Uncharted Waters: Effects of Maritime Emission Regulation

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Abstract

Maritime shipping emits as much fine particulate matter as half of global road traffic. We are the first to measure the consequences of US maritime emissions standards on air quality, human health, racial exposure disparities, and behavior. The introduction of US maritime emissions control areas significantly decreased fine particulate matter, low birth weight, and infant mortality. Yet, only about half of the forecasted fine particulate matter abatement was achieved by the policy. We show evidence consistent with behavioral responses among ship operators, other polluters, and individuals that muted the policy's impact, but were not incorporated in ex-ante models.

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Roughly 90 percent of global trade is conducted via ship, yet historical international standards for ship exhaust are strikingly weak in comparison to standards for other forms of transport that occur close to populated areas. For example, in 2008, the maximum allowable sulfur content of marine fuel along US coastlines was 3,500 times higher than that allowed in vehicles. Pollution from ship exhaust is a main component of poor air quality, not only at ports, but also in coastal communities near ship routes.[1] Since half of the US population lives within 200 km of heavy ship traffic and ship traffic continues to increase, maritime emissions represent a significant threat to human and ecosystem health (U.S. EPA, 2009b,a, 2016). Yet, we lack a comprehensive understanding of the exposed population demographics and health effects of maritime emission regulation. Because ships are mobile and emissions occur off-shore, the health benefits from regulation are likely to be different than the effects of regulating land-based pollution sources.

Efficient design of maritime emission regulations is difficult for several reasons. First, the benefits to human health are uncertain. The health effects are likely to differ from regulation of other pollution sources because of the especially high sulfur content of ship fuel, the distinct coastal population exposed to ship traffic, and the degree to which individuals can avoid ship exhaust relative to other sources. Second, uniform regulation of maritime emissions along the coast will have heterogeneous effects due to the non-uniform population distribution and location of ships. The mobile nature of ship traffic makes it difficult to predict how ship routes and emissions may respond to regulation. Moreover, efficient regulation of maritime emissions must balance competing environmental objectives. Specifically, requirements to remove the sulfur content in ship exhaust may exacerbate climate change because the aerosols in traditional ship exhaust provide radiative cooling that counteracts the consequences of climate change in the short term (Sofiev et al., 2018; Liu et al., 2016). Without comprehensive evidence accounting for spatial heterogeneity in the effects of maritime emission regulations on coastal population health, uniform regulation of maritime fuel risks both abating too little of emissions near coastal populations and too much of emissions far from coastal populations.

[1] Roughly 70 percent of maritime emissions occur within 400 km of coasts, and maritime emissions elevate ambient fine particulate matter as much as 2 micrograms per cubic meter (Corbett et al., 2007). Maritime emissions account for roughly 38 percent of sulfur dioxide emissions on the US East Coast and 20 percent on the US West Coast (Wang et al., 2007). In areas adjacent to busy ports, they may equal or exceed those of land-based sources (Capaldo et al., 1999). Eyring et al. (2005) show maritime emissions are comparable to other transport modes. Smith et al. (2015) provide an emissions inventory.

We provide the first evaluation of a major US environmental policy in the maritime shipping industry. In 2012, the US government, in coordination with the International Maritime Organization (IMO), introduced its seminal regulation of maritime pollution, called emission control areas (ECAs) (U.S. EPA, 2010). ECA regulation required all commercial ships to operate with low-sulfur fuel within 200 nautical miles off the coast or to install abatement equipment, or face penalties. In 2020, following this initial ECA regulation, the IMO extended similar standards globally, which were estimated would cost the shipping industry \$10 to \$60 billion per year (Corbett et al., 2016). Despite the consequential scale and cost of these regulations, ex-post evidence on the effectiveness and health benefits of such regulation has not been previously established.

In this paper, we measure the success of US maritime emissions standards and show evidence consistent with behavioral responses that diminished the policy's effectiveness relative to ex-ante predictions. With administrative data on air quality, infant health, and infant mortality, we use a differences-in-differences design and leverage variation in (i) the timing of the regulation and (ii) the intensity of the regulation across locations. Intensity of exposure to the policy is based on predictions from the Community Multiscale Air Quality Modeling System (CMAQ) obtained from U.S. EPA (2009b). CMAQ both represents policymakers' expectations of the effectiveness of the policy and provides a scientific prior of the policy's intended intensity at each location that accounts for atmospheric dispersion, disposition, and chemical interactions of pollution once emitted. After estimating the policy's ex-post benefits, we then test whether the changes in air quality from the policy were equal to the predicted improvements from the EPA's pre-policy analysis. We explain gaps between the ex-ante and ex-post predictions with behavioral responses on the part of the industry regulated by the policy, other pollution sources, and individuals, all of which can lessen the effectiveness of policy.

We find that the introduction of maritime emissions control areas around the US coastline led to a 4 percent decrease in the population-weighted average fine particulate matter across counties within 200km of heavy ship traffic.[2] We also find less of the disproportionate effects on minorities that have been documented as a result of land-based emissions, such as emissions from ports.

[2]Once primary pollutants such as sulfur exhaust are emitted in the atmosphere, they form secondary pollutants, such as particulate matter, through chemical interaction. Accordingly, the regulation defined fuel content limits for sulfur exhaust as a means to abate fine particulate matter and protect health from both primary and secondary pollutants (U.S. EPA, 2008, 2009b,a, 2016).

Consistent with the air quality improvements, we find that the policy results in a 1.7 percent average reduction in the incidence of low birth weight. We also find a 3.5 percent decline in infant mortality. We further show that using an atmospheric aerosol transport model instead of distance as a proxy for exposure provided a meaningful improvement in estimation. Using distance in lieu of the CMAQ output would have yielded substantially less precision in the estimated effects of the policy.

These improvements in air quality and health demonstrate a substantial policy achievement. We estimate the ECA led to 1,536 fewer low birth weight infants and 290 fewer infant deaths per year. Our back-of-the-envelope calculation finds these improvements led to a savings of about $2.9 billion per year. These benefits to improved infant health alone equal about 90 percent of the estimated cost of the policy, $3.2 billion in 2020. In terms of lives saved, the ECA had about one-fifth of the effect of the initial 1970 CAA NAAQS (Chay and Greenstone, 2003), one-quarter of the effect of requiring scrubbers at power plants in Germany (Luechinger, 2014), and eight times the effect of having cheating diesel emissions (Alexander and Schwandt, 2021). Despite these substantial benefits to human health, the ex-post impact on air quality was still weaker than the regulator's ex-ante expectation. Only about 53 percent of the predicted fine particulate matter abatement was realized under the ECA policy. We reject the hypothesis that the ex-ante and ex-post estimates are equivalent.

To better understand why policymakers' expectations were not fully realized, we provide evidence consistent with three types of behavioral responses that altered the policy's effectiveness and were not taken into account in ex-ante predictions. First, we provide evidence indicating that ships altered their routes to avoid using the costly low-sulfur fuel required in the ECA. We find that air quality improvements were significantly more muted in areas with a narrower ECA boundary. Second, we provide evidence consistent with "regulatory rebound" in relation to the National Ambient Air Quality Standards (NAAQS) of the Clean Air Act. We find that air quality improvements from the ECA were more muted in counties far from the regulatory threshold for non-compliance with NAAQS, and thus where the risk of crossing the threshold to face regulatory penalties under NAAQS was low. This evidence is consistent with the hypothesis that additional on-land emissions offset some of the decline in emissions from maritime ships. Finally, in addition to disparities in the realized air quality improvements, we found gaps in the human health benefits. We estimated that the ECA policy increased time spent outdoors and visits to national park sites, activities which increased individuals' exposure to air pollution. Each of these three types of behavioral responses affected the realized pollution and health benefits of the policy, yet were not incorporated into ex-ante models.

This paper makes several important contributions to the literature. First, we estimate the impact of maritime fuel emissions on air quality and human health. The North American ECA policy was the first major US environmental regulation of the maritime shipping industry and we are not aware of prior work that evaluates its success. The existing literature on the impacts of ECAs and maritime fuel emissions has relied exclusively on ex-ante prediction approaches or has been conducted in other settings.[3] Predictive models do not take into account compliance or the potential behavioral responses of the regulated industry, other sources, or individuals in response to the policy. Our ex-post evaluation finds meaningful improvements in air quality from maritime fuel regulation; yet, the improvements are more muted than the predictions from this existing work. We provide a significant advance over the prior literature by documenting that adaptation post-policy critically influences policy effectiveness.

Second, in addition to evaluating the success of the policy, we evaluate the accuracy of the regulator's ex-ante policy analysis. Policy evaluations typically estimate net benefits while ignoring the extent to which those benefits achieved the stated objectives of the policy. Our findings of discrepancies between the policy target and achievement are connected to an existing literature that documents behaviors that diminish the effectiveness of regulation (Becker and Henderson, 2000; Auffhammer and Kellogg, 2011; Fowlie et al., 2016; Zou, 2021). Moreover, our results link shortcomings in the regulator's ex-ante analysis to specific behavioral reactions, including responses by ship operators, other industry, and individuals, and are useful to the design of future policy. These features suggest additions to models to better predict policy effects as well as amendments to policy to improve future regulation of this sector (Duflo, 2017).

Third, this paper contributes to a small but growing literature that incorporates atmospheric aerosol transport models into economics research. Defining where and to what extent the ECA policy affected air pollution for the on-land population is a first-order challenge in this setting. A common approach in economics defines exposure based on distance to the pollution source, but

[3] See Corbett et al. (2007); Winebrake et al. (2009); U.S. EPA (2009b); Sofiev et al. (2018); Liu et al. (2016); Viana et al. (2020); Zhu and Wang (2021); Lindgren (2021).

the mobile nature of ship pollution makes this approach difficult. Instead of the "distance" method, we use atmospheric aerosol transport model output as a scientifically grounded prior for pre- and post-policy exposure to pollution.[4] We show that the distance method's failure to account for the complexity of atmospheric interactions can meaningfully reduce precision. Further, our use of transport model output is a new instrument for policy-induced changes in air quality.[5]

The fourth contribution of this work is measuring the infant health effects of transportation emissions in a new setting: at-sea maritime emissions. Infant health has been shown to be sensitive to air pollution and has implications for many later life outcomes, including earnings, cognitive development, IQ, educational attainment, and welfare take-up (Figlio et al., 2014; Black et al., 2007; Oreopoulos et al., 2008). Prior studies in economics have established a link between infant health and air pollution exposure (Currie and Neidell, 2005; Currie et al., 2009; Arceo et al., 2016), road-vehicle traffic and gasoline content regulations (Currie and Walker, 2011; Knittel et al., 2016; Marcus, 2017; Alexander and Schwandt, 2021), and alternative sources of transportation pollution, such as jets (Schlenker and Walker, 2015). Within this literature, no paper examines a link between maritime fuel content regulation and infant health, even though emissions from shipping fuel have a high concentration of toxic sulfides and comprise a large portion of coastal air pollution. While some work has focused on health effects of port emissions (Moretti and Neidell, 2011; Gillingham and Huang, 2021), we expand our focus to study all at-sea emissions as well, and our results are not driven exclusively by emissions in the vicinity of ports. Our setting expands beyond ports to study the impact of ship emissions on the entire continental US coastline, comprising half of the US population, and focuses on infant health.

Finally, we document how the demographic composition of populations exposed to maritime emissions is distinct from the exposed population in other pollution contexts. The environmental justice literature has documented higher exposure to pollution among disadvantaged populations for many land-based pollution sources.[6] Unlike exposure to stationary pollution sources, we show

[4]Some economic research has used atmospheric transport models in other ways. For example, researchers may take estimates of facility-level emission changes driven by regulation and use atmospheric dispersal models to determine impacts of point-source regulation on nearby areas without comparing the model output with in situ observations. For example, Hernandez-Cortes and Meng (2021) analyze resulting changes from cap-and-trade on nearby "environmental justice" gaps, and Sanders and Barreca (2021) analyze the effect of the acid rain program on nearby crop yields.

[5]Since we interpret the transport model output as the policymakers' planned air quality change, this instrument mirrors the method in Baum-Snow (2007).

[6]Some examples are Superfund sites, hazardous waste sites, landfills, and large polluters from the Toxic Release

the proportion of black individuals is smaller for higher levels of maritime emissions. If there are heterogeneous effects of pollution exposure, perhaps due to differences in underlying health conditions, avoidance, or access to care, the realized health effects of maritime emission regulation may be affected by the underlying demographic characteristics of the exposed population. The combination of a demographically distinct exposed population and the unique mixture of pollutants released from ship exhaust makes this an unexamined context in which to explore the impact of maritime fuel regulation, not only on pollution, but also on health.

1 Policy Background

The ECA regulation requires ships to reduce their emissions of air pollutants, primarily sulfur oxides. Figure 1 plots a summary of the policies. Prior to July 2009, the only relevant standard was the IMO global standard, which allowed ships to emit up to 4.5 percent sulfur oxides by mass (m/m) at any location. This global standard was reduced slightly to 3.5 percent in January 2012.

While the global standard applies to any location, stricter standards can be set near coastlines. In July 2009, California enacted a state standard that allowed at most 1.0 percent sulfur oxides by mass (m/m) in ship emissions within 24 nautical miles of the California coastline. Due to California's limited jurisdiction, however, many ships responded to this restriction by altering their routes to travel just outside the California ECA in order to minimize use of the expensive low-sulfur fuel (Klotz and Berazneva, 2022; Moore et al., 2018).[7] Using detailed ship location transponder data, Klotz and Berazneva (2022) study the impact of California's ECA on ship traffic patterns. They find a sharp reduction in distance traveled, speed, and fuel consumption within California's ECA, along with an even larger increase in fuel use just outside the ECA due to ships traveling greater distances, and in some cases higher speeds, to avoid the California ECA. Because ships continued to use high sulfur fuel just outside the narrow boundary, there was limited scope for the California ECA to improve air quality. In fact, we fail to find a sustained improvement in air quality in areas most exposed to ship traffic after this policy.[8]

Inventory (Currie, 2011; Gamper-Rabindran and Timmins, 2011; Banzhaf et al., 2019). Tessum et al. (2021) provide an overview.

[7] California altered its emission control area in December 2011 by extending a portion of the boundary to include the area around the Channel Islands in an effort to encourage ship traffic to return closer to shore.

[8] We estimate the effect of California's ECA using 2007-2011 data from California only. We modify equation 1

The most significant policy change occurred in August 2012, when the full North American ECA took effect. Low-sulfur fuel of up to 1.0 percent sulfur oxides was required across the mainland US and Canada. The North American ECA, depicted in Figure 2, typically applied within 200 nautical miles of the coast, significantly limiting the scope for avoiding the use of low-sulfur fuel. Yet, the North American ECA boundary is less than 200 nautical miles from the US coastline in certain areas. While Canada does participate in the ECA, Mexico does not, with the result that southern California and southern Texas are closer to the exterior of the ECA boundary. Similarly, the ECA boundary in southern Florida is narrower due to the proximity of the Bahamas and Cuba. The reduced boundary size in these areas, combined with the high cost of low-sulfur fuel, may have created incentives for behavioral responses by ship operators, similar to the response observed when ships avoided California's narrow ECA. For example, ships approaching ports with a narrow regulatory boundary could easily substitute to adjacent routes outside of the regulated area and use high-sulfur fuel. This behavior would mitigate air quality improvements of the ECA by modestly relocating rather than removing emissions. We explore the extent to which areas with a narrow ECA boundary had differential improvements in air pollution from the North American ECA, given the increased incentives for avoidance.

In subsequent years, the fuel content restrictions were further tightened. In January 2014, California made its state standard more stringent: it allowed up to only 0.1 percent sulfur oxides. In January 2015, the full North American ECA also reduced the allowance to 0.1 percent sulfur oxides.[9] The tightening of these standards may have led to a growth in the effect of the policy over time.

In addition to requirements for the use of lower sulfur fuel near coastlines, the ECA regulation tightened standards for engine emissions of nitrogen oxides. These additional standards applied to only a small subset of ship traffic: new US-flagged ships delivered after the policy came into effect. Since this aspect coincides with the sulfur oxide regulation, we cannot separately estimate

such that the post-policy indicator is equal to one after California's ECA is in place, July 1, 2009. We estimate a small and positive coefficient (0.22), which is not statistically different from zero. Results are available upon request.

[9]As with other environmental standards, the pattern of California preceding federal environmental standards with strict state standards arguably motivated coordinated action from industry groups and the federal government. In a 2012 speech, the chairman of the International Chamber of Shipping stated: "If major trading nations such as the US adopt rules that are at variance to those agreed by governments at IMO we have chaos; and if individual US states decide to implement their own rules in conflict with federal requirements, it is even worse, we actually run the risk of double chaos" (Polemis, 2012).

its contribution; however, we expect this to have a minuscule additional effect in the years immediately after implementation because only a small percentage of total ships were subject to this requirement.

