude the zip codes having less than 1,000 race-specific population in our analysis. We also do not plot the observations with annual hospitalization rates greater than 1,000.

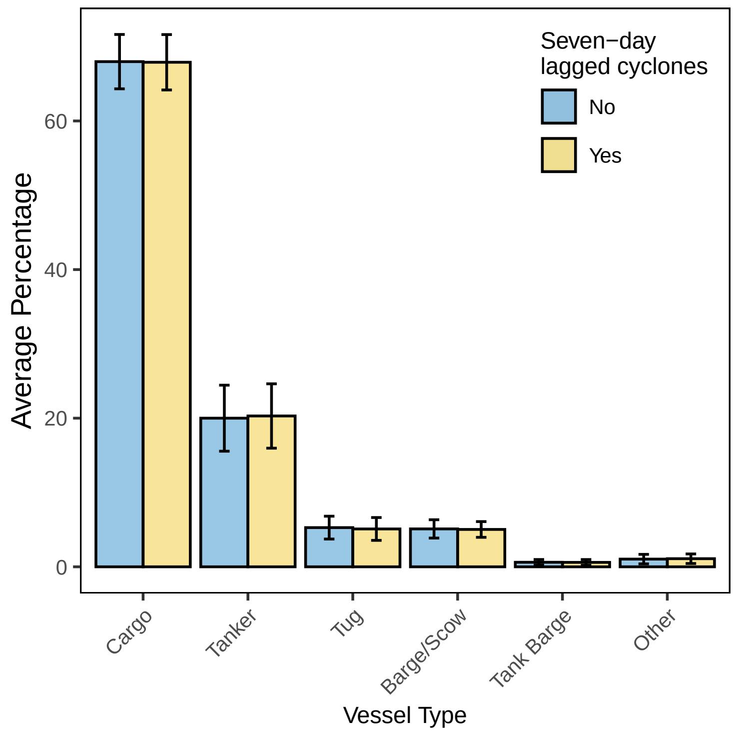

Figure B.4: Average daily share of vessel type in ports.

Notes: This figure presents the average daily share of vessel types in major 27 U.S. 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 devations. The data are obtained from the U.S. Army Corps of Engineers.

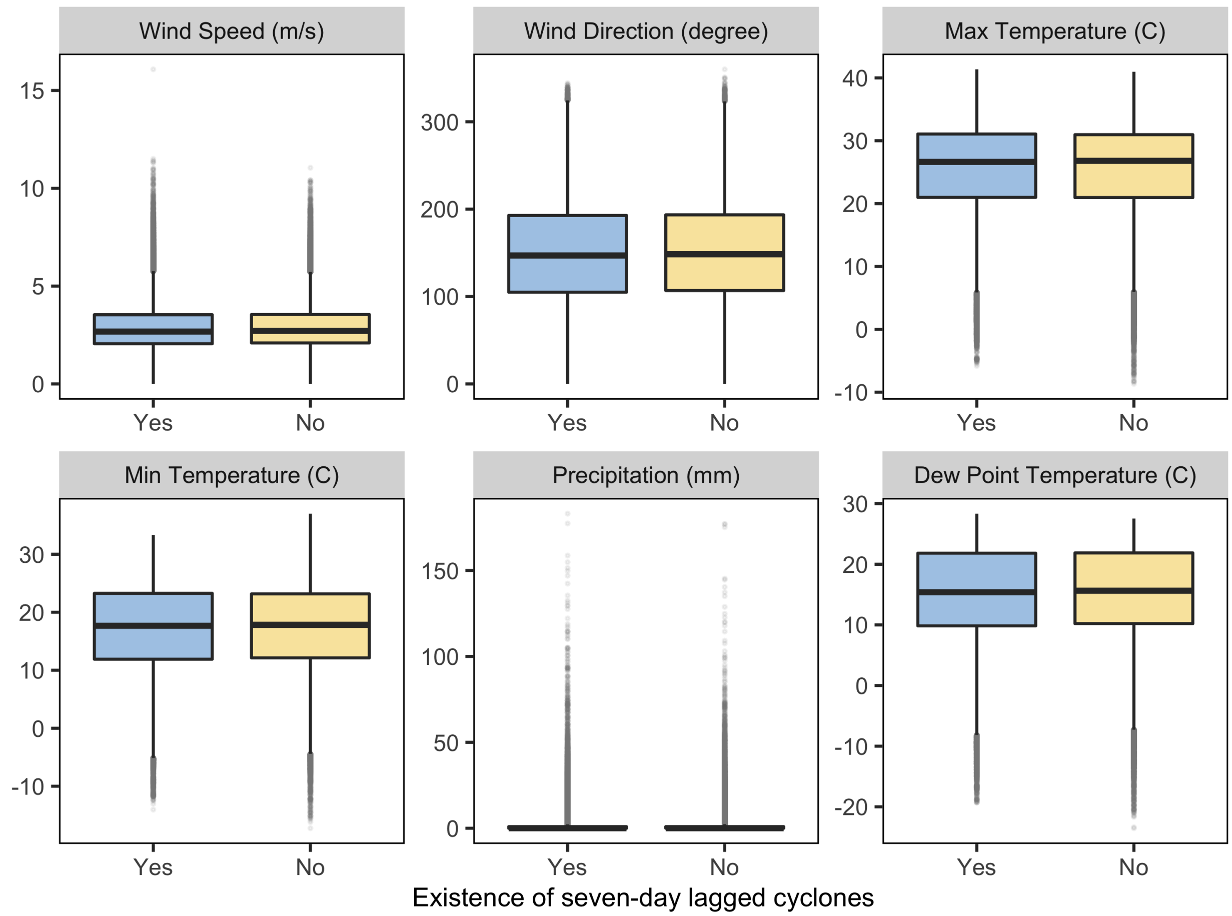

Figure B.5: Boxplots of local weather in port areas.

Notes: This figure presents the boxplots of weather variables in the U.S. 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 grey dots represent outliers. The data are obtained from the NOAA Integrated Surface Database.

