Estimating the Causal Effects of Cruise Traffic on Air Pollution using Randomization-Based Inference

Léo Zabrocki
Marion Leroutier
Marie-Abèle Bind

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Abstract

Local environmental organizations and media have recently expressed concerns over air pollution induced by maritime traffic and its potential adverse health effects on the population of Mediterranean port cities. We explore this issue with unique high-frequency data from Marseille, France’s largest port for cruise ships, over the 2008-2018 period. Using a new pair-matching algorithm designed for time series data, we create hypothetical randomized experiments and estimate the variation in air pollutant concentrations caused by a short-term increase in cruise vessel traffic. We carry out a randomization-based approach to compute 95% Fisherian intervals (FI) for constant treatment effects consistent with the matched data and the hypothetical intervention.

At the hourly level, cruise vessels’ arrivals increase concentrations of nitrogen dioxide ($NO_2$) by 4.7 µg/m$^3$ (95% FI: [1.4, 8.0]), of sulfur dioxide ($SO_2$) by 1.2 µg/m$^3$ (95% FI: [-0.1, 2.5]), and of particulate matter ($PM_{10}$) by 4.6 µg/m$^3$ (95% FI: [0.9, 8.3]). At the daily level, cruise traffic increases concentrations of $NO_2$ by 1.2 µg/m$^3$ (95% FI: [-0.5, 3.0]) and of $PM_{10}$ by 1.3 µg/m$^3$ (95% FI: [-0.3, 3.0]). Our results suggest that well-designed hypothetical randomized experiments provide a principled approach to better understand the negative externalities of maritime traffic.

Keywords: time series matching, randomization inference, Fisherian intervals, vessel emissions

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1Paris School of Economics and École des Hautes Etudes en Sciences Sociales, Paris, France. Email: leo.zabrocki@psemail.eu
2Paris School of Economics, Université Paris 1 Pantéon-Sorbonne, Paris, France / CIRED. Email: marion.leroutier@psemail.eu
3Biostatistics Center, Massachusetts General Hospital, Boston, MA, USA. Email: ma.bind@mail.harvard.edu
1 Introduction

Particulate matter pollution induced by maritime traffic was estimated to cause 60,000 premature deaths worldwide in 2007, with the highest burden in the Mediterranean area (Corbett et al. 2007). In the past few years, local environmental organizations and media have increasingly raised concerns over air pollution induced by cruise ships’ traffic (Friedrich 2017, Chrisafis 2018). Due to historical urban planning, many Mediterranean cities have their port in the city center and a large fraction of their population is exposed to vessels’ emissions (project 2015). Besides, the Mediterranean region is not yet part of an Emission Control Area (ECA), unlike US coasts, where stringent regulations on fuel sulfur content have been implemented. In this context, understanding the influence of vessel traffic on air pollutant concentrations is a major issue of public health.

Our study focuses on the Mediterranean city of Marseille. In France, Marseille is the second largest city, with 870,000 inhabitants, and the second largest port, with 3 million passengers in 2019 (INSEE 2020, de Marseille Fos Grand Port Maritime de Marseille 2020). Pollution levels in Marseille are high relative to the World Health Organization’s recommendations and European legal standards. Emission inventories have established that maritime traffic contributes to 40% of local nitrogen dioxide ($\text{NO}_2$) emissions, 33% of local sulfur dioxide ($\text{SO}_2$) emissions, and 13% of local particulate matter with a diameter below 10 micrometers ($\text{PM}_{10}$) emissions (Atmosud 2018a). If maritime traffic contributes to the pollution exposure of residents in similar proportions to its emissions, it could be a key sector to target in order to improve ambient air quality. Yet, isolating the contribution of vessel emissions to observed air pollutant concentrations is methodologically challenging. Complex meteorological patterns can prevail along coastal sites and ports are often located near major roads and industrial complexes (Sorte et al. 2020).
To identify the short-term causal effects of vessel traffic on ambient air pollution concentration in Marseille, we relate the variation in vessel traffic to the change in air pollutant concentration (Contini et al. 2011, Moretti and Neidell 2011). We build a unique dataset combining high-frequency data on vessel traffic, weather patterns, and air pollutant concentrations over the 2008-2018 period. Our study is framed within the Neyman-Rubin Causal Model, which enables us to separate the design phase of the observational study from its statistical analysis (Rubin 1974, Holland 1986, Rubin 2005). Using variation in vessel traffic, we emulate hypothetical randomized experiments designed to estimate the impact of an increase in vessel traffic on air pollutants. We focus on cruise vessels, which represent 48% of the traffic volume and have received the most attention from the media in the recent period (Grolee 2021). We carry out two types of analysis: one at the hourly level and one at the daily level. We first construct pairs of comparable periods using a new pair-matching algorithm designed for time series data, which allows us to adjust for observed covariates in a nonparametric manner (Sommer et al. 2018, Ho et al. 2007, Sommer et al. 2021a). We then implement a randomization-based approach to estimate the set of constant treatment effects that are consistent with our data and thereby avoid relying on asymptotic approximating distributions (Fisher et al. 1937, Rosenbaum et al. 2010). The causal inference pipeline we rely on can be considered as an alternative strategy to source apportionment and dispersion modeling methods (Sorte et al. 2020, Viana et al. 2014, Mueller et al. 2011, Piga et al. 2013, AtmoSud 2018b).
Figure 1: Map of Marseille’s Port surrounding Area and Hourly Vessel Traffic Variation.