The new standards apply to all commercial ships and distributors of marine fuel. To reduce emissions to the maximum allowed concentration of sulfur oxides, ships could use compliant low-sulfur fuel or an approved equivalent method, such as a scrubber. Although compliant fuel was more costly than typical bunker fuel, ships were already equipped with multiple fuel tanks and could easily switch to a tank with compliant fuel as they approached the regulated area. Scrubber installation required investment in new equipment and was uncommon except among cruise and passenger ships (Hellenic Shipping News, 2014). The US Coast Guard (USCG) is responsible for enforcement and ensures compliance through scheduled and unscheduled examinations and inspections.[10] Vessel operators must provide documentation of fuel purchase and delivery, fuel samples, written fuel oil changeover procedures, and a fuel oil changeover log book that records the volume of compliant fuel in each tank as well as the date, time and position of the ship when any fuel oil changeover operation was completed. Violations are governed by the provisions in the Act to Prevent Pollution from Ships. Non-compliance is penalized with fees of up to $25,000 for each violation, and each day of continuing violation could constitute a separate offense. In cases where an incoming ship could establish that compliant fuel was not available, it is granted an exemption from penalties.

2 Data

Our analysis combines data on EPA air quality predictive models, observed air pollution, infant health, mortality, weather, county characteristics, and data on outdoor activities. We describe each of these data sources in detail below.

[10] The USCG can check for ECA compliance during normally scheduled port state control exams, domestic vessel inspection, and vessel safety examinations. Vessel operators may be required to demonstrate compliance to USCG port state control examiners, marine inspectors, and boarding officers who attend vessels for a variety of purposes both in port and at sea.

2.1 Variables and Sources

2.1.1 Air Quality Model and Exposure Data

For our measure of intensity of exposure to the policy, we employ the EPA's Community Multiscale Air Quality Modeling System (CMAQ). Our main treatment variable is the predicted reduction in PM2.5 as a result of the ECA regulation. The EPA developed these predictions as a component of their proposal to justify the ECA policy (U.S. EPA, 2009b). We obtained the output of the CMAQ ECA analysis in 10km resolution raster grids for (i) 2020 annual mean PM2.5 concentration under business as usual and (ii) 2020 annual mean PM2.5 concentration under the ECA regulation. Our independent variable of interest, CMAQ change, is the value at the county population-weighted centroid of (i) minus the county average of (ii) and is shown in Figure 3, where darker colors indicate higher predicted CMAQ change. The CMAQ predictions are based on 2002 ship traffic and fleet characteristics. Traffic is scaled to approximate 2020 ship traffic levels but is not adjusted for behavioral adaptations in shipping activity as a result of the ECA regulation.

To compare the patterns of exposure and the results we obtain with the CMAQ model with the exposure and results we would have obtained had we not accounted for the mobile and at-sea characteristics of maritime shipping pollution, we repeat our analysis with distance to a principal port as an alternative proxy for treatment under the ECA policy. We obtain the point-locations of principal ports, as defined by the US Army Corps of Engineers, from the National Oceanic and Atmospheric Administration. For purposes of comparison, we use the 27 major ports for ocean-going vessels as defined in Gillingham and Huang (2021).

Using spatial data on 2010 ship traffic, we limit our sample to the counties shown in Figure A1 whose centroids are within 200km of heavy ship traffic. Heavy ship traffic is defined as the top 5th percentile of raster grid cells. Counties more than 200km from heavy ship traffic are less suitable as controls, but we show in robustness checks that our results are not sensitive to this sample selection criterion.

2.1.2 Air Quality Data

Our main air quality outcome is fine particulate matter (PM2.5). Although sulfur dioxide (SO2) emissions were regulated at sea, sulfur dioxide does not last in the atmosphere for long periods, nor does it travel significant distances. We focus on over-land secondary PM2.5. PM2.5 is both a direct and secondary pollutant of ship exhaust, and over-land secondary PM2.5 was the criterion pollutant targeted by the ECA fuel content regulation (U.S. EPA, 2009b).[11]

Our air quality data comes from the United States Environmental Protection Agency Air Quality System (AQS) database.[12] The AQS records provide daily summaries from outdoor air quality monitors across the United States for a variety of pollutants. We average monitors within-county to construct county mean air quality. Observations are missing if a monitor is scheduled to be down for maintenance, if the collection does not meet the data quality standards, or if a new monitor location is introduced mid-sample. To ensure against bias arising from these events, we only use monitors that were observed at least once per year from 2008 to 2016. We collapse the data to county-month means.[13] More details are provided in Appendix Section 8.1.

2.1.3 Birth Data

Because the policy was implemented to protect human health from maritime fuel emissions near the coast, we focus on birth outcomes as a direct measure of health that has been shown to be sensitive to air pollution and has implications for many later life outcomes, including earnings, cognitive development, IQ, educational attainment, and welfare take-up (Figlio et al., 2014; Black et al., 2007; Oreopoulos et al., 2008). Unlike measures of adult health, infant health reflects exposure to air pollution during gestation, rather than the cumulative exposure over an adult's lifetime. This is especially useful in detecting the immediate effects of cleaner burning maritime fuel, which should be reflected in air pollution and infant health immediately following the switch to low-sulfur fuel.

Infant health data comes from the National Center for Health Statistics Vital Statistics Natality records from 2005 to 2017. The data includes information reported on US birth certificates, covering a large set of demographic characteristics of the mother, characteristics of the pregnancy,

[11] Nitrogen oxide and its derivative, ozone, were separate components of the ECA regulation. We do not include these pollutants because the regulation targeted them with a slowly phased-in engine requirement, and we do not expect to capture the effects of this component with our research design.

[12] AQS data are collected to ensure compliance with state and federal air quality regulations as well as to support air pollution research. They are the principal source of historical air quality and have been previously employed in numerous studies (Fann et al., 2016).

[13] Figure A1 shows counties with balanced and unbalanced monitors. In Table 5, we show that our results are robust to relaxing our balanced monitor requirement.

labor and delivery, and details about the health status of the newborn. Counties with few births are excluded for anonymity. Further, the sample is restricted to singleton births, hospital births in the continental US, mothers between ages 18 and 45, and births with non-missing birth date, birth weight, and gestation.

Birth weight is measured in grams, with newborns under 2,500g classified as low birth weight. Gestation is measured in weeks; births before 37 weeks are classified as preterm births. Mother-infant variables included as controls are indicators for mother's years of education $\{< 12, = 12, 13-15\}$, mother's race {black}, Hispanic, mother's age $\{19-24, 25-34, > 35\}$, two previous live births, three or more previous live births, and cigarette use during pregnancy. For each control variable, an indicator is included for missing observations.

We map each birth to month of conception based on the reported gestational age and month of birth. We collapse birth observations to county-month cells for computational efficiency. Each county-month of conception observation includes the average birth weight, gestation, incidence of low birth weight and preterm births per 1,000 births, and the total number of live births conceived, as well as the average of each control. In the subsequent analysis, county-month observations are weighted by the number of conceptions unless otherwise noted.

2.1.4 Mortality Data

We supplement the birth outcome data with county-level mortality data from the National Center for Health Statistics Vital Statistics Mortality records from 2006 to 2016. We calculate the death rates per 1,000 population using age-specific county population measures from the Surveillance, Epidemiology, and End Results Program (SEER) data. Because young children are more sensitive to air pollution, we focus especially on mortality under age one.

2.1.5 Outdoor Activity Data

We use two sources of data to measure outdoor activity in order to observe whether individuals exhibit behavioral changes in response to changing air quality. First, we make use of recreation data from Recreation.gov, which maintains data on millions of visitors to federal parks. We use data on campsite reservations from 2008 to 2016, which include over 24 million individual reservations at over 3,400 facilities. We limit the sample to campsites in the continental US.[14] We collapse the visit-level data to the facility-by-month level and focus on number of visits, total people visiting, and number of days.

We supplement this with data from the American Time Use Survey (ATUS) from 2008 to 2016. Conducted by the US Census Bureau and the Bureau of Labor Statistics, the ATUS asks respondents to provide a detailed time diary of all activities over a 24-hour period, including the location of each activity. We use the location information to measure respondents' time spent outdoors. Additional information records respondents' county of residence, gender, race, ethnicity, education, age, presence of a child in the household, and information on the day of the week and whether the survey was conducted on a holiday.

2.1.6 Weather and Other Data

In addition to the treatment and outcome variables, we collect data on several key control variables. We adjust for weather because the influence of at-sea emissions on on-land air quality is highly dependent on meteorological conditions that transport and disperse air pollution. These meteorological conditions also directly affect infant health (Barreca and Schaller, 2020). We use the PRISM Daily Weather Data for the Contiguous United States.[15] This data features a balanced panel of weather station records from 1950-2018 that are combined to daily 2.5 by 2.5 mile grids of minimum temperature, maximum temperature, and total precipitation. We compute the county-day means for each weather variable as the average of the grid-cell-day observations within the county. Our baseline weather controls include cubic functions of county-day minimum temperature, maximum temperature, and total precipitation, as well as the interactions of precipitation with minimum temperature and maximum temperature. Last, we average over the county-day observations to form county-month observations for each weather variable. We also show that our results are robust to controlling for more flexible weather bins. For each weather variable, we include 7 bins: below 5th percentile, 5 bins for even intervals from the 5th to 95th percentile, and above the 95th percentile.

[14] About 94 percent of facilities are classified as "sites." The remaining categories include facilities classified as entrance, lottery, POS, and tour. We exclude these categories to capture a homogeneous set of campsites where we are confident that visitors are spending time outdoors, but the results are robust to including the other categories.

[15] We employ the March 2020 version from http://www.columbia.edu/~ws2162/links.html.

We adjust for local economic conditions and other air pollution regulation that might affect the outcomes. We proxy for local economic conditions with controls for county-month unemployment rate from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS).

Last, we use two data sets on counties' air quality performance relative to the National Ambient Air Quality Standards (NAAQS). In robustness checks, we control for county attainment status. We obtain attainment status for each pollutant, standard, county, and calendar year from the US EPA Green Book. We focus explicitly on PM2.5 1997, 2006, and 2012 standards; PM10 1987 standards; sulfur dioxide 1971 and 2010 standards; nitrogen dioxide 1971 standards; ozone 1979, 1997, 2008, and 2015 standards; and carbon monoxide 1971 standards. We include as controls indicators for whether part or all of the county is in non-attainment of any of the listed standards for each pollutant. In our analysis of behavioral responses, we classify counties based on their degree of compliance or non-compliance with the NAAQS PM2.5 standards in 2012. To determine compliance with the NAAQS, the US EPA requires raw monitoring data to meet stringent quality standards and follows particular formulas for aggregating. We employ the EPA's output of these calculations, called the design values. We obtain the cross-section of the 2012 PM2.5 design values, based on data from 2010-2012, for each country and standard (24-hour and annual) from the US EPA.

2.2 Descriptive Statistics

Table 1 provides summary statistics for counties in our sample. Statistics are weighted by the number of conceptions in the county-month. Column (1) reports means for all counties within 200km of heavy ship traffic, and column (2) restricts the sample of counties to only those with a balanced sample of air quality monitors. The samples appear very similar across all outcomes and control variables. For this sample, the average level of fine particulate matter is about 9 $\mu g m^{-3}$, about 6 percent of births are classified as low birth weight, and average birth weight is about 3,300 grams.

Despite existing evidence of disproportionate pollutant exposure for disadvantaged groups from land-based pollution sources, prior work has not examined the exposure gap for a source that is mobile and at-sea. We highlight the differences in the demographics of the population exposed to maritime fuel emissions versus comparable stationary on-land sources in Figure 4. Figure 4 shows the correlations between race/ethnicity and two measures of exposure to maritime pollution: distance to ports (stationary on-land) and the overall intensity of ship emissions, as measured by the CMAQ model (mobile at-sea).[16] We report results for non-Hispanic white, non-Hispanic black, non-Hispanic other race, and Hispanic. We use demographic information from 2010 census tract data. We restrict our sample for analysis to tracts within 200km of heavy ship traffic. Each of the 100 circles represents the population-weighted average for equal-sized bins of census tracts.

First, panels (a)-(d) show the relationship between race/ethnicity and distance to ports. We calculate the distance from the population-weighted centroid of each tract to the nearest large port. Counties further to the right are closer in distance to a port. Consistent with the environmental justice literature, the population near ports is less likely to be white (panel (a)), and more likely to be black, other race, or Hispanic (panels (b)-(d)).

While ports are an important source of air pollution, exposure to maritime pollution from shipping routes is not captured by the distance-to-port measure. To account for the total contribution of ship emissions to a local area's pollution levels, panels (e)-(h) show the correlation between race and intensity of ship emissions, as measured by the predicted change from requiring low-sulfur maritime fuel, based on the CMAQ model. The x-axis reports the predicted change in fine particulate matter. Census tracts further to the right are predicted to have larger improvements in air quality from the maritime fuel regulation. Interestingly, the correlation between the proportion of non-Hispanic black individuals and maritime emissions intensity shown in panel (f) is negative. This pattern is in contrast to most other pollution contexts, including distance to ports. All other race/ethnicity groups show correlations in the same direction as those observed for distance to ports. However, the slopes of each differ somewhat, especially for Hispanics.

Figure 5 shows an alternative way to visualize these patterns. Here we present the cumulative distribution function of the proportion of individuals in each race/ethnicity group over distance to port (panel (a)) and intensity of ship emissions (panel (b)). A few interesting patterns stand out and are consistent with Figure 4. First, panel (a) shows that non-Hispanic blacks are more likely to live very near ports. In general, non-white individuals are more likely to live near ports and non-

[16]Figure A2 shows the distance to ports, and Figure 3 shows the overall intensity of ship emissions based on the CMAQ model.

Hispanic whites are least likely to live near ports, consistent with the large environmental justice literature looking at stationary land-based pollution sources. However, the pattern is different in panel (b), which shows the cumulative distribution of individuals by intensity of exposure to overall ship emissions, as measured by CMAQ. Unlike panel (a), black and white individuals have almost identical distributions, suggesting they experience a much more similar distribution of exposure to overall ship emissions. Moreover, both groups are less likely to live with high exposure to ship emissions, relative to Hispanics and non-Hispanic other race groups.

Given that the exposed population is different from most land-based pollution sources, the health effects of this policy are likely to be different than other reductions in air pollution. This is likely to be the case if, for example, pollution has a heterogeneous health impact across demographic groups, perhaps due to differences in underlying health conditions or access to care. In addition, the dose of exposure to maritime pollution may differ across demographic groups due to differences in time spent outdoors or differential avoidance behaviors. We compare the magnitude of our health results to the health effects of pollution found in other contexts to better understand the extent to which these differences in the demographics of individuals exposed to maritime emissions yield different overall effects on health.

3 Empirical Strategy

To estimate the causal effect of the ECA regulation on air quality and health outcomes, we exploit variation from the policy timing and intensity across locations. The intuition of our approach is that we compare changes in outcomes in counties that were highly exposed to pollution from ship exhaust relative to changes in outcomes in counties that were less exposed to pollution from ship exhaust, before and after policy adoption.

While distance is commonly used to proxy for intensity of exposure to pollution in other contexts, other factors influence exposure. Exposure to emissions from ship exhaust is a combination of ship traffic, fuel content, distance, atmospheric interactions, and meteorological factors that disperse emissions. Including interactions of ship traffic, distance, and weather to proxy for exposure presents several concerns for estimation. Instead, we employ the predictions of an atmospheric aerosol transport model to combine these components into an exposure index. This approach provides several advantages.

First, ex-post observations of ship traffic and emissions are likely endogenous to the policy. Although ex-post observations of ship traffic/emissions can yield quasi-exogenous short-run variation in air pollution, which can be used to estimate effects of air pollution (as in Knittel et al. (2016) and Moretti and Neidell (2011)), ex-ante observations are more appropriate for determining policy effectiveness, for a few reasons. First, it is plausible that ship traffic falls as a result of the regulation if it is no longer profitable to deliver to US ports or if ships alter routes to avoid traversing the regulated areas. If the econometrician used ex-post traffic as a metric of exposure to the policy, they would fail to attribute pollution change from lower traffic to the policy. Second, ex-post ship traffic reflects economic conditions that influence other sources of air pollution as well as infant health. The econometrician risks overstating the changes from the policy if the measure of exposure is correlated with other changes in air pollution.

A second primary concern with using interactions of ship traffic, distance, and weather is bias from assuming an incorrect functional form of their interaction. For example, assuming a linear relationship between destination air quality and distance to source overstates the contribution of the source at distances beyond its average dispersion range. While the econometric methods exist to fit the data and determine an appropriate model specification, this exercise is cumbersome because transportation of air pollution and the creation of secondary pollution depends on many combinations of atmospheric conditions that vary by source location, destination location, and time, among others. By contrast, output from aerosol transport models incorporates these various factors *a priori*.

For these reasons, we employ output from the EPA's Community Multiscale Air Quality Modeling System (CMAQ) as our measure of intensity of exposure to the policy. The EPA developed these predictions as a component of their proposal to justify the ECA policy (U.S. EPA, 2009b). Our main treatment variable is the predicted reduction in PM2.5 as a result of the ECA regulation, and represents the policymakers' ex-ante expectations of the policy's effects on air quality. This measure is convenient in that we can directly compare the ex-post realized effects of the policy to ex-ante predictions. We provide additional evidence consistent with endogenous behavioral responses to the policy by ship operators, other industry, and individuals that can help explain why ex-ante predictions were not fully realized.

3.1 Reduced Form

We start by estimating the reduced form effect of exposure to the policy, as measured by the CMAQ prediction, on each of our outcomes of interest. Denote county i in year-month ym, where m indicates the calendar month (January-December) and y indicates the year (2008-2016). The outcomes of interest y_{iym} are the mean air pollution, PM2.5, and health measures. The main health outcomes are rate of low birth weight and preterm birth for births conceived in county i in year-month ym along with overall mortality rate and infant mortality rate for county i in year-month ym. The exposure variable is $CMAQ_i$, which is the CMAQ prediction of the reduction in PM2.5 due to the ECA.