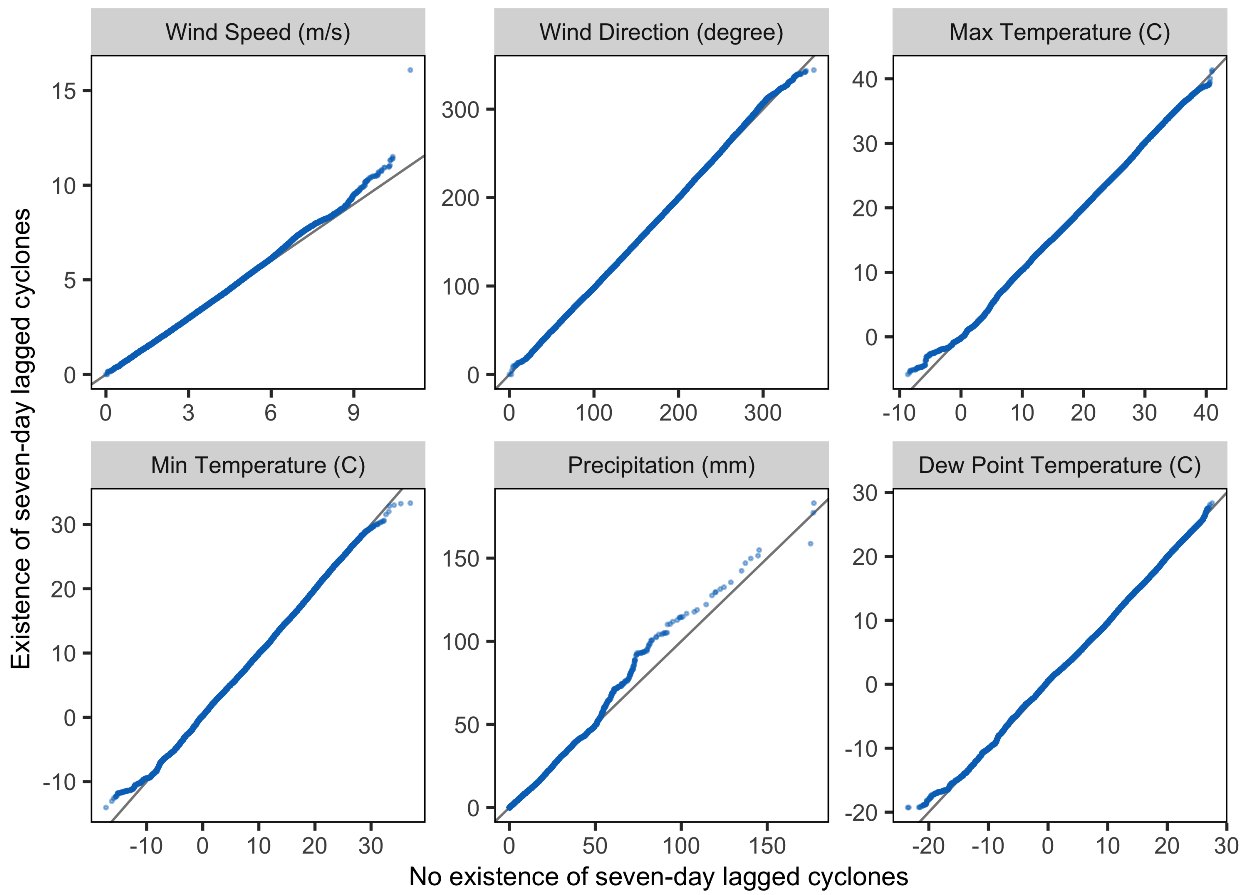

Figure B.6: Empirical quantile-quantile plots of local weather in port areas.

Notes: This figure presents the QQ plots of weather variables in the U.S. port areas. The panels compare two data samples: one for the month-days when there exist seven-day lagged and 500-mile distant tropical cyclones in the ocean and the other for the same month-days when there are no such cyclones. The data are obtained from the NOAA Integrated Surface Database.

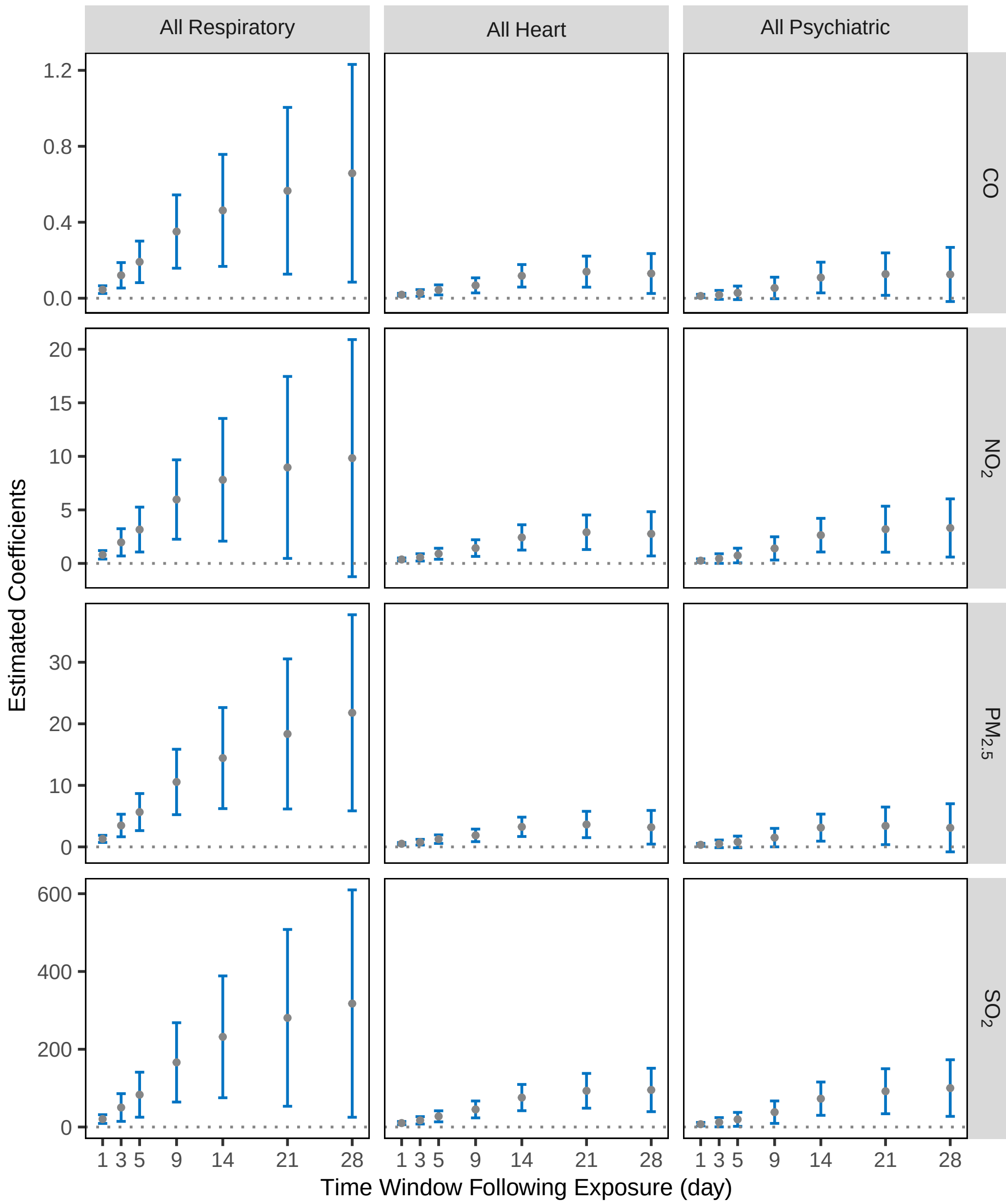

Figure B.7: Effect of air pollution on hospitalization rate for the overall population with different time windows following pollution exposure in California port areas.