Panel A displays a map of Marseille city with its port and the two air quality monitoring stations located in Lonchamp and Saint-Louis neighborhoods. Grey lines represent the road network of the city. Panel B shows the average hourly variation in the gross tonnage of vessel arriving and departing the port. Gross tonnage is a unitless measure of the volume of a ship.
2 Materials and Methods

2.1 Data

We built two datasets for the 2008-2018 period, one at the hourly level with 96,432 observations, and one at the daily level with 4,018 observations. Below we detail the data sources and variables used. See the SI Appendix, Sections 2-4 for additional information and figures.

2.1.1 Vessel Traffic Data

We obtained data on 41,015 port calls from the Marseille Port authority. These represent the universe of all port calls between 2008 and 2018. For each vessel docking at the port, we know the exact date and hour of arrival and departure, as well as its name, its type, and its gross tonnage, which is a nonlinear and unitless measure of a vessel’s overall internal volume. This measure of a vessel’s volume can be related to its emissions of air pollutants and has been used in other studies as a proxy for the intensity of vessel traffic (Contini et al. 2011, Moretti and Neidell 2011). Using information on vessel characteristics, we defined three broad categories: cruise, ferry, and other types of ships. We then calculated, for each vessel type, the total sum of gross tonnage at the hourly and daily levels. As shown in the Panel B of Figure 1, vessel traffic is regular: most vessels dock in the port in the morning and leave in the evening.

2.1.2 Air Pollution and Weather Data

We retrieved air pollution data from the two background monitoring stations managed by the local air quality agency AtmoSud. The first station, Saint-Louis, is the closest to the cruise terminal. It is located two kilometers away from the cruise ter-
minal (North-Western extremity of the port) and six kilometers away from the ferry terminal (South-Eastern extremity of the port) (See Panel A of Figure 1). It only monitors NO$_2$ and PM$_{10}$. The second station, Longchamp, is located six kilometers away from the cruise terminal and three kilometers away from the ferry terminal (See Panel A of Figure 1). The Longchamp station monitors NO$_2$, SO$_2$, ozone (O$_3$), particulate matter with a diameter below 2.5 $\mu m$ (PM$_{2.5}$) and PM$_{10}$. Sulphur oxides (SOx), nitrogen oxides (NOx), and fine particulate matter are emitted to the atmosphere as a direct result of the combustion of maritime fuel (Sorte et al. 2020). SOx and NOx emissions directly produce NO$_2$ and SO$_2$, and contribute to the formation of secondary pollutants such as particulate matter of a larger size (i.e., PM$_{2.5}$ and PM$_{10}$), and O$_3$ (Viana et al. 2014).

Weather data come from Météo-France, the French national meteorological service. We downloaded data from the closest weather station, located 25 kilometers away from the city center, at Marseille airport. We calculated hourly and daily values for weather variables: rainfall height (mm), average temperature ($^\circ$C), humidity (%), wind speed (m/s), and wind direction measured on a 360 degrees compass rose where 0° is North.

Missing values were imputed using a chained random forest algorithm provided by the R package missRanger (Mayer 2019).

### 2.1.3 Road traffic Data

We obtained hourly data on the average flow of vehicles over the 2011-2016 period from the Direction Interdépartementale des Routes, a decentralized state administration in charge of managing, maintaining, and operating roads. We selected hourly data for the six traffic monitoring stations with the best available recordings, two located North and four located East of the city.
2.2 Method

We conceptualize plausible but hypothetical randomized experiments to estimate the effects of an increase in vessel traffic on air pollutant concentrations in Marseille. We follow a “causal inference pipeline” (Sommer et al. 2018, Rosenbaum et al. 2010, Bind and Rubin 2019, Sommer et al. 2021b) conceived to analyze observational data in a rigorous and transparent manner.

2.2.1 Stage 1: Formulating Plausible Interventions on Vessel Traffic

We are interested in the following causal question: *Does cruise vessel traffic contribute to background air pollutant concentrations in Marseille?* The “ideal” experiment would randomly allocate hours or days to high versus low cruise vessel traffic. We could then confidently attribute the resulting differences in pollutant concentrations to vessel emissions. In the absence of such randomized experiment in Marseille, we try to approximate an experimental setting by comparing pairs of short time series that are as similar as possible on a set of observed covariates but differ in their level of vessel traffic. We define below our hypothetical randomized experiments using the framework of the Neyman-Rubin Causal Model (Rubin 1974, Holland 1986, Rubin 2005).