We estimate the overall reduced-form effect of the policy in the post-period with the following difference-in-difference specification:

$$y_{imy} = \beta CMAQ_i \times postECA_{my} + \delta X_{imy} + \tau_{ry} + \alpha_{is} + \epsilon_{imy} \tag{1}$$

where $postECA_{my}$ is an indicator equal to one after the ECA policy came into effect in August 2012, τ_{ry} are region-by-year fixed effects (i.e., Gulf Coast 2008, Gulf Coast 2009, ... Gulf Coast 2016), α_{is} are county-by-season fixed effects (i.e., Marin County Spring, Marin County Summer, ...), and X_{imy} are additional controls for county-month-year weather and unemployment rate. In the baseline estimation of (1), county-month-year observations are weighted by the number of conceptions in county i in year-month ym. For mortality outcomes, we weight observations by age-specific county population. When estimating (1) with infant health outcomes, mother-child covariates are included and weather controls are included by trimester. For example, X_{imy} includes the max temperature in the first trimester, second trimester, and third trimester for conceptions in each year, month, and county. Robust standard errors are clustered by county.

We also estimate event-study specifications to test the parallel trends assumption and explore the effects over time. We expect that counties with higher CMAQ-modeled pollution reductions from the policy will have greater improvements in air quality and health outcomes in the years after the regulation came into effect. For the pollution and mortality event-studies, we omit the year before policy adoption, 2011, and note that 2012 is a partially treated year because the policy was implemented in August 2012. Births conceived in the latter portion of 2011 were exposed to the policy when it came into force in 2012, but no births conceived in 2010 were exposed to the policy during their nine-month gestation; therefore, 2010 is the reference year for conception. Births conceived in 2013 were exposed to the policy during their entire gestation.

For our estimates to measure the effect of the policy, we must assume that there are no omitted time-varying, county-specific features correlated with the ECA timing and exposure that also affect our outcomes of interest. This assumption would be violated if, for example, another environmental regulation came into effect at the same time and its intensity was correlated with ship pollution exposure. These concerns are mitigated by the inclusion of controls for arbitrary region-year shocks, as well as arbitrary county-season seasonality. In robustness exercises, we show the results are robust to including state-year fixed effects and also to controlling for county compliance with environmental regulations. Any violation of the identifying assumption would need to follow the same timing and county specific-intensity as the ECA regulation for the violation to affect our outcomes.

The absence of such violations implies that outcomes do not trend differently between counties with higher and lower anticipated CMAQ pollution reductions in a world without the policy. To support this assumption, we show that an additional unit of predicted CMAQ pollution reduction does not affect the trend in air quality in the years before the ECA implementation in our event study specifications. As additional evidence, we show that maternal demographic characteristics are not changing systematically with the policy variation.

A distinct advantage of using the CMAQ reductions as the "treatment" variable is the ability to compare the realized changes in air quality to the intended changes in air quality. Even if the CMAQ model is imperfect, the CMAQ-predicted reductions represent policymakers' plans. If each unit of planned PM2.5 reductions yielded one unit of actual reductions, the measured effect, β, would equal -1. Consequentially, we interpret estimates for PM2.5 that deviate from -1 as evidence that the intentions were not fully realized.

3.2 Two-stage Least Squares

In addition to the reduced-form impacts of the policy estimated in equation (1), we also use the ECA policy variation to instrument for fine particulate matter, in order to estimate the impact of reductions in fine particulate matter on health. This provides an estimate that is more easily comparable to the existing literature. Given the unique composition of pollution and the unique exposed population in our setting, we might expect the health effects to differ as well.

The first stage specification is provided in equation (1) and the second stage is shown below:

$$health_{imy} = \gamma \widehat{PM2.5}_{imy} + \delta X_{imy} + \tau_{ry} + \alpha_{is} + \epsilon_{imy} \tag{2}$$

The exclusion restriction requires that the ECA policy implementation affects health only through its effect on pollution. While we focus on fine particulate matter as our primary pollutant of interest, we note that the policy is likely to impact multiple pollutants simultaneously. To that extent, our estimates may not solely capture the effect of fine particulate matter. This problem plagues most estimates of the health impacts of air pollution because air pollutants are inherently correlated. Nevertheless, this exercise helps put our estimates into context with the existing literature.

3.3 Behavioral Responses

The anticipated reduction in pollution may not be fully realized if the CMAQ model used by policymakers was misspecified, if inputs were mismeasured, or if the CMAQ output was mostly right, but compliance with the policy was imperfect. In addition, the policy may lead to behavioral changes along multiple dimensions that are not incorporated into the CMAQ model. Behavioral changes among ship operators or other pollution sources may lead to deviations in realized pollution reductions, while behavioral changes among individuals may lead to deviations in realized health effects. We explore these behavioral responses to the ECA policy.

3.3.1 Shipping Behavior

We expect that shippers exhibited behavioral responses such as changing ship routes, speed, and frequency. Due to geography and the fact that Mexico did not participate in the North American ECA, certain coastal areas in the US were closer than the full 200 nautical miles to the exterior of the ECA boundary. We expect that ships had greater incentives to avoid fuel restrictions in the ECA in areas where the distance to exit the ECA — and therefore the cost — was lower. We estimate the following equation:

$$
\begin{aligned}
y_{imy} = &\beta_1 full_i \times CMAQ_i \times postECA_{my} + \beta_2 partial_i \times CMAQ_i \times postECA_{my} \\
&+ \delta X_{imy} + \tau_{ry} + \alpha_{is} + \epsilon_{imy}
\end{aligned} \tag{3}
$$

where $full_i$ equals one for counties exposed to the full 200 nautical mile ECA and $partial_i$ equals one for counties located less than 200 nautical miles from the exterior of the ECA. Other variables are defined analogously to equation (1). Because we are interested in the spatial distribution of pollution reductions in this part of the analysis, rather than health effects, we do not weight by population. Standard errors are clustered by county.

3.3.2 Other Emissions Behavior

Alongside changes in the location of ship emissions, we hypothesize that other polluters could also respond to the implementation of the ECA policy. The Clean Air Act requires counties to maintain ambient fine particulate matter concentrations below the National Ambient Air Quality Standards (NAAQS). Counties with ambient air pollution in excess of the standards are designated "non-attainment" and face costly regulation. Counties that experience air quality improvements due to ECA have less need to engage in costly efforts to reduce pollution from other sources. We expect the incentives for this "rebound" effect to vary across counties as a function of their risk of falling into non-attainment status. Thus, we anticipate that counties that were closest to the threshold of non-attainment had the lowest likelihood of allowing emissions from a non-maritime source to increase in response to a given decline in pollution from ships. To examine this pattern, we allow the effect of the ECA to differ along with the distance to the regulatory threshold. We estimate the following equation:

$$
y_{imy} = \sum_k \beta_k \mathbb{1}[D_i \in k] \times CMAQ_i \times postECA_{my} + \delta X_{imy} + \tau_{ry} + \alpha_{is} + \epsilon_{imy} \tag{4}
$$

where D_i represents county i's pre-policy distance to the regulatory threshold. We define D_i as the county 2012 PM2.5 maximum design value as a percent of the standard.[17] We classify this

[17] We obtained the EPA records used to determine compliance with the NAAQS. For 2012, the NAAQS required counties' PM2.5 to meet two thresholds: (i) annual mean PM2.5 averaged over three years, $\text{DV}^{1\text{ year}}$, less than

distance into seven bins of 2012 PM2.5 as a fraction of the standard: less than 60%, 60-70%, 70-80%, 80-90%, 90-100%, 100-110%, and over 110%. We expect regulatory "rebound" to be lowest just below the non-attainment threshold, 90-100%. Other variables are defined as in equation (1). The estimates are unweighted and standard errors are clustered at the county level.

3.3.3 Individual Behavior

Finally, we explore the role of individual behavioral response. Our outcomes of interest include the natural log of the number of campsite visits, days, and visitors, as well as the inverse hyperbolic sine of minutes spent outdoors.[18] We estimate the following reduced form equation for the campsite reservation data,

$$y_{pimy} = \beta CMAQ_i \times postECA_{my} + \delta X_{imy} + \tau_{ry} + \alpha_{is} + \epsilon_{pimy} \tag{5}$$

where p indexes a park facility located in county i in year-month ym. We include region-by-year, τ_{ry}, and county-by-season, α_{is} fixed effects. The other variables are defined analogously to equation (1). We also show robustness to including park facility-by-season fixed effects and year-by-month fixed effects.

For the time use data, we estimate the following reduced form equation,

$$y_{jimy} = \beta CMAQ_i \times postECA_{my} + \delta X_{imy} + \pi Z_{ijmy} + \tau_{ry} + \alpha_{is} + \theta_{ym} + \epsilon_{ijmy} \tag{6}$$

where j indexes individuals in county i in year-month ym. The regression includes an additional set of individual-level controls, Z_{ijmy}, which include gender, race, ethnicity, education, age, presence of children in the household, and indicators for the day of the week of the survey and whether it was a holiday. The regression includes region-by-year (τ_{ry}), county-by-season (α_{is}), and year-by-month (θ_{ym}) fixed effects. Other variables are defined analogously to equation (1) and the regression is weighted using survey weights.

$12\mu\text{gm}^{-3}$ and (ii) 98th percentile of daily mean PM2.5 averaged over three years, $\text{DV}^{\text{24 hours}}$, less than $35\mu\text{gm}^{-3}$. We then defined distance to the regulatory threshold, $D_i = 100 * \max\{\frac{\text{DV}^{\text{1 year}}}{12}, \frac{\text{DV}^{\text{24 hours}}}{35}\}$.

[18] We use the inverse hyperbolic sine transformation rather than log transformation for time spent outdoors due to the presence of zeros. The inverse hyperbolic sine allows for the same interpretation as taking the natural log, but preserves zeros (Burbidge et al., 1988).

4 Results

4.1 Impacts of ECA on Air Pollution and Health

4.1.1 Air Pollution

First, we show the direct effect of maritime fuel regulation on air pollution. Figure 6 plots the event-study for fine particulate matter. The figure shows that air pollution was not trending differently in counties with different levels of CMAQ-predicted pollution improvements prior to the regulation. We fail to reject the null that each of the pre-policy coefficients is statistically different than zero. In the post-regulation period, there is a decline in PM2.5 among counties with greater exposure to ship traffic. We reject the null that the post-policy coefficients are jointly equal to zero.

Column 1 in Table 2 reports the difference-in-difference coefficient from estimation of equation (1). Consistent with Figure 6, there is a significant reduction in fine particulate matter after the ECA policy was implemented. One additional unit (μgm^{-3}) of predicted reduction in PM2.5 led to a 0.53 unit (μgm^{-3}) fall in PM2.5 after the policy. Relative to the average level of fine particulate matter, this represents a 6 percent decline. To measure the overall effect on fine particulate matter, we scale the county-level CMAQ-predicted improvement by our estimated coefficient (0.53) and take a population-weighted average across all counties within 200km of heavy ship traffic. Figure A3 shows the scaled county-level fine particulate matter improvements. We calculate that fine particulate matter decreased by about 0.4 units on average, or about 4 percent relative to the mean of 9.21 units.

While this result is statistically significant and economically meaningful, the fine particulate matter point estimates indicate that air pollution fell by roughly 53 percent of the amount policy-makers intended when they designed and implemented the policy. The coefficient is statistically significantly different from one ($p < 0.001$). Therefore, we can reject the hypothesis that the decline in fine particulate matter forecasted by the CMAQ model was realized.

4.1.2 Infant Health

Even though the forecasted effect of the ECA on air pollution was not fully realized, the policy still led to meaningful improvements in health. We start by looking at the reduced-form policy impacts on health. Figure 7 shows the event-study figures using the low infant birth weight rate and preterm birth rate as the outcomes. Here, the omitted period includes conceptions in 2010, because conceptions in 2011 and 2012 may have been partially exposed to the policy during gestation. Conceptions in 2013 and after were exposed to the policy for the entire duration of the pregnancy.

The patterns in the infant health measures are consistent with the trends in air pollution in Figure 6. In support of the parallel trends assumption, we found CMAQ did not predict changes in infant health relative to the omitted period in the years before the regulation for each of the infant health outcomes. Panels (a) and (b) indicate that the ECA regulation led to significant improvements in the rates of low birth weight and preterm birth. As expected, the effect is somewhat muted for conceptions in 2011 and 2012, because these observations were only partially exposed during gestation to the ECA policy. For fully treated cohorts, 2013 and after, the coefficients indicate a sizable improvement in low birth weight and preterm birth rates.

Columns (1) and (2) in Panel A of Table 3 show the corresponding overall difference-in-difference regression results from estimation of the reduced-form equation (1) for each of the infant health measures. Additional infant health measures are reported in Appendix Table A1. The effect on all outcomes is statistically significant. For low birth weight, one additional unit of CMAQ-predicted PM2.5 reduction lowered the rate by 1.3 births per 1,000 after the introduction of the ECA, a 2 percent improvement relative to a baseline of 61 low weight births per 1,000 births. Using the mean CMAQ-predicted change, 0.76, this coefficient suggests that the number of low birth weight infants declined by 1 per 1,000 births, or 1.7 percent relative to the mean. One unit of CMAQ-predicted change led to 2.1 fewer preterm births per 1,000, or 2 percent. For the mean CMAQ-predicted change, 0.76, the coefficient suggests preterm births declined by 1.6 per 1,000, or 1.7 percent.

We explore the distributional effect on birth weight further in the reduced form results in Panel A of Table A2, which shows the effect of the policy on bins of birth weight. Consistent with the stronger effects on infant health at the lower end of the distribution, we find large reductions in births for the four smallest bins in the birth weight distribution and increases in births in the middle of the distribution. These results suggest that there are important impacts not only for low birth weight (less than 2,500 g) infants, but also very low birth weight (less than 1,500 g) and extremely low birth weight (less than 1,000 g) infants. The negative health consequences are especially severe for very and extremely low birth weight infants, so improvements in these categories are quite beneficial.

Next, we instrument for fine particulate matter using our policy variation to estimate the impact of fine particulate matter on infant health. Panel B in Table 3 first reports the two-stage least squares results from estimation of equation (2), while Panel C reports the ordinary least squares results. When we instrument for fine particulate matter with our policy variation, we find that a one-unit increase in fine particulate matter leads to 2.8 fewer low birth weight infants per 1,000, or a 4.6 percent increase relative to the mean of low birth weights. We compare the magnitude of our estimates to the literature in Table 4, following Alexander and Schwandt (2021), who consider the effect of a 10 percent pollution increase. Our results suggest that a 10 percent increase in pollution would increase low birth weight by 4.2 percent. The magnitude of our estimated impact for low birth weight is slightly smaller than existing estimates in the literature. This could be due to the unique bundle of pollutants impacted by the regulation or to the differences in the demographics of the population most exposed to the regulation.

4.1.3 Mortality

In addition to infant health, we explore the effect of the ECA on mortality rates in columns (3) and (4) of Table 3. Panel A reports reduced form estimates based on equation (1) and are weighted by age-specific county population.

Column (3) reports the overall effect on the all-age death rate per 1,000 population. A one-unit predicted change in fine particulate matter measured by CMAQ leads to a statistically significant reduction of 0.006, or about 1 percent relative to the mean, after the ECA is adopted. For the average CMAQ-predicted change, 0.76, this is a change of about 0.7 percent.

Column (4) reports the effect on infant mortality (under age one). In Panel A, a one-unit predicted change in PM2.5 based on CMAQ leads to a statistically significant 0.024 percentage point, or 4.7 percent, reduction in the rate of infant mortality (3.5 percent for the mean CMAQ prediction).[19] Event study results confirm these results in Figure 8. For both overall mortality and

[19] As the elderly also tend to be particularly sensitive to air pollution, we explore the effects on elderly mortality in the appendix. Table A3 and Figure A4 show that the policy led to statistically significant declines in mortality for individuals age 75-84 and age 85 and over. A one-unit predicted change in PM2.5 from CMAQ led to declines in elderly mortality of 0.04 and 0.16 percentage points, or 1.1 and 1.5 percent for ages 75-84 and above 85, respectively.

infant mortality, there is little evidence of a pre-trend in years prior to policy adoption, but there is a decline in mortality in areas with heavy ship traffic following adoption of the ECA.

Next, we estimate the impact of fine particulate matter on mortality using two-stage least squares and OLS in Panels B and C, respectively. Columns (3) and (4) of Panel B show that a one-unit increase in fine particulate matter leads to a 1.7 percent increase in overall mortality and an 8.7 percent increase in infant mortality. We compare the estimated effects of pollution on infant mortality to the existing literature in Table 4. For a 10 percent increase in fine particulate matter, our results suggest an 8 percent increase in infant mortality. Our estimated effect is in line with the recent existing literature, especially recent studies focusing on fine particulate matter.