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 2. The pollution measures are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, wind speed, and their 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. 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.

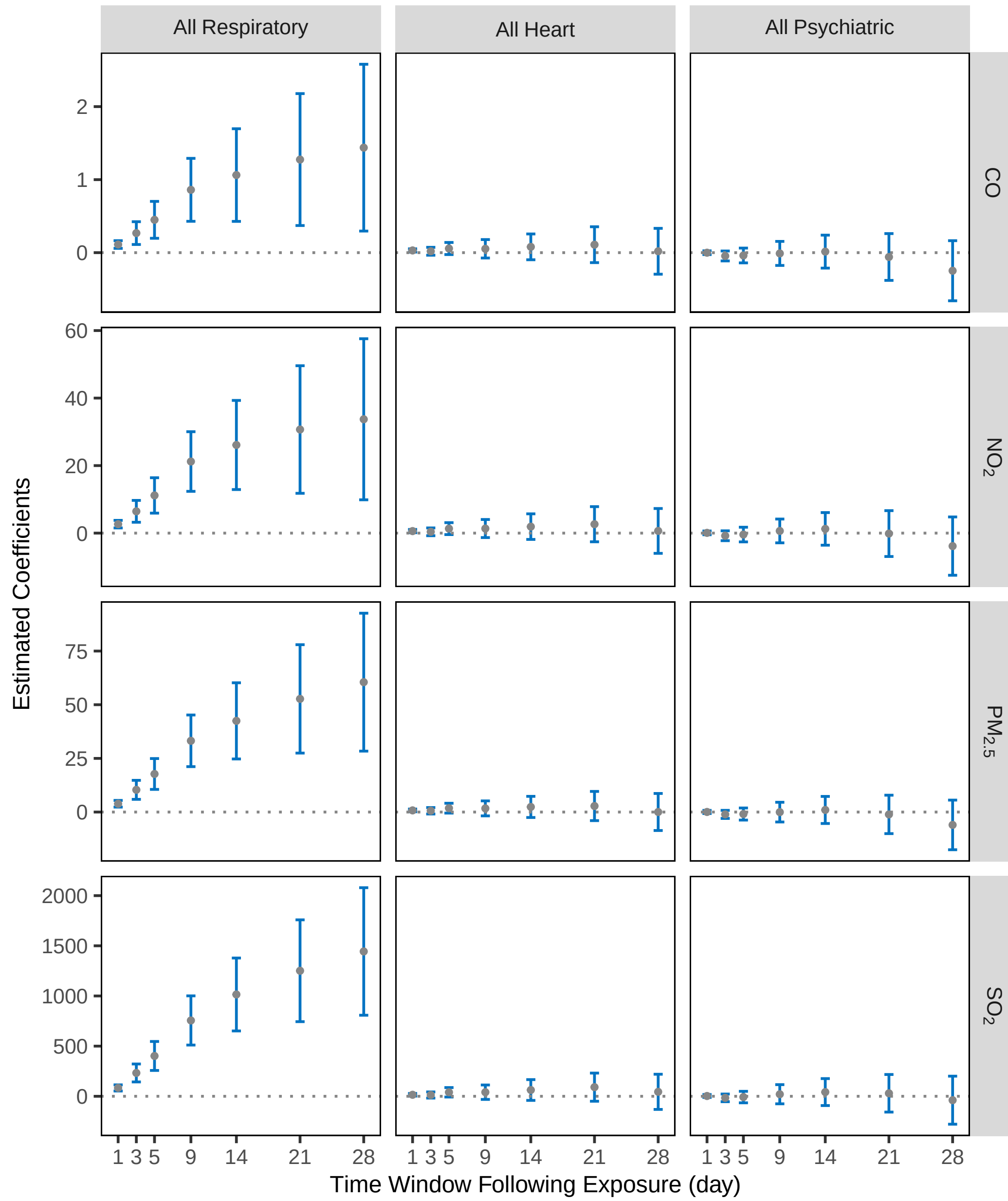

Figure B.8: Effect of air pollution on hospitalization rate for Blacks with different time windows following pollution exposure in California port areas.

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 2. The pollution measures are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, wind speed, and their 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. 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.

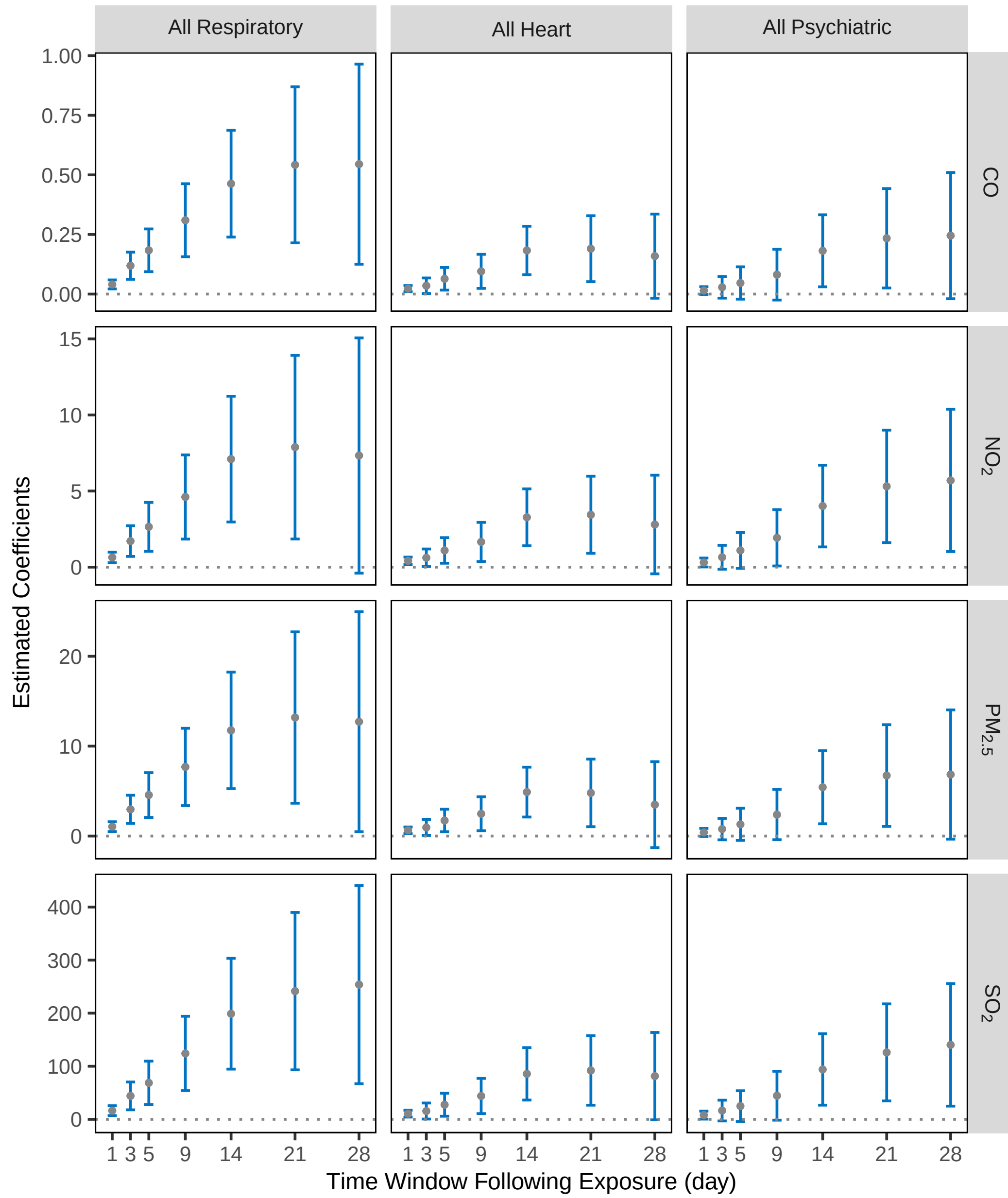

Figure B.9: Effect of air pollution on hospitalization rate for whites with different time windows following pollution exposure in California port areas.

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 2. The pollution measures are instrumented by fitted vessel tonnage in ports, relative wind direction between port and zip code, wind speed, and their 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. 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.

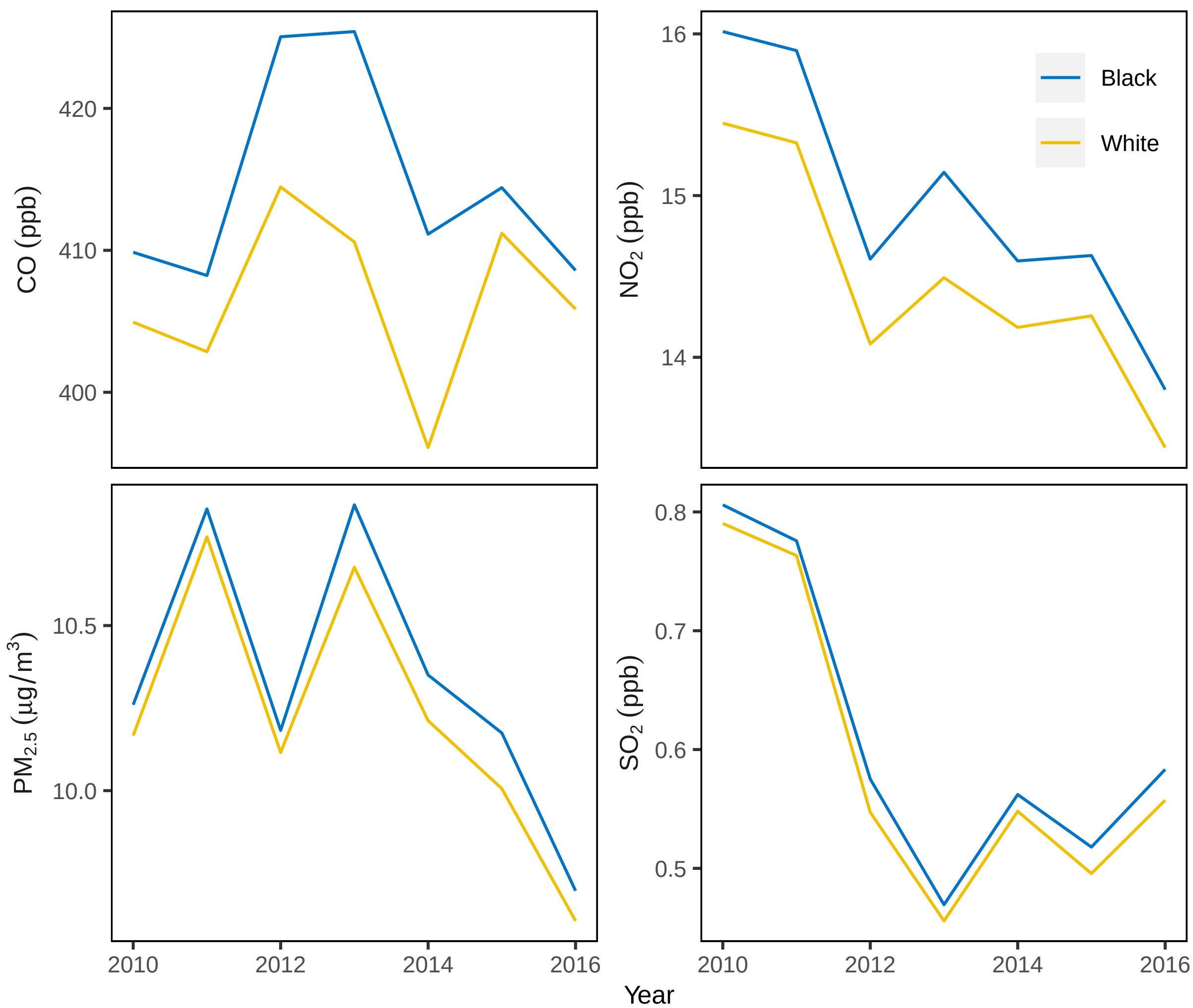

Figure B.10: Annual baseline air pollution exposure.

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 the years 2010–2016. The pollution data are obtained from the U.S. EPA Air Quality System and the hospital visit data are obtained Office of Statewide Health Planning and Development of California.