4.1.4 Robustness

A potential concern with our estimation of the ECA's effects on health at birth is that the introduction of the ECA could have been correlated with changes in mother characteristics. For example, if the introduction of the ECA was correlated with an increase in conceptions for mothers with high proclivity for prenatal care in coastal counties, then our results reflect the change in the composition of mothers rather than the change from the air quality improvement the policy induced. We show evidence that maternal characteristics are not changing simultaneously with the policy exposure in column (2) of Table 2 and Figure 9. The outcome is a measure of the predicted birth weight based only on observed maternal characteristics, including education, marital status, race, ethnicity, age, smoking status, and diabetes. There is no observable change in predicted birth weight based on maternal characteristics after the policy was put in place. Similarly, column (2) of Table 2 shows there is no evidence of a systematic change in underlying maternal characteristics that corresponds to the policy variation, which is reassuring.

Moreover, our results are robust to a number of alternative specifications, as shown in Table 5. The main results for fine particulate matter, low birth weight and infant deaths are shown in row 1 for reference. The main results limit the sample to counties whose centroids are within 200km of heavy ship traffic, because counties far from the coast are less likely to provide suitable counterfactuals. We show that our results are robust to alternative choices for inclusion in the sample.

Panels (a) and (b) of Figure A4 show little evidence of pre-trends in years prior to the policy for elderly mortality and a decrease in mortality in areas with heavy ship traffic after the ECA policy.

Rows 2 and 3 of Table 5 show very similar estimates when we limit the sample to counties within 150km or 300km as well.

While our main specification includes region-by-year fixed effects, we show that the results are robust to more flexible state-by-year fixed effects in row 4. Row 5 includes more flexible weather controls. For each weather variable, we include 7 bins: below 5th percentile, 5 bins for even intervals from the 5th to 95th percentile, and above the 95th percentile. Next, rows 6-7 relax the balanced panel requirement for air quality monitors. Rather than restricting the sample to balanced monitors from 2008 to 2016, row 6 only requires balance between 2009 and 2014. This increases our sample of counties from 232 to 251. Row 7 relaxes the requirement for a sample of balanced monitors and reports the unbalanced panel results. In row 8, we use an alternate measure of intensity of treatment that is based on the CMAQ prediction of total emissions from maritime shipping.

Next, we address concerns that other pollution abatement policies may occur during our sample period. First, we exclude counties with a port in row 9 to show our results are not driven by any port-specific policy changes that may have been adopted during our sample period. Our results are not driven by port counties alone. Second, row 10 shows our results are robust to controlling for Clean Air Act non-attainment status for each county over time. For each of these robustness exercises in rows 1 through 10, the estimates remain significant and are similar in magnitude across each outcome.

Finally, row 11 tests whether the tightening of the fuel content standard in 2015 had any additional impact on improving air quality. We find no statistically significant impact on air quality or health outcomes from this tightening. This is not surprising, as the 2015 fuel standard tightening was a relatively small change and many ships were already using compliant fuel.

4.1.5 Comparison with Previous Approaches

Employing the CMAQ output as a measure of intensity of exposure to the ECA policy improves on approaches that rely on imprecise proxies for source-specific exposure. To illustrate the distinction, we perform our analysis using distance to a port as the proxy for ship pollution exposure in lieu of CMAQ output. We define distance to a port as the kilometers from the county population-weighted centroid to the nearest major US port. We highlight two main concerns with distance metrics. First, distance is a poor proxy for exposure to improvements from the policy because atmospheric interactions play a major role in the dispersion of pollution. This concern would lead to bias from measurement error. Second, there does not exist an *a priori* functional form for the relationship between the distance from a pollution source and pollutant exposure from the source. This concern would lead to bias from misspecification.

Table 6 reports the results of estimating equation (1) where intensity of exposure to the policy is measured by either CMAQ or distance. We report the results for infant deaths, low birth weight, and fine particulate matter in panels A-C, respectively. We standardize the coefficients and standard errors into units of standard deviations so that the results are comparable across candidate treatment variables. First, we compare the Bayesian information criteria (BIC), which is a criterion for model selection based, in part, on the likelihood function. As the model with the lowest BIC is preferred, we observe that the estimates based on CMAQ consistently yield a lower BIC across all outcomes, suggesting that CMAQ is preferred. Similarly, we note that, across all outcomes, the CMAQ model appears to reduce measurement error, as expected. The T-statistic is larger and standard errors are smaller for CMAQ relative to distance in all panels. In terms of magnitude of the estimated coefficients, the estimated effect of a one standard deviation increase in distance relative to a one standard deviation increase in CMAQ exposure led to a slightly larger reduction in infant deaths and low birth weight, but a slightly smaller reduction in fine particulate matter. However, we do not emphasize these differences because the confidence intervals of these estimates overlap. Nevertheless, these models show meaningful improvements in precision when CMAQ is used to measure exposure to the ECA policy.

4.2 Distributional Effects

As documented in section 2.2, the demographic composition of the population most exposed to ship traffic, as measured by the CMAQ model, differs from many land-based pollution sources. Whereas stationary sources, such as Superfund sites, hazardous waste sites, landfills, and even ports, tend to be closer to disadvantaged populations (Currie, 2011; Gamper-Rabindran and Timmins, 2011; Banzhaf et al., 2019), exposure to ship pollution is negatively correlated with the percent of the population that is black, for example. The demographic composition of the exposed population in the context of ship pollution may drive differences in the health effects that we observe relative to the previous literature.

In this section, we explore the degree to which the ECA has a heterogenous effect on the exposed population. As noted above, improvements in air pollution may differ across demographic groups due to differences in health status or access to care. In addition, the exposure to maritime pollution may differ across demographic groups due to differences in time spent outdoors or avoidance behaviors.

We estimate two-stage least squares from equation (2) on subsamples of mothers by demographic characteristics at the individual level. Table 7 shows the results by race/ethnicity, education, age, and marital status. Column (1) reports the baseline estimates for the full sample at the individual level. The magnitude of the effect is similar to the main results for low birth weight in Panel B of Table 3, which both show about a 0.2 percentage point, or 4 percent, increase in low birth weight for a one-unit increase in fine particulate matter. Columns (2) - (5) show results for non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic mothers. The magnitude of the effects are largest for non-Hispanic white mothers and non-Hispanic other race mothers. The estimated effects show that a one-unit increase in fine particulate matter leads to a 6.6 percent and 12.6 percent increase in low birth weight for non-Hispanic white and non-Hispanic other race mothers, respectively. The results for mothers with high education in column (6) are similar in magnitude to the overall effects, suggesting that heterogeneity is driven less by education level. Column (7) reports results for married mothers only. The magnitude of the effect is only slightly smaller for married mothers, still about 4 percent from the mean. Finally, columns (8) to (10) report results for mothers age 19-24, 25-34, and over 35. The main results appear to be driven by mothers over 25.

4.3 Behavioral Responses

While the effect of the ECA regulation led to a statistically significant improvement in fine particulate matter and health, the estimated effect was less than anticipated. If each unit of planned PM2.5 reductions yielded one unit of actual reductions, our estimation of β_k from equation (1) would equal -1. However, we reject this hypothesis (p < 0.001), which provides evidence that the intentions of the policy were not fully realized.

One explanation is that the CMAQ model did not take into account behavioral changes. Requiring more expensive low-sulfur fuel near the coast may have led ships to re-optimize their routes, speed, and frequency of trips. These behavioral changes may result in unexpected heterogeneity in realized pollution reductions. Declines in ship pollution may have been accompanied by "regulatory rebound," as efforts to control pollution by other industries were relaxed in areas at low risk of violating the Clean Air Act. Finally, improvements in air quality may have yielded behavioral changes among individuals, such as altering recreational activities or the amount of time spent outdoors. This may lead to deviations in realized health effects of the pollution reduction. In this section, we explore whether there is evidence of any behavioral change along these three dimensions in response to the ECA.

4.3.1 Shipping Behavior

We hypothesize that ships most likely exhibited behavioral responses that diminished the effectiveness of the policy in coastal areas where the cost of avoiding the ECA is lowest. As shown in Figure 2, southern parts of California, Florida, and Texas were less than 200 nautical miles from the exterior of the ECA. In these areas, it was less costly to travel to exit the ECA and avoid using costly low-sulfur fuel, and the use of higher-sulfur fuel outside the ECA was nearer to coastal populations. In addition, Klotz and Berazneva (2022) provide evidence that a narrow 24 nautical mile boundary led to substantial behavioral response among ships. Therefore, we hypothesize that areas fully exposed to the ECA, at least 200 nautical miles from the exterior of the ECA boundary, had larger impacts on air quality than areas with only partial exposure to the ECA.

We estimate an event study specification to test this hypothesis in Figure 11. Neither panel shows evidence of a pre-trend in fine particulate matter prior to the ECA implementation. In panel A, for the areas exposed to the full ECA, there is a clear and statistically significant decline in fine particulate matter after policy adoption. However, in panel B, areas with only partial exposure to the ECA show a somewhat noisier and more muted effect of the policy, as expected. In terms of magnitude, the post-policy coefficients in panel A are not statistically distinguishable from -1 in each year from 2013 to 2016, suggesting that the anticipated declines in fine particulate matter were realized in areas fully exposed to the 200nm boundary. While the coefficient is smaller than

-1 in 2012, this is expected, as the policy only came into effect in August 2012. By contrast, the estimated coefficients in panel B suggest that the ex-post decline in PM2.5 was less than the anticipated decline in areas only partially exposed to the ECA.

Table 8 summarizes these effects. First, column (1) replicates the effect of the ECA in the full sample without population weights. The coefficient is very similar to column (1) of Table 3 and shows the decline in fine particulate matter was about half of the expected decline overall. Column (2) estimates equation (3) for counties partially and fully exposed to the 200nm boundary. A one-unit increase in CMAQ is associated with a 0.87 and 0.44 unit (or 10 percent and 5 percent) decline in fine particulate matter in areas fully and partially exposed to the policy, respectively. The decline in fine particulate matter in areas partially exposed to the ECA is statistically significantly smaller than the decline in fine particulate matter among fully exposed areas ($p < 0.05$). This is consistent with the hypothesis that behavioral response among ships in areas partially exposed to the ECA, where avoiding the ECA was easiest, led to a muted effect of the policy on air pollution. However, in areas fully exposed to the ECA, the CMAQ-predicted reductions in fine particulate matter were statistically indistinguishable from the realized reductions, suggesting the policy was effective in these areas.

4.3.2 Other Emissions Behavior

Figure 11 reports the results of estimating equation (4). We found that counties at greatest risk of violating the Clean Air Act threshold experienced the greatest declines in PM2.5 as a result of the ECA policy. For these counties, defined as those with air pollution from 90 to 100 percent of the regulatory standard, a one-unit increase in CMAQ prediction is associated with a 1.9 unit decline in PM2.5 resulting from the ECA policy. Although this decline appears larger than what the ECA plausibly delivered, we fail to reject the null that the magnitude is equivalent to -1. By contrast, in other counties, we found a pattern consistent with our hypothesis that increases in on-land emissions offset declines from at-sea emissions: as the county's risk of violating the regulatory threshold decreased, the impact of the ECA was more muted.

Table 8 column (3) summarizes the differential effects of the ECA for counties further from the Clean Air Act regulatory threshold relative to counties close the regulatory threshold. It reports the estimates of a variation of equation (4) where the counties with pre-policy PM2.5 within 90 to 100 percent of the regulatory threshold are the omitted category. We found that all counties had significantly smaller declines in PM2.5 resulting from the ECA relative to the group that was closest to violating the Clean Air Act. The most significant offsetting effects occurred in counties below and furthest from the threshold. Among counties with pre-policy PM2.5 below 80 percent of the regulatory threshold, the results indicate that a “rebound" from other emissions entirely offset the air quality improvements from the ECA.

4.3.3 Individual Behavior

Next, we explore whether policy-induced improvements in air quality had a subsequent impact on individuals’ behavior. Increased time spent outdoors, for example, could increase individuals’ duration of exposure to the now lower level of air pollution. Because ex-ante models do not take into account such behavioral changes, realized health benefits may differ from anticipated benefits. Understanding the impact of air quality improvements on behavior is important in order to predict the impact of future policy changes on health.

First, we explore the effect of the ECA adoption on campsite reservations using data from national park sites. Figure 12 shows the event-study style results from estimating equation (5) for the natural log of the number of visits, people, and days. All outcomes show very similar patterns. Prior to policy adoption in 2012, there is no evidence of differential pre-trends. After the policy began in 2012, there is a statistically significant increase in campsite reservations, as measured by visits, people, or days, and this increase is significant throughout the post-policy period. Table 9 shows the complementary difference-in-difference regression results for each outcome. Columns (2), (4) and (6) show regression results similar to the main specification, while columns (3), (5), and (7) include additional controls for facility-by-season and year-by-month fixed effects. A one-unit increase in CMAQ prediction is associated with a 10-15 percent increase in the number of visits, people, and days, after the ECA was implemented.

Next, we supplement these findings with data on time spent outdoors from the ATUS. As described in the data section, this survey records a detailed time diary of activities over a 24-hour period for each respondent, which includes the location of each activity. Our outcome of interest is the inverse hyperbolic sine of total minutes spent outdoors.[20] Figure 13 shows the event-study

[20]We use the inverse hyperbolic sine rather than log transformation, because this transformation allows the reported

style results from estimating equation (6). There is no evidence of differential pre-trends prior to policy adoption. After the ECA was adopted, there was a gradual increase in time spent outdoors. Table 9 shows the corresponding regression results. Column (7) suggests that a one-unit increase in CMAQ prediction leads to an 8 percent increase in minutes spent outdoors. In Table A4, we provide additional placebo tests on time spent on activities that are unlikely to be impacted by changes in air quality, such as sleeping, housework, and buying groceries. Reassuringly, we find no statistically significant impacts on these outcomes.

Across both datasets and a variety of measures, results suggest that policy-induced changes in air quality led to increased time spent outdoors. These findings are consistent with existing work showing that elevated ozone levels reduce national park visitation, especially when levels trigger Air Quality Index (AQI) warnings (Keiser et al., 2018). These behavioral changes can impact the reduced form effect of the ECA policy on health through decreased exposure to pollution or increased exercise, for example. Such complex behavioral changes make it especially important to quantify the health benefits of pollution regulation through ex-post policy evaluation.

5 Discussion & Conclusion

This study examines the effect of maritime emissions regulation on air quality, infant health, and infant mortality. We combine administrative data sets on air pollution and health with the output of atmospheric transport model scenarios specific to our research setting. We document greater improvements in air quality and health for counties that the EPA's CMAQ model predicted would improve most from the policy.

Policymakers frequently rely on the predictions of scientific models to anticipate the air quality improvement from a policy; yet, researchers infrequently test for differences between ex-ante and ex-post estimates. In this setting, only about half of the intended fine particulate matter improvements were realized, and we document evidence consistent with behavioral responses among shippers, other polluters, and individuals that are likely to contribute to deviations from the policy's anticipated impact. Our approach may be replicated in other settings with scientific research

coefficients to be interpreted in the same way as the natural log but does not require us to determine the best way to handle observations without any reported time spent outdoors (Burbidge et al., 1988).

employing atmospheric transport model scenarios to improve estimation and policy evaluation.

Our results provide the first ex-post evaluation of US maritime emissions regulation. The US ECA led to meaningful improvements in fine particulate matter, infant health, and mortality as a result of maritime emissions controls. Combining CMAQ measurements with our estimated effect — that one unit of predicted fine particulate matter reduction from the ECA led to a 2 percent decline in low birth weight infants — and scaling by population, we calculate that the US ECA led to approximately 1,536 fewer low birth weight infants per year in areas near ship traffic. Similarly, we calculate that the policy resulted in a reduction of approximately 290 deaths per year under age one.[21] Using the EPA's value of a statistical life, this translates into $2.76 billion per year. The total benefits from improved health increase by an additional $139 million per year when we incorporate the effects of low birth weight on earnings (using estimates from Bharadwaj et al. (2018)) and the census bureau's work-life earnings. The benefits to improved infant health alone are almost as large as the estimated cost of the policy, $3.2 billion in 2020. Incorporating additional health benefits from cleaner air, such as fewer emergency room visits and hospitalizations, would likely lead to even higher total benefits. Moreover, to the extent that individuals reduced costly avoidance behavior in response to reduced air pollution from the policy, the health benefits alone can be considered a lower bound of the total benefits.

These findings are especially important given the IMO's recent adoption of a new global maritime sulfur emission standard in 2020, reducing sulfur content from 3.5 percent to 0.5 percent globally. Low-sulfur fuel can cost 30-50 percent more than bunker fuel, and fuel accounts for up to 75 percent of an ocean carrier's operation costs. This new regulation was estimated to cost the shipping industry between $10 to $60 billion per year depending on fuel prices (Corbett et al., 2016). Yet, our results suggest the potential for large benefits to human health in coastal areas throughout the world that have not yet adopted an ECA regulation. As of 2020, only the North American ECA, Baltic Sea ECA, and North Sea ECA were in effect. The health benefits from the IMO's new global standard are likely to be quite large given that most countries had not regulated maritime sulfur emissions near coastal areas as of the time of our study.

[21] Figures A5 and A6 show the distribution of these health improvements spatially.