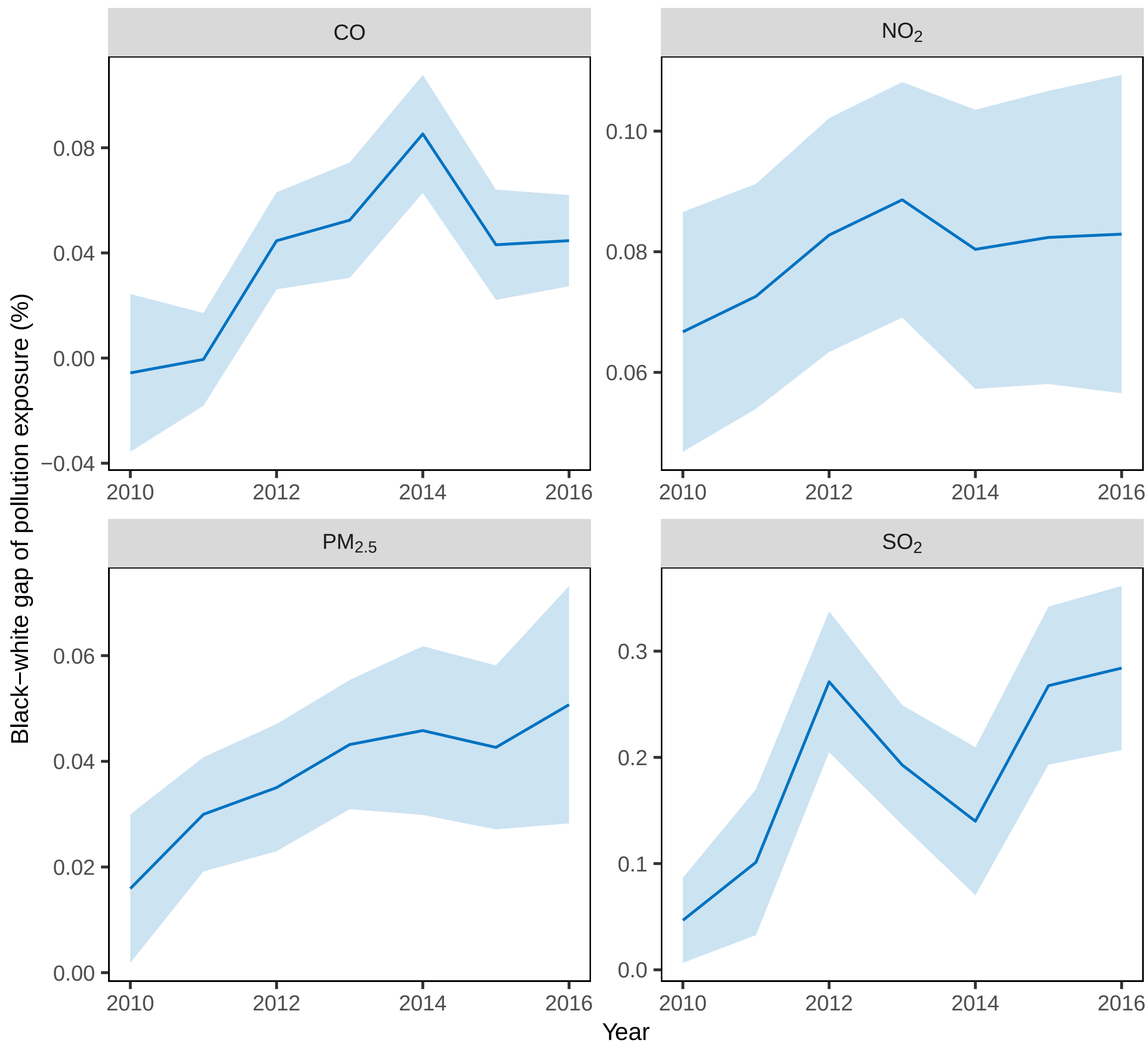

Figure B.11: Black-white gap of pollution exposure separately by year.

Notes: This figure plots the year-specific estimated coefficients, regressing log of pollution concentration on an indicator for whether a patient is Black, controlling for zip code-level weather (defined in equation (1)) and month, day of week, and holiday fixed effects. The patients living within 25 miles from ports in California visit hospitals due to psychiatric, respiratory, and heart-related illnesses during the years 2010–2016. Ribbons correspond to 95 percent confidence intervals, where standard errors are clustered by zip code and date. The pollution data are obtained from the U.S. EPA Air Quality System and the hospital visit data are obtained Office of Statewide Health Planning and Development of California.

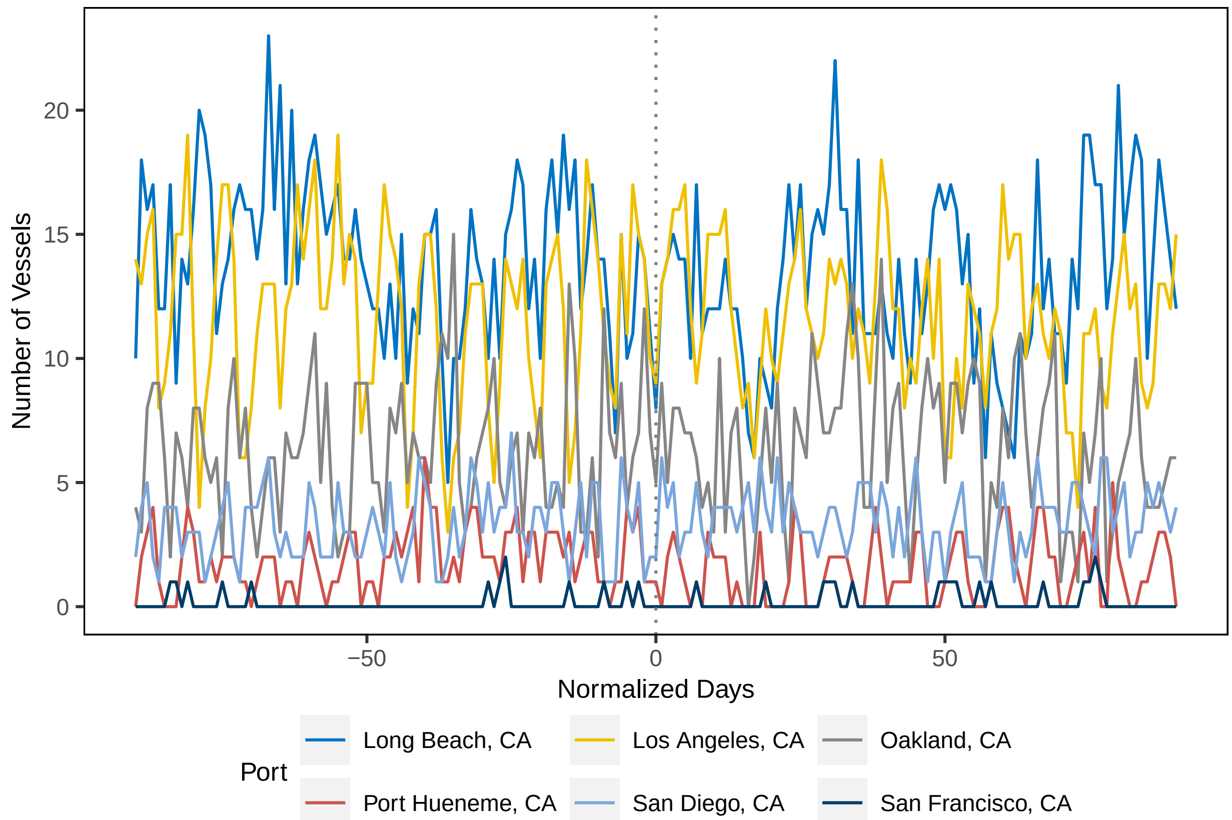

Figure B.12: Vessel counts in ports before and after the Californian at-berth regulation.

Notes: This figure plots the number of vessels in ports before and after the first phase of the Californian at-berth regulation (i.e., January 1, 2010).