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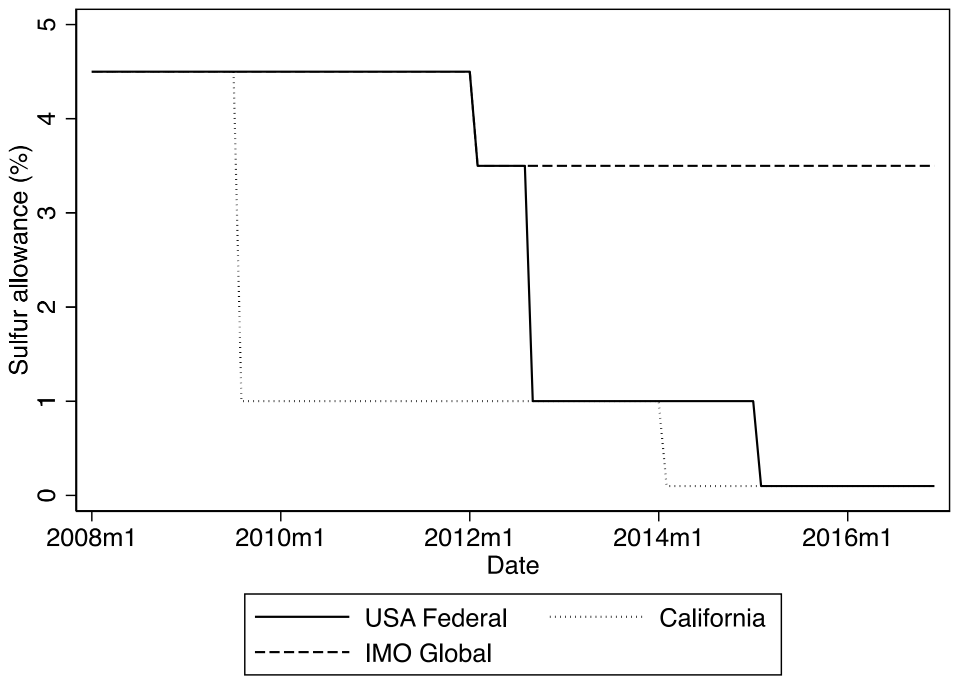
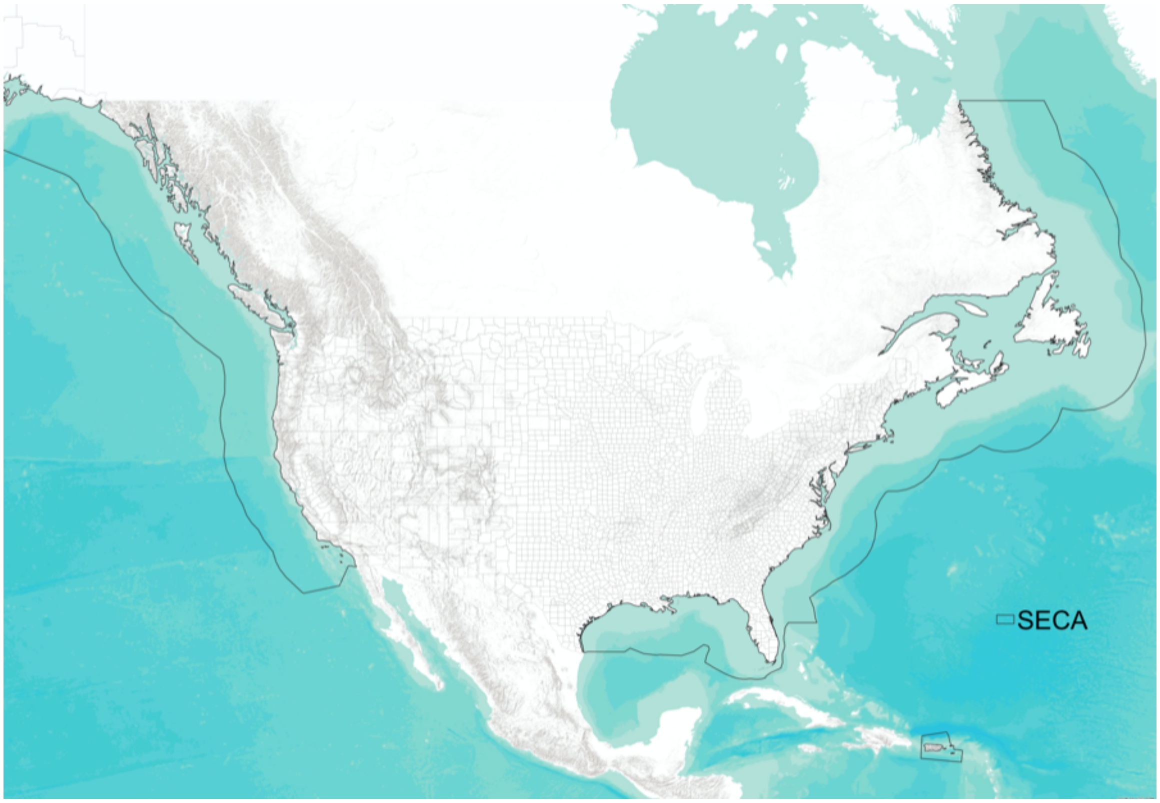
6 Figures

Figure 1: **Summary of Sulfur Allowance Limits Within and Outside ECAs**



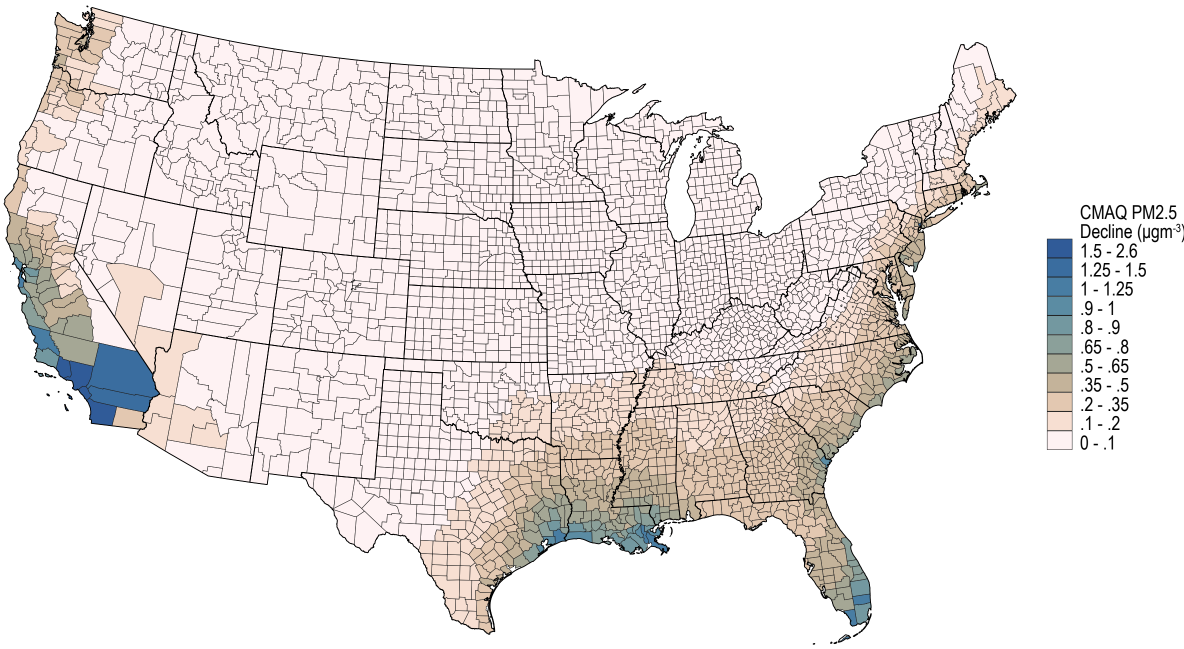
Note: California standard applies within 24 nautical miles of California's coast. USA federal standard applies within 200 nautical miles of coast. IMO's global standard applies elsewhere.

Figure 2: **North American Emission Control Area Boundary**



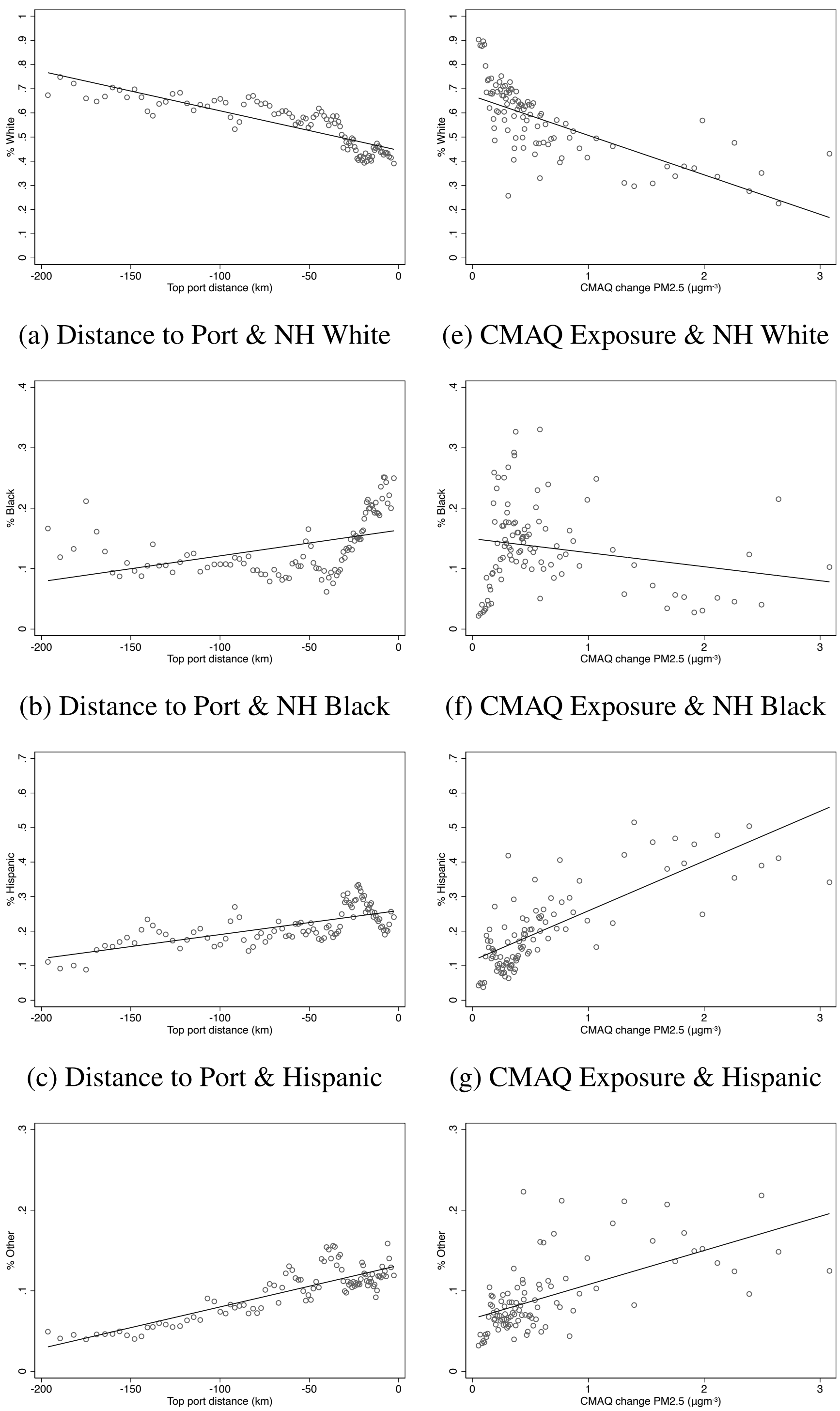
Note: Figure shows the regulated area for the North American Emission Control Area. Low sulfur fuel was required within the outlined boundary.

Figure 3: **CMAQ Predicted Decline in PM2.5 from ECA**



Note: Figure shows the predicted decline in fine particulate matter from implementation of the North American Emission Control Area based on the CMAQ model. Counties were assigned the difference between the CMAQ scenarios of ambient PM2.5 in 2020 (i) without the ECA policy and (ii) with the ECA policy at the population-weighted centroid. Data are from U.S. EPA (2009b).

Figure 4: **Demographics of the Population Exposed to Maritime Pollution**



(a) Distance to Port & NH White (e) CMAQ Exposure & NH White

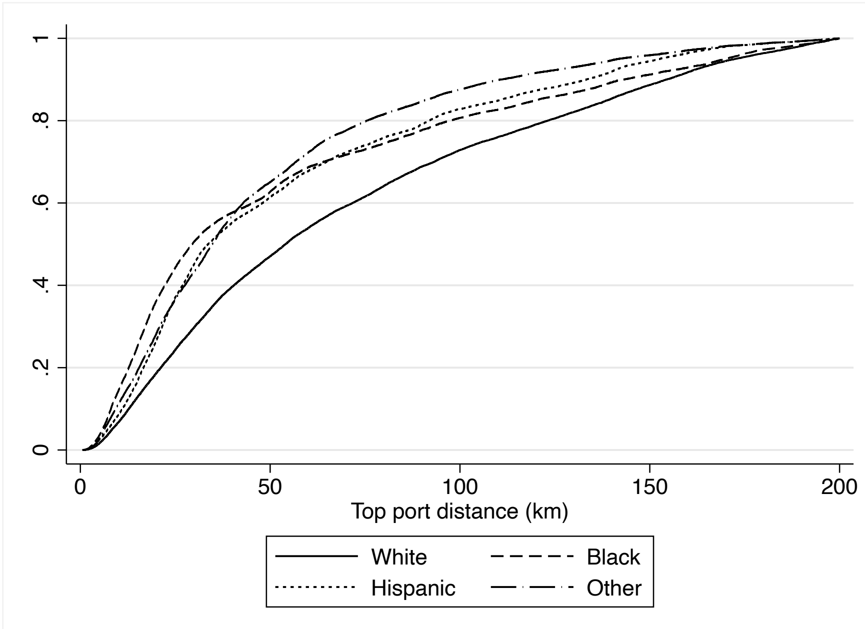
(b) Distance to Port & NH Black (f) CMAQ Exposure & NH Black

(c) Distance to Port & Hispanic (g) CMAQ Exposure & Hispanic

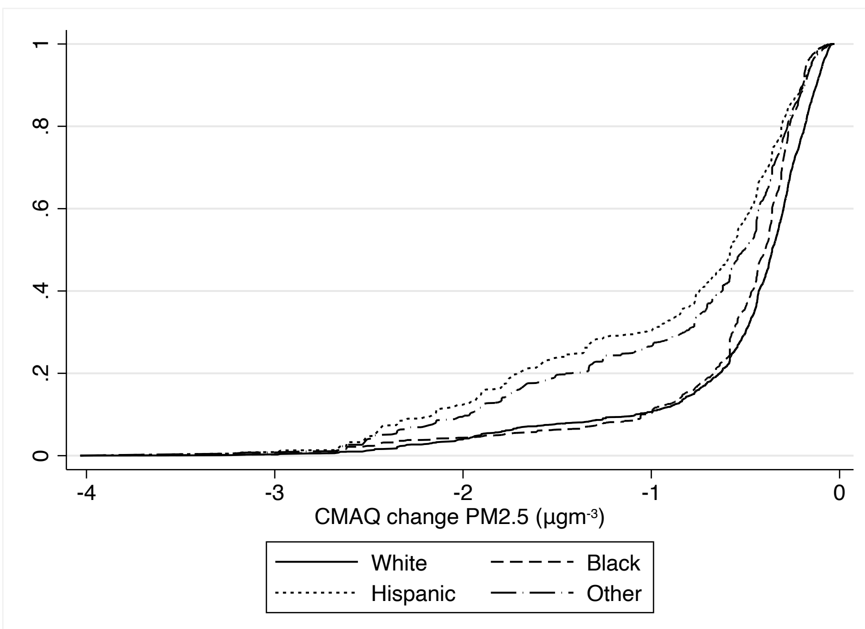
(d) Distance to Port & NH Other (h) CMAQ Exposure & NH Other

Note: Demographic information on the proportion of non-Hispanic whites, non-Hispanic blacks, non-Hispanic other race, and Hispanics from 2010 census tract data. We restrict to our analysis sample, which includes tracts within 200km of heavy ship traffic. Each of the 100 circles represents the population-weighted average for equal-sized bins of census tracts. Panels (a)-(d) show the correlation between race/ethnicity groups and distance to ports. We calculate distance from the population-weighted centroid of each tract to the nearest major port. Counties further to the right are closer in distance to a port. Panels (e)-(h) show the correlation between race/ethnicity and the intensity of ship emissions, as measured by the predicted change from requiring low sulfur maritime fuel from the CMAQ model at the centroid of each tract. The x-axis is the predicted change in fine particulate matter. Counties further to the right have higher ship emission exposure.