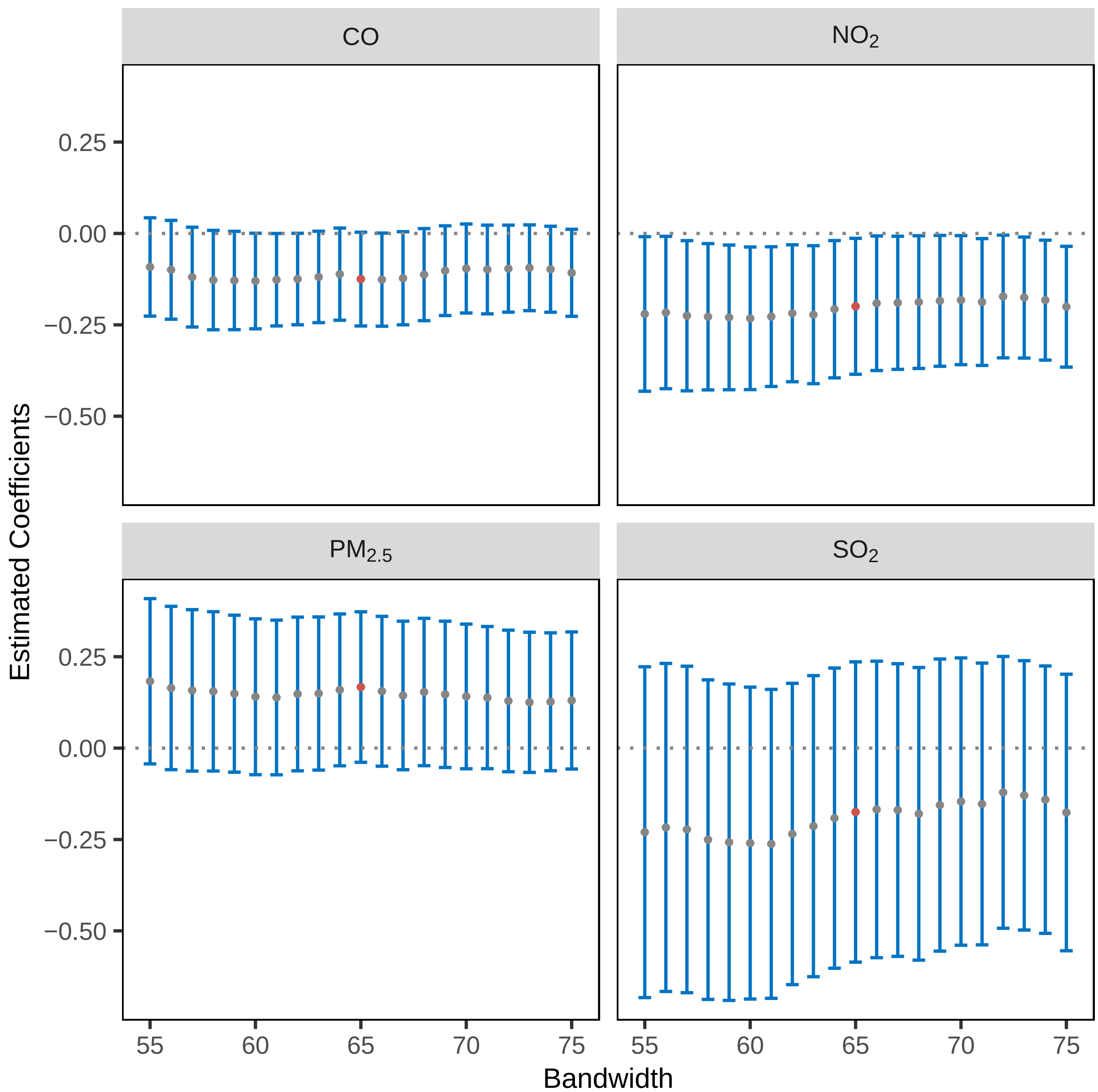

Figure B.13: Robustness check for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollution with varying RDD bandwidths.

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.

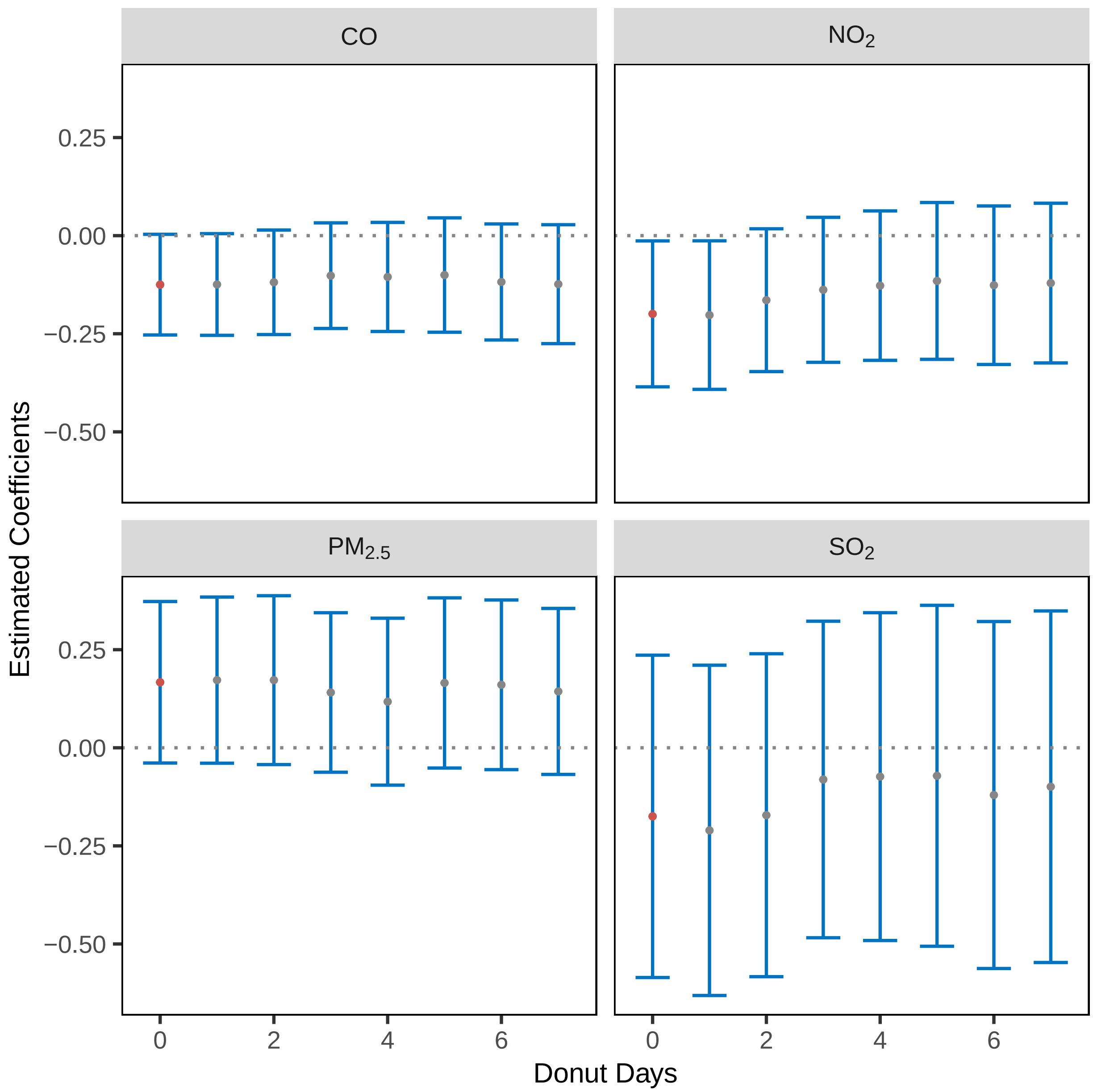

Figure B.14: Robustness check for the effect of California Ocean-Going Vessel At-Berth Regulation on air pollution with varying RDD "donut" periods.