Figure 5: **Disproportionate Exposure Among Populations Exposed to Maritime Pollution**



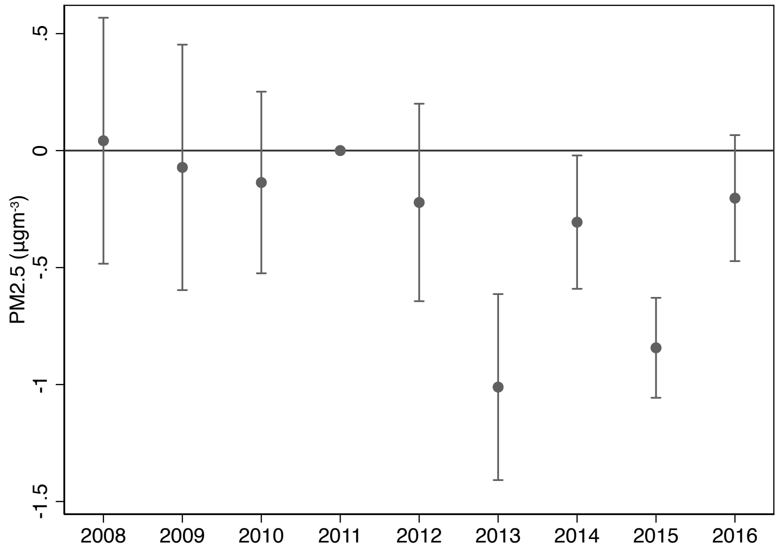
(a) Distance to Port



(b) CMAQ Exposure

Note: Demographic information on the proportion of non-Hispanic whites, non-Hispanic blacks, non-Hispanic other race, and Hispanics from 2010 census tract data. We restrict to our analysis sample, which includes tracts within 200km of heavy ship traffic. Figure shows the cumulative distribution of individuals by race/ethnicity over distance to a port in panel (a) and intensity of ship emissions in panel (b). We calculate distance in kilometers from the population-weighted centroid of each tract to the nearest major port. The intensity of ship emissions is measured by the predicted change from requiring low sulfur maritime fuel from the CMAQ model at the centroid of each census tract.

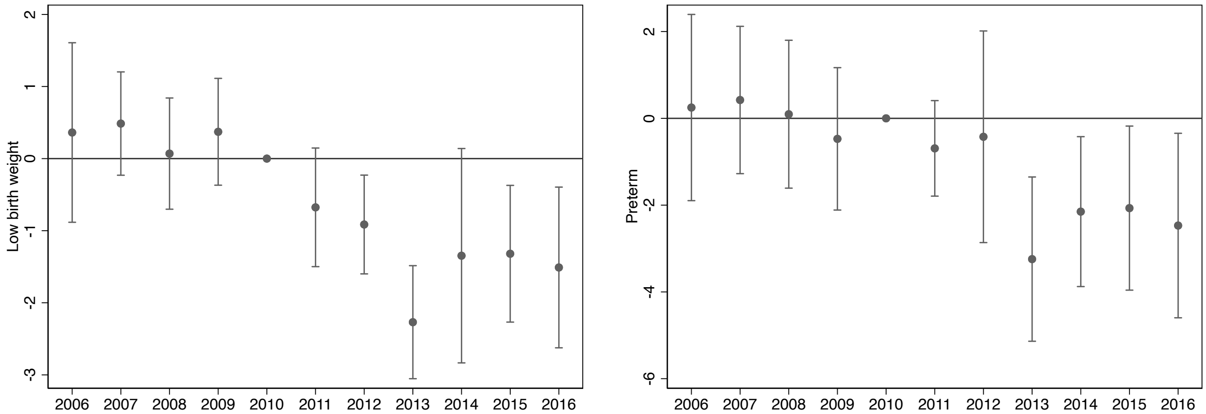
Figure 6: **Effects of ECA on Air Quality**



(a) PM2.5

Note: The unit of observation is a county-year-month. The observations are weighted by the number of births conceived in county i in year-month ym. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to the year before the ECA came into effect. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 7: **Effects of ECA on Infant Health**

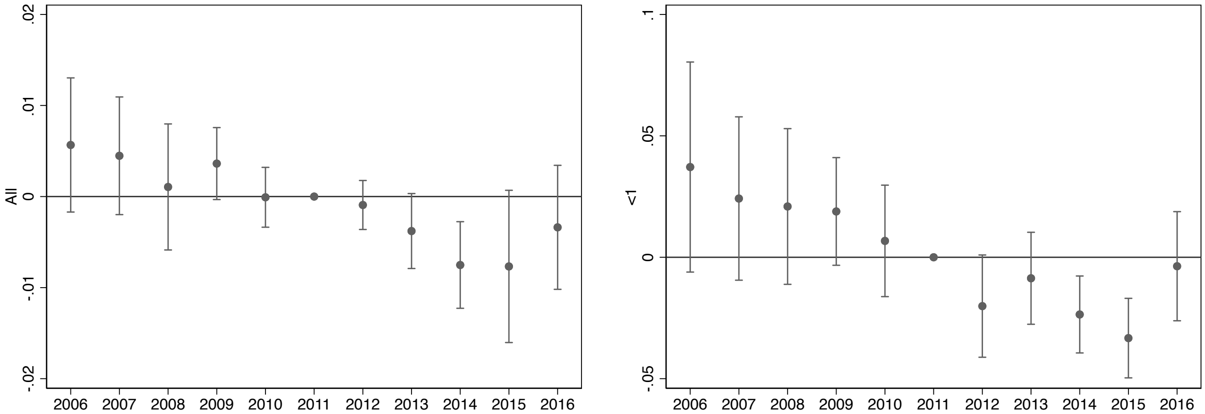


(a) Low Birth Weight

(b) Preterm Birth

Note: The unit of observation is a county-year-month. The observations are weighted by the number of births conceived in county i in year-month ym. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each conception year relative to 2010. Conceptions in 2011 and 2012 may be partially treated, while conceptions in 2013 and after are fully treated during gestation. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 8: **Effects of ECA on Mortality**

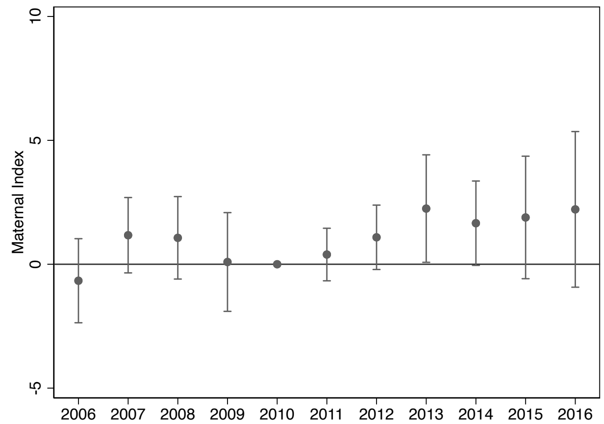


(a) All Ages

(b) Under 1

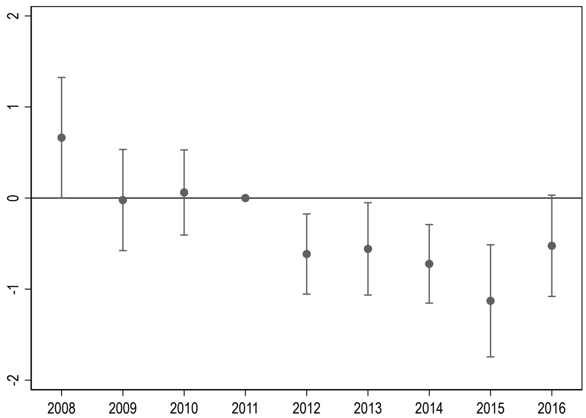
Note: The unit of observation is a county-year-month. The observations are weighted by the total population in panel a and the population under age 1 in panel b. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to 2011. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 9: **Maternal Demographics and CMAQ Exposure**

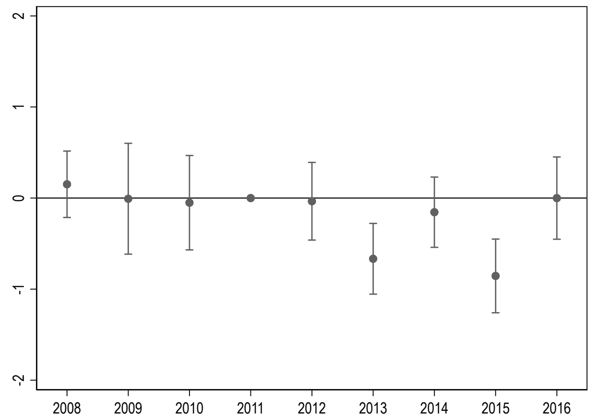


Note: The unit of observation is a county-year-month. The observations are weighted by the number of births conceived in county i in year-month ym. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The outcome is predicted birth weight based on observed characteristics and coefficients obtained from regressing birth weight on maternal characteristics, including education, marital status, race, ethnicity, age, smoking status, and diabetes. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to the year before the ECA came into effect. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 10: **Ship Behavioral Response: Full vs. Partial ECA**



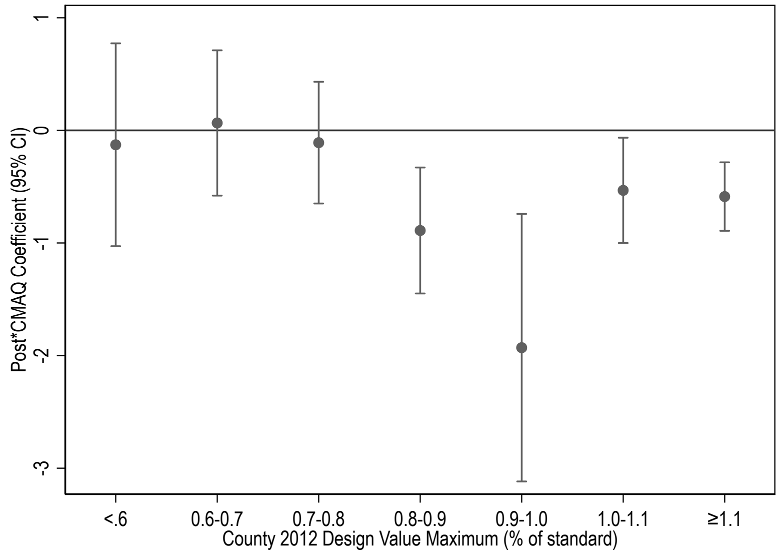
(a) Full ECA



(b) Partial ECA

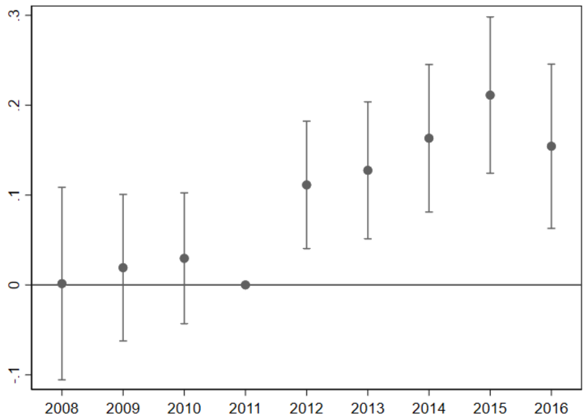
Note: The unit of observation is a county-year-month. The observations are unweighted. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to the year before the ECA came into effect. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 11: **Emissions Behavioral Response: Clean Air Act Regulatory Rebound**

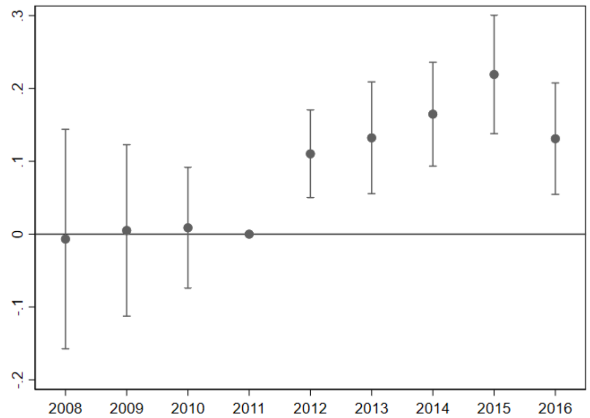


Note: The unit of observation is a county-year-month. The observations are unweighted. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in post-ECA (July 2012) time periods relative to pre-ECA time periods. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 12: **Individual Behavioral Response: Campsite Reservations**



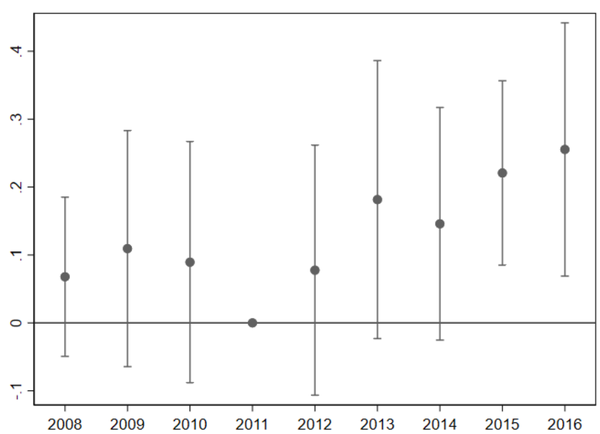
(a) Log Visits



(b) Log Days

Note: The unit of observation is the facility-year-month. The observations are unweighted. The sample includes all facilities in the continental US. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to 2011, the year prior to policy adoption. Panels a and b show the estimates for outcomes variables (a) natural log of total visits and (b) natural log of total days each month, respectively. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

Figure 13: **Individual Behavioral Response: Time Spent Outdoors**



Note: The unit of observation is the individual-county-year-month. The observations are weighted by sample weights. The sample includes individuals in counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor. The depicted coefficients are the estimated effect of a one-unit increase in a county's CMAQ predicted reduction from the ECA in each year relative to 2011, the year prior to policy adoption. The outcome is the inverse hyperbolic size transformation of minutes spent outdoors. Robust standard errors are clustered at the county level. The confidence intervals are $\pm$ 1.96 standard errors.

7 Tables

Table 1: **Summary Statistics 2008-2016**

	All in 200k	In 200k and PM2.5 monitor
Outcomes		
PM2.5	9.21	9.21
Low birth weight (per 1,000)	61.61	60.53
Birth weight (g)	3,304.18	3,305.18
Pre-term (per 1,000)	95.55	93.82
Gestation(weeks)	38.77	38.78
Deaths (per 1,000) - Under 1	0.48	0.52
Deaths (per 1,000) - All	0.63	0.63
Mother characteristics		
Married	0.59	0.58
$>$ HS Education	0.51	0.52
White	0.72	0.72
Hispanic	0.30	0.34
Over 35	0.18	0.19
Other controls		
Min temperature	9.87	9.88
Max temperature	21.41	21.40
Precipitation	2.80	2.64
Unemployment rate	7.72	7.85
Observations		
N conceptions/month	201.54	496.89
N counties	740.00	232.00

Note: The unit of observation is the county-year-month. The observations are weighted by the number of births conceived in county i in year-month ym. The sample in column 1 includes all counties with population-weighted centroids within 200km of heavy ship traffic. Column 2 drops counties without a PM2.5 monitor with at least one observation per year from 2008-2016. Means are reported for the main outcomes, demographic variables, and key control variables.

Table 2: **Effects of ECA on Air Quality and Demographic Characteristics**

	(1) PM2.5	(2) Maternal Index	(3) N conceptions
Post-ECA*CMAQ	-0.532	0.879	-54.121
	(0.096)***	(0.676)	(35.861)
R^2	0.59	0.95	1.00
N	24,901	25,052	25,052
N-counties	232	232	232
Mean	9.21	3305.18	497.12
%Change	-5.78	0.03	-10.89

Note: The unit of observation is the county-year-month. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor from 2008-2016. The observations are weighted by the number of births conceived in county i in year-month ym in Columns 1-2 and unweighted in Column 3. Reduced-form estimates are obtained from equation 1. The first-stage impact on PM2.5 is reported in column 1. Column 2 reports the effect on a measure of predicted birth weight based only on observed maternal characteristics, including education, marital status, race, ethnicity, age, smoking status, and diabetes. Column 3 repeats column 2 with the number of conceptions as the outcome variable. The insignificant coefficients in Columns 2-3 indicate there is no evidence of changes in underlying maternal characteristics or demographics that are correlated with the CMAQ policy variation. Robust standard errors clustered at the county level are reported in parentheses: : * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: **Effects of ECA and Air Quality on Health**

	(1) Low birth weight	(2) Preterm	(3) All Deaths	(4) Under 1 Deaths
Panel A. Reduced Form				
Post-ECA*CMAQ	-1.326	-2.082	-0.006	-0.024
	(0.348)***	(0.782)***	(0.003)**	(0.007)***
R^2	0.57	0.63	0.92	0.64
N	25,052	25,052	25,056	24,840
N-counties	232	232	232	230
Mean	60.53	93.82	0.64	0.52
% Change	-2.19	-2.22	-0.92	-4.66
Panel B. 2SLS				
PM2.5	2.780	4.305	0.011	0.045
	(1.062)***	(2.165)**	(0.006)*	(0.017)***
R^2	0.45	0.52	0.91	0.60
N	24,901	24,901	24,905	24,689
F	19.91	19.91	33.48	32.90
N-counties	232	232	232	230
Mean	60.54	93.82	0.64	0.52
% Change	4.59	4.59	1.72	8.73
Panel C. OLS				
PM2.5	-0.005	0.016	0.002	0.001
	(0.036)	(0.056)	(0.000)***	(0.001)
R^2	0.57	0.64	0.92	0.64
N	24,901	24,901	24,905	24,689
N-counties	232	232	232	230
Mean	60.54	93.82	0.64	0.52
% Change Post-ECA	-0.01	0.02	0.29	0.17

Note: The unit of observation is the county-year-month. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor from 2008-2016. The observations are weighted by the number of conceptions (columns 1-2), population (column 3), and population under age 1 (column 4). In Panel A, reduced-form estimates are obtained from equation 1. Panel B reports two-stage least squares estimates based on equation 2. Panel C reports the naive OLS estimates of pollution on health. The effects are reported for outcomes: low birth weight (<2,500g) per 1,000 (column 1), pre-term birth (<37 weeks) per 1,000 (column 2), deaths per 1,000 (column 3), and infant deaths per 1,000 (column 4). Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4: **Comparison of Magnitude to the Literature**

Study	Outcome	Pollutant	$\%\Delta$ from 10% pollutant increase
Currie and Walker 2011	Low birth weight	NO2, SO2	17.65
Alexander and Schwandt 2020	Low birth weight	PM2.5, PM10, O3	10.3
H-L and Marcus	Low birth weight	PM2.5	4.2
Chay and Greenstone 2003 A	Infant mortality	TSP	5
Chay and Greenstone 2003 B	Infant mortality	TSP	3.5
Currie and Neidell 2005	Infant mortality	CO	1.01
Luechinger 2014	Infant mortality	SO2	0.89
Gutierrez 2015	Infant mortality	PM2.5, PM10	7.1
Knittel, Miller, Sanders 2016	Infant mortality	PM10	10.3
Alexander and Schwandt 2020	Infant mortality	PM2.5, PM10, O3	9.5
H-L and Marcus	Infant mortality	PM2.5	8.0

Note: Source of calculations from Alexander and Schwandt (2021).