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.

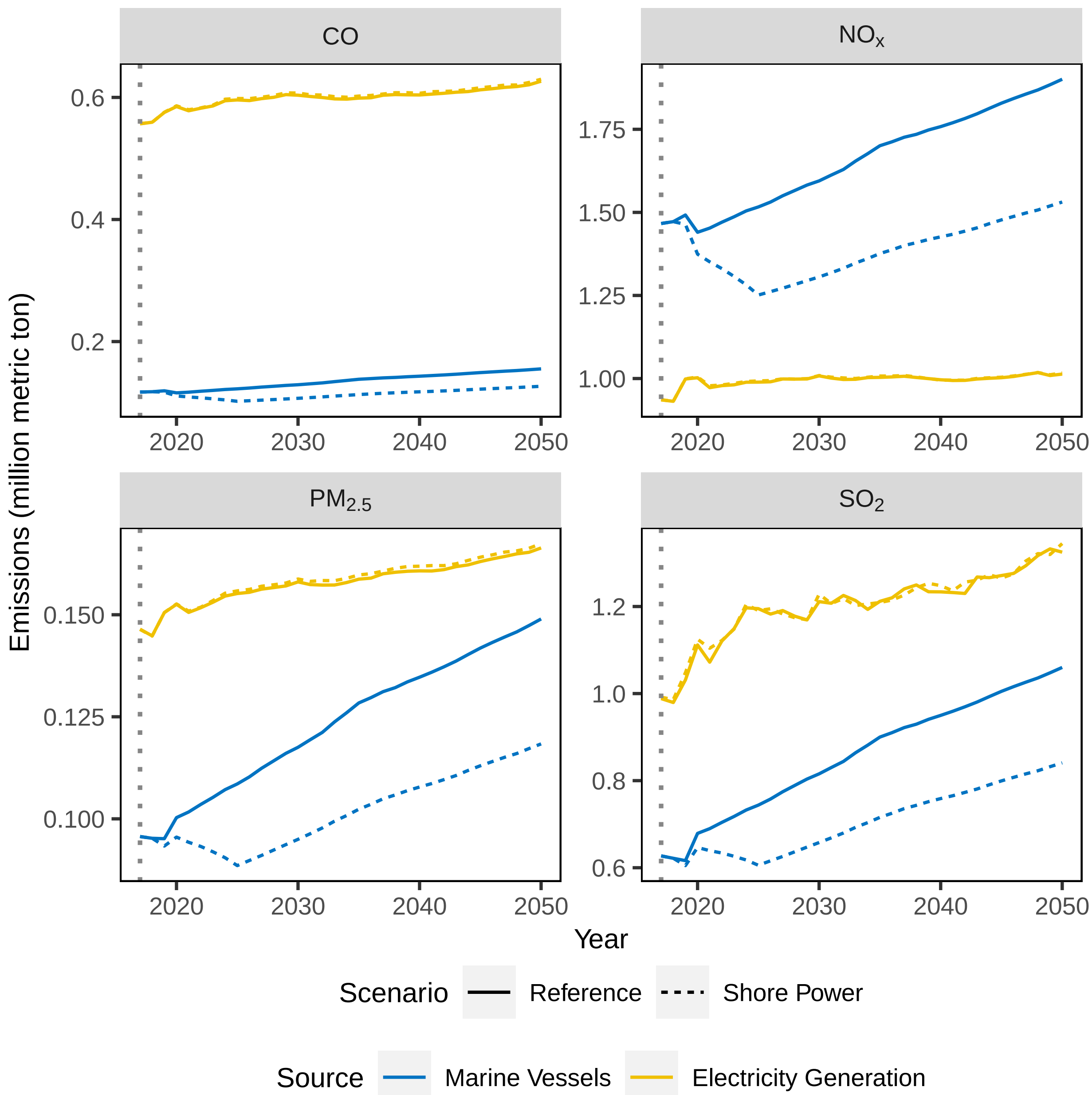

Figure B.15: Projected emissions of local air pollutants from marine vessels and electricity generation in the United States.

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

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 show the estimates of the reduced-form relationship between vessels in ports and human health.

Effect of vessels in ports on air pollution. We first compare our estimates in Table 1 in the main text 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, U.S. EPA estimates that ocean-going vessels contribute to 7 percent of NO_x emissions in Ports of Baton Rouge/New Orleans and up to 61 percent 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 in Table 1 show that one percent increase in vessel tonnage in a port per day leads to 0.3–0.4 percent increases in pollution concentrations for NO_2 and SO_2. This suggests that marine shipping in ports contributes to 40 percent of local air pollution in port areas in the United States, 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 pollution concentration cannot exceed 35 parts per million (ppm) more than once per year. Our results show that average gross vessel tonnage in ports results in a 0.18 ppm increase in CO pollution.[3] Combining this increase with the average daily maximum of CO, the estimated resulting concentration is 0.99 ppm (0.18 + 0.81), which is far below the EPA standard. Similarly, the resulting pollution concentrations 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 ($\mu g/m^3$). Adding the increase in $PM_{2.5}$ concentrations 4.59 $\mu g/m^3$ (43×10.67/100) (owing to average gross vessel tonnage in ports) to the daily 24-hour average (10.67 $\mu g/m^3$) results in a concentration of 15.26 $\mu g/m^3$, which is around 44 percent of the EPA standard. Note

[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 0.18 ppm increase is calculated from 37×0.49/100 based on the estimates in Table 1 and summary statistics reported in Table A.3.

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

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 economic and epidemiological literature examining the effect of air pollution on health, it is natural to compare our estimates in Table A.15 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 smaller. For example, we find that a one ppm increase in CO pollution leads to a 20 percent increase in all respiratory hospital visits, while Schlenker and Walker (2016) find a 37 percent increase. The areas near airports in their study usually have higher CO concentrations—airports are considered one of the largest CO emitters—and people living nearby may have become more sensitive to CO pollution concentrations. Other epidemiological studies show the effect of a one ppm increase in CO pollution on respiratory hospital visits in a range of 1–8 percent (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 $\mu g/m^3$ increase in $PM_{2.5}$ concentration leads to a 0.36 percent increase of hospital visits, which is higher than the estimates 0.13–0.15 percent in the epidemiological literature (e.g., Dominici et al., 2006; Bell et al., 2008). Two recent epidemiological studies find evidence that a 0.11 percent increase in psychiatric hospital visits is attributed to a one $\mu g/m^3$ increase in $PM_{2.5}$ concentration, which is also smaller than our estimate 0.23 percent. We find consistent larger estimates for the effect of air pollution on hospital visits because we may include a more extensive set of illnesses in our health categories, or our quasi-experimental framework corrects the attenuation bias.