Table 5: **Robustness of Main Results**

	PM2.5		Low BW		Death <1		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	β	p-value	β	p-value	β	p-value	N counties
(1) Baseline	-0.53	0.00	-1.33	0.00	-0.02	0.00	232.0
	(0.10)		(0.35)		(0.01)		
(2) 150 km	-0.54	0.00	-1.32	0.00	-0.02	0.00	202.0
	(0.10)		(0.38)		(0.01)		
(3) 300 km	-0.54	0.00	-1.28	0.00	-0.02	0.00	280.0
	(0.09)		(0.32)		(0.01)		
(4) State-year FE	-0.44	0.00	-1.05	0.00	-0.02	0.03	202.0
	(0.12)		(0.35)		(0.01)		
(5) Bins of weather	-0.53	0.00	-1.37	0.00	-0.02	0.00	232.0
	(0.09)		(0.32)		(0.01)		
(6) 2009-2014 balance	-0.60	0.00	-1.38	0.00	-0.02	0.00	251.0
	(0.11)		(0.43)		(0.01)		
(7) Unbalanced panel	-0.49	0.00	-1.25	0.00	-0.02	0.00	286.0
	(0.10)		(0.31)		(0.01)		
(8) Ships' contribution	-0.36	0.00	-1.10	0.00	-0.02	0.00	232.0
	(0.10)		(0.28)		(0.01)		
(9) No ports	-0.62	0.00	-1.39	0.06	-0.04	0.01	192.0
	(0.18)		(0.74)		(0.01)		
(10) CAA controls	-0.41	0.00	-1.27	0.00	-0.02	0.00	232.0
	(0.11)		(0.34)		(0.01)		
(11) 2015 0.1ppm	-0.01	0.90	0.21	0.64	-0.01	0.48	232.0
	(0.10)		(0.45)		(0.01)		

Note: Row 1 replicates the baseline results for PM2.5, low birth weight, and infant deaths from Panel A of Table 3. Columns 1, 3, and 5 report coefficients from estimating equation 1. Columns 2, 4, and 6 report p-values. Column 7 reports total number of counties included in each specification. Robust standard errors clustered at the county level are reported in parentheses. Rows 2-11 present robustness checks. Rows 2 and 3 limit the sample of counties to those with population-weighted centroids within 150km and 300km of heavy ship traffic, respectively. Row 4 replaces region-by-year fixed effects with state-by-year fixed effects. Row 5 includes more flexible binned weather controls. Rows 6-7 relax the balanced panel requirement for air quality monitors by restricting to a sample of balanced monitors from 2009 to 2014 (row 6) and to a sample of all counties that ever have PM2.5 data during the period of study (row 7). Row 8 examines the robustness of the treatment definition by employing the CMAQ prediction of total emissions from maritime shipping. Row 9 excludes counties with a port. Row 10 includes controls for Clean Air Act attainment status. Row 11 examines the effect of tightening the fuel content standard nationally in 2015.

Table 6: **Comparison of Treatment Variables on Main Outcomes**

	BIC	T-stat	Coefficient	Std error
Panel A: PM2.5 (μgm^{-3})				
CMAQ	107,175.227	-5.575	-0.056	0.010
-Distance port	107,300.016	-1.686	-0.044	0.026
Panel B: Low birth weight				
CMAQ	190,136.703	-3.806	-0.015	0.004
-Distance port	190,155.156	-2.177	-0.019	0.009
Panel C: Deaths <1				
CMAQ	8,306.867	-3.418	-0.012	0.004
-Distance port	8,307.829	-2.354	-0.026	0.011

Note: Table reports results of estimating equation 1 where the intensity of exposure to the policy is measured by either the CMAQ prediction or distance to the nearest major port. County-year-months are weighted by the number of conceptions. We report the results for fine particulate matter, low birth weight, and infant deaths in panels A-C, respectively. Coefficients and standard errors are standardized into units of standard deviations so that the results are comparable across candidate treatment variables. Column 1 reports the Bayesian information criteria (BIC), where the lowest BIC is preferred. Columns 2-4 report the T-statistic, coefficient, and standard error, respectively.

Table 7: **Heterogeneity of Effects of ECA on Low Birth Weight**

	(1) All	(2) NH White	(3) NH Black	(4) NH Other	(5) Hispanic	(6) High Educ	(7) Married	(8) Age 19-24	(9) Age 25-34	(10) Age 35
PM2.5	0.00277	0.00307	0.00223	0.00792	0.00113	0.00233	0.00186	0.00111	0.00277	0.00437
	(0.00093)***	(0.00151)**	(0.00267)	(0.00211)***	(0.00063)*	(0.00107)**	(0.00059)***	(0.00089)	(0.00106)***	(0.00121)***
R^2	0.01	0.01	0.01	-0.00	0.00	0.01	0.01	0.01	0.01	0.01
N	12,426,807	5,062,128	1,860,002	1,337,613	4,167,051	6,436,488	7,238,190	2,911,813	6,967,317	2,317,026
F	23.56	12.48	11.76	28.83	26.18	21.10	21.46	21.16	21.97	29.73
N-counties	232	232	232	231	232	232	232	232	232	232
Mean	0.06	0.05	0.11	0.06	0.06	0.05	0.05	0.07	0.06	0.07
%Change	4.57	6.56	2.09	12.59	2.02	4.33	3.72	1.64	5.00	6.71

Note: The unit of observation is the individual-year-month. The sample includes individuals in counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor from 2008-2016. Observations are unweighted. Results show two-stage least squares estimates based on equation 2. Column 1 includes the entire sample and reports results analogous to Table 3 panel B, column 2, but at the individual level. Columns 2-10 restrict the sample to individuals of different demographic groups, including non-Hispanic white, non-Hispanic black, non-Hispanic other, Hispanic, highly educated, married, age 19-24, age 25-34, and age 35+. Within county-season R^2 is reported. Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: **Effect of ECA on Ship and Other Emissions Behavior**

	(1) PM2.5	(2) PM2.5	(3) PM2.5
Post*CMAQ	-0.577	-0.865	-1.935
	(0.125)***	(0.186)***	(0.599)***
Post*CMAQ*1(ECA$<$200nm)		0.426	
		(0.172)**	
Post*CMAQ*1(0.8$<$DV)			1.895
			(0.555)***
Post*CMAQ*1(0.8 $\leq$ DV $<$ 0.9)			1.043
			(0.588)*
Post*CMAQ*1(DV $\geq$ 1.0)			1.361
			(0.575)**
R^2	0.59	0.59	0.55
N	24,905	24,905	19,992
N-counties	232	232	186
Mean	8.30	8.30	8.72
% Change:			
All	-6.96		
ECA=200nm		-10.47	
ECA$<$200nm		-5.14	
DV $<$ 0.8			-0.53
0.8 $\leq$ DV $<$ 0.9			-10.62
0.9 $\leq$ DV $<$ 1.0			-19.20
DV $\geq$ 1.0			-6.04

Note: The unit of observation is the county-year-month. The sample includes counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor from 2008-2016. County-year-months are not weighted. Column 1 shows the results of estimating equation 1. Column 1 repeats the estimate of Table 2 column 1 with unweighted data. Column 2 repeats column 1 with an additional interaction for whether the ECA boundary is less than the full 200 nm from the county population-weighted centroid, $1(\text{ECA<200 nm})$, as per equation 3. Column 3 repeats column 1 with additional interactions for counties' pre-policy distance to the regulatory threshold, DV, defined as the county 2012 PM2.5 maximum design value as a percent of the standard, as per equation 4. Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9: **Effect of ECA on Individual Behavior**

	Campsite Reservations (Log)						Time Outdoors
	Visits	Visits	People	People	Days	Days	(IHS)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
post-ECA × CMAQ	0.114***	0.146***	0.104**	0.144***	0.111**	0.150***	0.0797*
	(0.0429)	(0.0335)	(0.0456)	(0.0362)	(0.0471)	(0.0310)	(0.0473)
Region-year FE	X	X	X	X	X	X	X
County-season FE	X		X		X		X
Facility-month FE		X		X		X	
Year-month FE		X		X		X	X
R-squared	0.357	0.934	0.420	0.899	0.399	0.933	0.064
Observations	37,765	37,374	37,764	37,373	36,212	35,811	29,516
N-counties	149	143	149	143	141	135	183

Note: For columns 1-6, the unit of observation is the facility-year-month, observations are unweighted, and the sample is campsites in the continental US from 2008-2016. In columns 1-6, we estimate equation 5 where the outcomes are the natural log of the number of visits (columns 1-2), the number of people (columns 3-4), and the number of days for the facility-year-month (columns 5-6). In column 7, the unit of observation is the individual-year-month, observations are weighted with survey weights, and the sample includes observations in counties with population-weighted centroids within 200km of heavy ship traffic and with a PM2.5 monitor from 2008-2016. In column 7, we estimate equation 6 where the outcome is the inverse hyperbolic sine of the number of minutes the respondent reported spending outdoors for the previous day. All regressions include region-by-year fixed effects; columns 1, 3, 5, and 7 include county-by-season fixed effects; columns 2, 4, and 6 include facility-by-month fixed effects; and columns 2, 4, 6, and 7 include year-by-month fixed effects. Column 7 also controls for gender, race, ethnicity, education, age, presence of children in the household, and indicators for the day of the week of the survey and whether it was a holiday. Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

8 Appendix

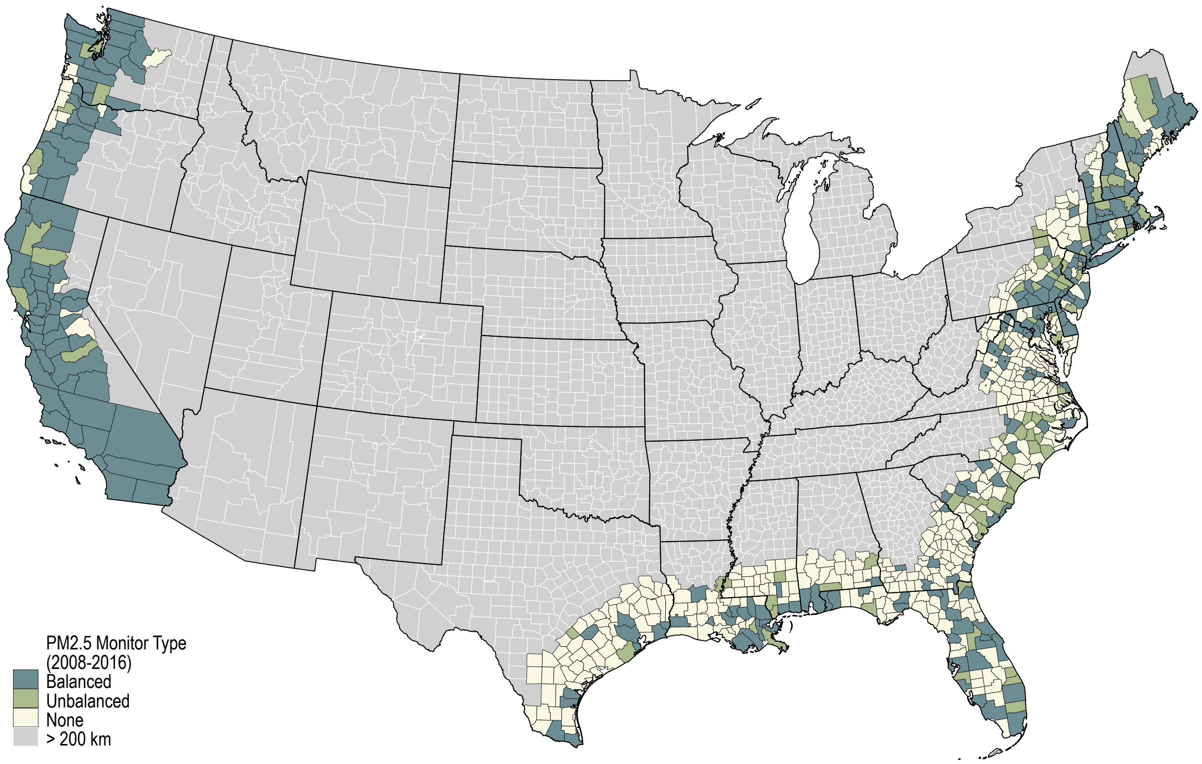
8.1 Air Pollution Data

The source is the US EPA Air Quality System (AQS). Raw observations are at the level of the pollutant-monitor-day. We construct PM2.5-monitor-day observations from 3 PM2.5 from pollutant codes. Our primary source is PM2.5 coded as pollutant 88101. For monitor-days where 88101 data are missing we substitute with PM2.5 coded as pollutant 88502. When both 88101 and 88502 are missing, we substitute with 88501. Thus, we obtain PM2.5-monitor-day observations.

Monitor-day observations are collapsed to monitor-week averages. The monitors are matched to the county in which the monitor is located. To construct a balanced panel of monitors, monitors that are not observed for at least one week each year from 2008-2016 are dropped. We then average the remaining monitor-weeks within each county to construct county-week observations of mean PM2.5. Last, we collapse county-week observations to county-month averages. Throughout, averages exclude missing observations.