C.2 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 hospitalization rate across illness categories. We use the ten-day lagged cyclones that are 500 miles distant from ports as the IV in our baseline specification.[5] Since the IV specification is similar to the one used in the main text, we do not present the results for IV validity checks.

Table C.1 presents the first-stage relationship between the cyclone IV and vessel tonnage in ports. The point estimate is statistically significant, suggesting the cyclone IV leads to a

[5]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.

five percent reduction in vessel tonnage in ports.

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

	Dependent variable: log of vessel tonnage
Tropical Cyclone	−0.05***
	(0.02)
First-stage F Stat.	10.80
Adjusted R^2	0.70
Observations	1,796,907

Notes: This table presents the first-stage results of the IV 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 ZCTA-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and ZCTA-port pair fixed effects. Standard errors are clustered by ZCTA-port pair and day. Estimates are weighted by ZCTA-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table C.2 presents the IV estimation for the effect of vessel tonnage on hospitalizations across seven illness categories. The t-statistics on the excluded instrument are 11.39 across the columns above the thresholds suggested in the literature. Most estimates associated with respiratory illnesses shown in columns (4)–(6) are statistically significant. They show that a one percent increase in gross vessel tonnage in a port results in an additional 1.07 hospital visits per million residents related to all respiratory illnesses. However, the estimates associated with psychiatric and heart illnesses have surprising signs, and they are either statistically significant at the 10 percent level or insignificant. We do not see strong results associated with psychiatric and heart illnesses, probably because the composition of air pollutants co-emitted from vessels together may not cause mental and heart illnesses.

Tables C.3 shows the OLS estimates for the effect of vessel tonnage on hospitalizations. The estimates for respiratory illnesses become insignificant or significant at the 10 percent level. They are also much smaller than the corresponding IV estimates, suggesting potential bias. The OLS estimates associated with psychiatric and heart illnesses are positive, but they are with small magnitudes.

Table C.4 contains the IV estimates for the effect of vessel tonnage on hospitalizations by non-Hispanic Black and white populations. Similar to Table C.2, only the estimates associated with respiratory illnesses are statistically significant and have expected signs. They provide additional evidence that port congestion can contribute to racial disparities in respiratory-related health outcomes.

Table C.2: Effect of vessel tonnage on contemporaneous hospitalizaton rate in California port areas, IV estimation

	Dependent variable: hospital visits/million residents						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log of Vessel Tonnage	12.73**	37.70***	106.91***	−2.06	−7.99*	−3.19	−22.91*
	(6.46)	(12.47)	(34.91)	(9.98)	(4.58)	(2.06)	(12.60)
Adjusted R^2	0.36	-0.05	0.09	0.35	0.19	0.16	0.36
Observations	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907

Notes: This table presents the IV estimation of the effect of vessel tonnage on the contemporaneous hospitalization rate for the overall population. 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 ZCTA-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and ZCTA-port pair fixed effects. Standard errors are clustered by ZCTA-port pair and day. Estimates are weighted by the ZCTA-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

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	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log of Vessel Tonnage	0.04	0.01	0.39	0.22*	0.17***	0.05**	0.42***
	(0.07)	(0.08)	(0.24)	(0.12)	(0.05)	(0.03)	(0.13)
Adjusted R^2	0.39	0.34	0.47	0.35	0.22	0.17	0.40
Observations	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907	1,796,907

Notes: This table presents the OLS estimation of the effect of vessel tonnage on the contemporaneous hospitalization 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 ZCTA-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and ZCTA-port pair fixed effects. Standard errors are clustered by ZCTA-port pair and day. Estimates are weighted by the ZCTA-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

Table C.4: Effect of vessel tonnage on contemporaneous hospitalizaton rate by race in port areas of California, IV estimation

	Dependent variable: hospital visits/million residents in each race group						
	Respiratory			Heart	Psychiatric		
	Asthma	Upper Respiratory	All Respiratory	All Heart	Anxiety	Bipolar Disorder	All Psychiatric
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Black							
Log of Vessel Tonnage	52.05*	71.36***	264.19***	−5.35	−17.15	−8.19	−77.48**
	(28.04)	(25.19)	(92.73)	(25.47)	(11.02)	(8.75)	(35.80)
Adjusted R^2	0.14	-0.01	0.04	0.13	0.04	0.06	0.16
Observations	880,584	880,584	880,584	880,584	880,584	880,584	880,584
Panel B: White							
Log of Vessel Tonnage	6.61	13.89**	60.64**	−3.39	−9.35	−8.61*	−30.01
	(7.11)	(6.45)	(27.99)	(16.79)	(7.72)	(4.57)	(21.14)
Adjusted R^2	0.17	0.04	0.27	0.28	0.14	0.14	0.31
Observations	1,671,854	1,671,854	1,671,854	1,671,854	1,671,854	1,671,854	1,671,854

Notes: This table presents the IV estimation of the effect of vessel tonnage on the contemporaneous hospitalization rate for the Black and white populations. Each entry 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 ZCTA-port pair. All regressions also include county-by-year, month, day-of-week, holiday, and ZCTA-port pair fixed effects. Standard errors are clustered by ZCTA-port pair and day. Estimates are weighted by the ZCTA-specific population. Significance levels are indicated by *** 1%, ** 5%, and * 10%.

D National Energy Modeling System

The National Energy Modeling System (NEMS) is an integrated energy-economy modeling system built by the U.S. EIA. A 2017 version of NEMS is currently hosted on a server at Yale University, and we call it Yale-NEMS. 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. The differences between the reference and scenarios highlight the effects of scenario designs.

D.1 Annual Energy Outlook 2017

We take Annual Energy Outlook (AEO) 2017 as the reference. AEO 2017 is a regular update of the U.S. 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 U.S. 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.

D.2 Marine Energy Consumption

In Yale-NEMS, the transportation demand module projects transit and auxiliary fuel consumption by marine vessels, within the U.S. Emission Control Area—the areas within 200 nautical miles of the U.S. 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 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 different fuel types, including distillate oil, residual oil, CNG, and LNG, based on fuel price changes using a logit model specification.

The original NEMS version does not explicitly model port-side electricity consumption. We add this feature to Yale-NEMS. First, we obtain historical data about 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 percentage 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. Forth, 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) at Yale-NEMS explicitly models the U.S. 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 in a cost-efficient way. 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 another important criterion pollutant $PM_{2.5}$, we apply a simplified method 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 U.S. ports implement shore power for auxiliary engines of vessels. Specifically, we allow the auxiliary fuel consumed by vessels to be gradually replaced by onshore electricity from 2020 to 2025, and after 2025 all docked vessels are powered by electricity. We then compare the emissions results between the reference and the shore power scenario, and the differences indicate the effect of implementing shore power in ports in the United States.

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