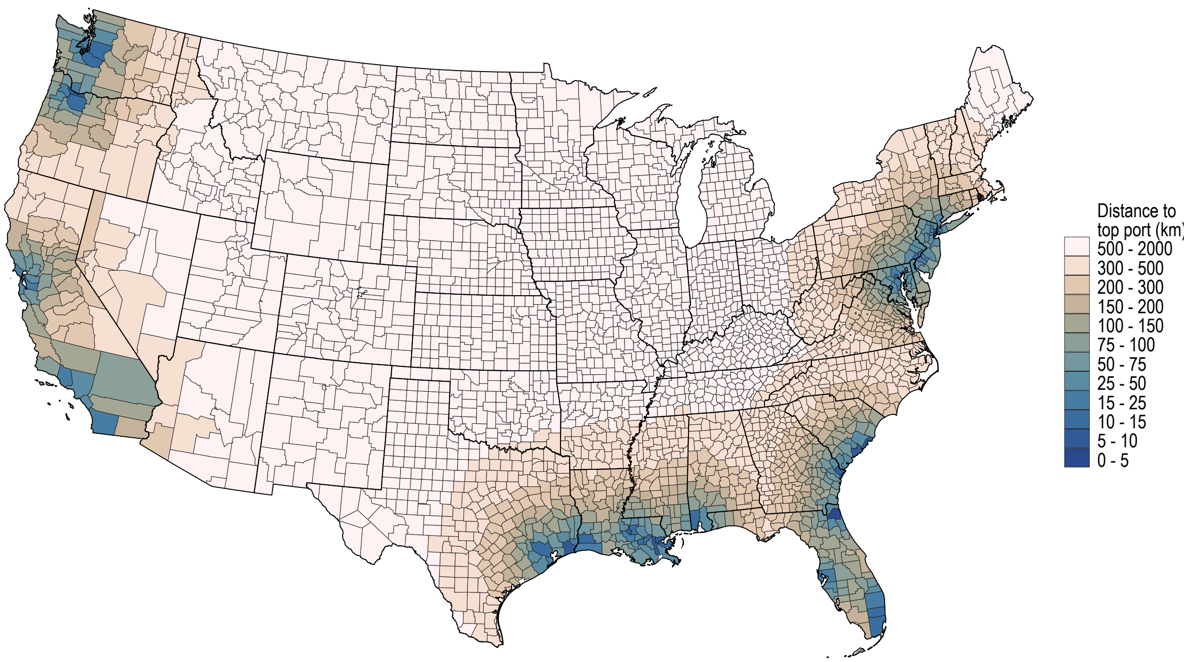
8.2 Tables & Figures

Figure A1: Analysis Sample



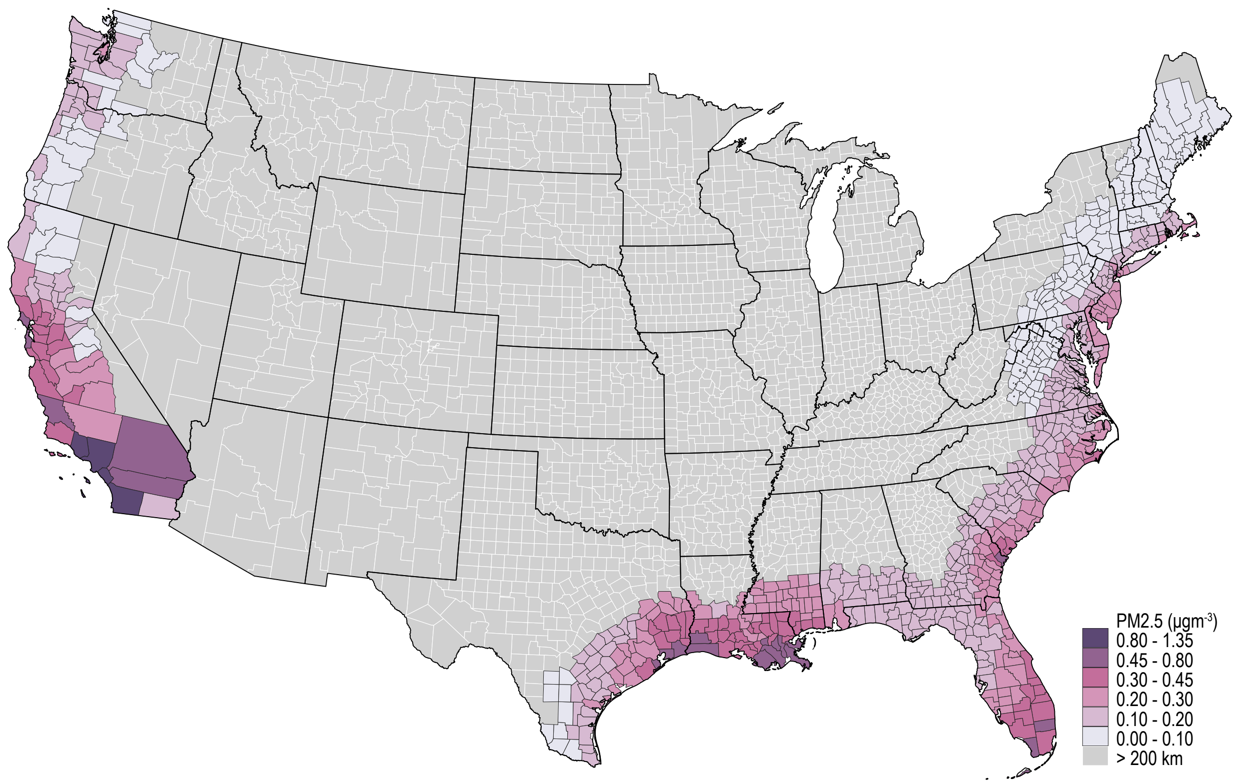
Note: Figure shows non-grey counties with population-weighted centroids within 200km of heavy ship traffic, as defined by the top 5th percentile of 2011 vessel density raster grid cells. Counties with population-weighted centroids further than 200km are shaded in grey. Blue counties are those with a balanced PM2.5 monitor. They have at least one PM2.5 monitor with at least one observation per year from 2008 to 2016. Green counties are those with only unbalanced PM2.5 monitors. They have PM2.5 monitor(s) but no single monitor with at least one observation per year from 2008 to 2016. Yellow counties have no PM2.5 monitors.

Figure A2: Distance to Ports



Note: Figure shows the distance from the population-weighted centroid of each county to the nearest principal port.

Figure A3: Scaled Reduction in PM2.5



Note: Figure shows the estimated reduction in ambient PM2.5 from the ECA at the county level. The estimated reductions are the county level CMAQ predictions depicted in Figure 3 scaled by the estimated ECA effect coefficient in Table 2 column 1.

Table A1: **Effects of ECA on Additional Health Outcomes**

	(1) Birth weight	(2) Gestation
Panel A. Reduced Form		
Post-ECA*CMAQ	1.622	0.012
	(0.874)*	(0.006)**
R^2	0.82	0.71
N	25,052	25,052
N-counties	232	232
Mean	3305.18	38.78
%Change	0.05	0.03
Panel B. 2SLS		
PM2.5	-3.445	-0.025
	(1.887)*	(0.011)**
R^2	0.80	0.66
N	24,901	24,901
F	19.91	19.91
N-counties	232	232
Mean	3305.10	38.78
%Change	-0.10	-0.06
Panel C. OLS		
PM2.5	0.088	-0.000
	(0.080)	(0.000)
R^2	0.82	0.71
N	24,901	24,901
N-counties	232	232
Mean	3305.10	38.78
%Change Post-ECA	0.00	-0.00

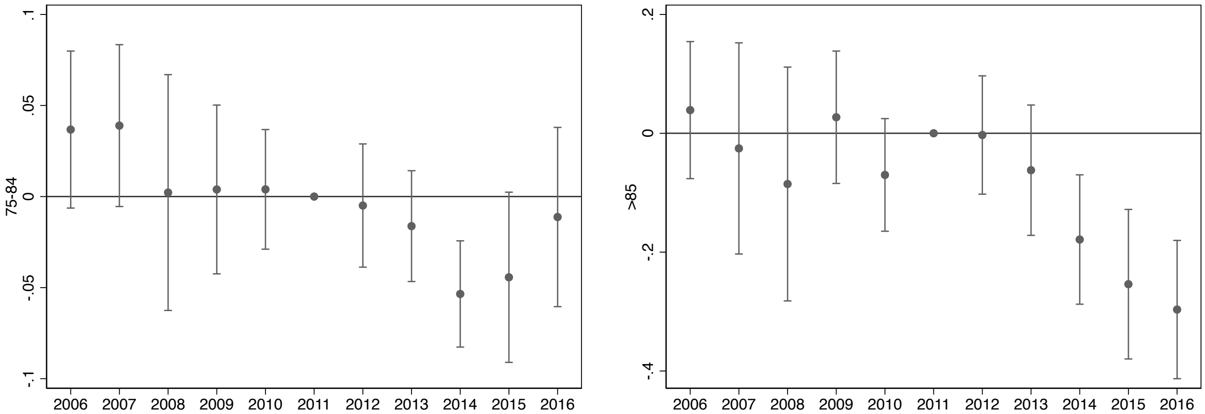
Note: Repeats the analysis of Table 3 column 1 with outcomes birth weight in grams (column 1) and gestation in weeks (column 2).

Table A2: **Effects of ECA on Birth Weight Distribution**

	(1) <1,000 g	(2) 1,000-1,500 g	(3) 1,500-2,000 g	(4) 2,000-2,500 g	(5) 2,500-3,000 g	(6) 3,000-3,500 g	(7) 3,500-4,000 g	(8) 4,000-4,500 g	(9) >4,500 g
Panel A. Reduced Form									
Post-ECA*CMAQ	-0.173	-0.111	-0.266	-0.777	-0.349	1.806	0.458	-0.465	-0.124
	(0.075)**	(0.073)	(0.115)**	(0.201)***	(0.593)	(0.483)***	(0.472)	(0.292)	(0.141)
R^2	0.26	0.16	0.20	0.42	0.61	0.34	0.60	0.58	0.28
N	25,052	25,052	25,052	25,052	25,052	25,052	25,052	25,052	25,052
N-counties	232	232	232	232	232	232	232	232	232
Mean	5.28	5.29	10.62	39.34	178.41	403.91	276.41	69.85	10.89
%Change	-3.27	-2.09	-2.50	-1.97	-0.20	0.45	0.17	-0.67	-1.14
Panel B. 2SLS									
PM2.5	0.364	0.233	0.555	1.629	0.780	-3.790	-0.972	0.943	0.258
	(0.171)**	(0.174)	(0.274)**	(0.624)***	(1.165)	(1.231)***	(0.997)	(0.656)	(0.314)
R^2	0.22	0.14	0.15	0.33	0.61	0.26	0.60	0.57	0.27
N	24,901	24,901	24,901	24,901	24,901	24,901	24,901	24,901	24,901
F	19.91	19.91	19.91	19.91	19.91	19.91	19.91	19.91	19.91
N-counties	232	232	232	232	232	232	232	232	232
Mean	5.28	5.29	10.62	39.35	178.44	403.94	276.38	69.82	10.89
%Change	6.89	4.41	5.22	4.14	0.44	-0.94	-0.35	1.35	2.37
Panel C. OLS									
PM2.5	-0.006	-0.003	-0.007	0.011	-0.029	-0.075	0.130	-0.029	0.007
	(0.010)	(0.010)	(0.015)	(0.027)	(0.057)	(0.057)	(0.059)**	(0.034)	(0.016)
R^2	0.26	0.16	0.20	0.42	0.61	0.34	0.60	0.58	0.28
N	24,901	24,901	24,901	24,901	24,901	24,901	24,901	24,901	24,901
N-counties	232	232	232	232	232	232	232	232	232
Mean	5.28	5.29	10.62	39.35	178.44	403.94	276.38	69.82	10.89
%Change Post-ECA	-0.11	-0.06	-0.06	0.03	-0.02	-0.02	0.05	-0.04	0.07

Note: Repeats the analysis of Table 3 column 1 with outcomes of births per 1,000 in 500 gram intervals of the domain of birth weight.

Figure A4: **Effects of ECA on Elderly Mortality**



(a) 75-84

(b) 85 and over

Note: Repeats the analysis of Figure 8. In column 1, the outcome is deaths per 1,000 among individuals aged 75 to 84 and the observations are weighted by the population aged 75 to 84. In column 2, the outcome is deaths per 1,000 among individuals aged 85 and older and the observations are weighted by the population aged 85 and older.

Table A3: **Effects of ECA on Elderly Mortality**

	(1) 75-84	(2) >85
Post-ECA*CMAQ	-0.041	-0.161
	(0.012)***	(0.049)***
R^2	0.77	0.64
N	30,600	30,600
N-counties	232	232
Mean	3.78	10.99
%Change Post-ECA	-1.07	-1.47

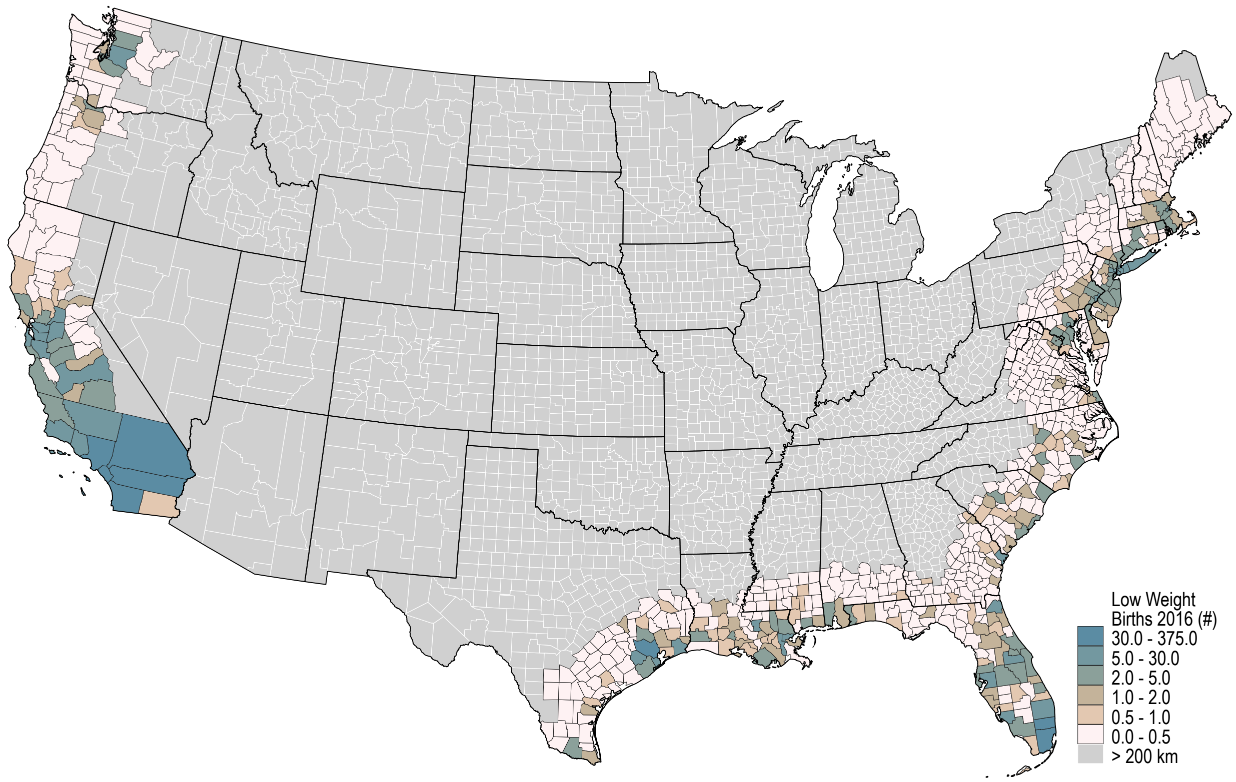
Note: Repeats the analysis of Table 3 Panel A column 4. In column 1, the outcome is deaths per 1,000 among individuals aged 75 to 84 and the observations are weighted by the population aged 75 to 84. In column 2, the outcome is deaths per 1,000 among individuals aged 85 and older and the observations are weighted by the population aged 85 and older.

Table A4: **Time Outdoors: Placebo Tests**

	(1) Sleep	(2) Housework	(3) Groceries
post-ECA × CMAQ	0.00112	0.0486	-0.0235
	(0.00669)	(0.0691)	(0.0301)
Region-year FE	X	X	X
County-season FE	X	X	X
Year-month FE	X	X	X
R-squared	0.083	0.153	0.063
Observations	29,516	29,516	29,516
N-counties	183	183	183

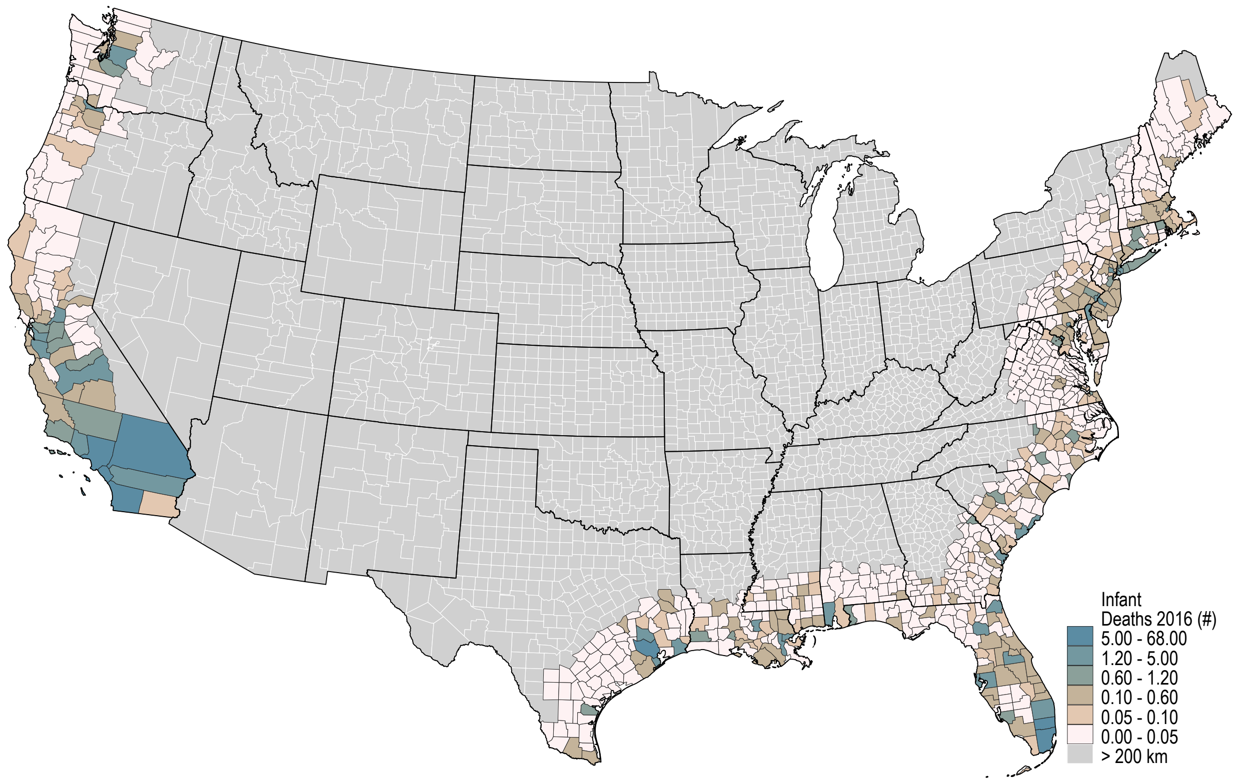
Note: The regression specifications are identical to those in Table 9, but for the following outcomes: time spent sleeping (activity code 010101), time spent doing housework (activity codes 020101-020199), and time grocery shopping (activity code 070101).

Figure A5: Reductions in Low Birth Weight Infants



Note: Figure shows the estimated reduction in low birth weight (<2,500 g) infants at the county-level from the ECA policy in 2016. See text for details.

Figure A6: Reductions in Infant Deaths



Note: Figure shows the estimated reduction in infant deaths at the county-level from the ECA policy in 2016. See text for details.