The units, which we index by $t (t = 1, \ldots, T)$, are either hours or days spanning over the 2008-2018 period, depending on the time scale of the experiment considered. At the hourly level, $V_{t,f}$ is the sum of the gross tonnage of cruise vessels docking or leaving Marseille port during hour $t$ for flow direction $f \in \{\text{arrival, departure}\}$. We consider separately the total gross tonnage for cruise vessels’ arrivals and departures as they may contribute to air pollution in the city with a different time frame. For example, cruise vessels leaving the port may start running their engines a few hours before effectively leaving, and therefore generate pollution over a long period.
of time. Cruise vessels entering the port may also take time to finish maneuvering and generate emissions while they are docked. Our treatment indicator is $W_{t,f}$ and takes two values:

$$W_{t,f} = \begin{cases} 
1 & \text{if } V_{t,f} > 0 \\
0 & \text{if } V_{t,f} = 0 
\end{cases}$$  \hspace{1cm} (1)

Hourly units with $W_{t,f}$ equal to one are considered as “treated” while units with $W_{t,f}$ equal to zero belong to the control group. A treated hour is an hour with cruise vessels docking or leaving the port (depending on the value of $f$). A control hour is an hour for which there was no cruise vessel traffic for a specific flow.

At the daily level, we create an hypothetical randomized experiment based on the combined total gross tonnage of cruise vessels entering and leaving the port. We define $V_t$ as the sum of the gross tonnage of cruise vessels entering or leaving Marseille port on day $t$ — we therefore leave out the index $f$. Our treatment indicator is $W_t$ and takes two values:

$$W_t = \begin{cases} 
1 & \text{if } V_t > 0 \\
0 & \text{if } V_t = 0 
\end{cases}$$  \hspace{1cm} (2)

Daily units with $W_t$ equal to one are considered as “treated” while units with $W_t$ equal to zero belong to the control group. A treated day is a day with cruise ship traffic. A control day is a day without any cruise ship traffic.

Finally, in our setting, each hourly and daily unit has two continuous potential outcomes whose values range in the set of plausible pollutant concentrations in $\mu g/m^3$. For hourly units, the potential outcome under the control status is $Y_{t,f}(0)$ if $W_{t,f}=0$ and the treatment potential outcome is $Y_{t,f}(1)$ if $W_{t,f}=1$. For daily units, we have $Y_t(0)$ if $W_t=0$ and $Y_t(1)$ if $W_t=1$. 

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2.2.2 Stage 2: Designing the Hypothetical Randomized Experiments

At the design stage, our goal is to obtain a sample of similar units for which the assignment to the treatment and control groups can be assumed to be unconfounded (Rubin 1991). Formally, this unconfoundedness assumption states that the assignment to treatment is independent from the potential outcomes given a set of observed confounders. We use a pair-matching algorithm to obtain treated and control units with similar values for observed covariates. Matching is a nonparametric method which prunes the observations to limit the imbalance between treated and control units (Ho et al. 2007, Rubin 2006, Stuart 2010, Imbens 2015). Concretely, let \( X_t \) be the vector of observed covariates for each unit, with \( t \) the time indicator and \( X_t^{(k)} \) the \( k \)th covariate. Our algorithm matches a treated unit to a control unit only if the component-wise distances between their covariate vectors \( (X_t^{(1)}, X_t^{(2)}, \ldots, X_t^{(K)}) \) are lower than pre-defined thresholds \( (\delta_1, \delta_2, \ldots, \delta_K) \). For a pair of covariate vectors \( X_t \) and \( X_{t'} \), we use the following distance:

\[
\Delta_{X_t, X_{t'}} = \begin{cases} 
0 & \text{if } |X_t^{(k)} - X_{t'}^{(k)}| < \delta_k \text{ for all } k \\
+\infty & \text{otherwise}
\end{cases}
\] (3)

To limit confounding, we select two sets of covariates. First, calendar variables (i.e., hour of the day, day of the week, bank day, holidays, month, and year) are related to both vessel traffic and air pollution. Second, weather covariates (i.e., average temperature, rainfall indicator, average humidity, wind direction blowing either from the East or West, and wind speed) could also influence both vessel traffic and air pollution. We use lags of these variables to ensure that treated and control units are as similar as possible before the treatment occurs. We define matching thresholds noting that they should be strict enough to make treated and control units comparable with each other, but not too strict to avoid reducing the sample size too
much. Given this trade-off, the thresholds are stricter for the hourly experiment for which the sample size is 24 times larger. Table 1 displays all thresholds values used in our matching procedure.

At the hourly level, we match exactly on calendar variables (hour of the day, day of the week, bank days, holidays) over the current and two previous hours before the treatment occurred (i.e., 0, 1, 2 lags) and allow a maximum distance of 30 days between treated and control units. For weather parameters, we carried out an iterative process, for which we tried different discrepancy values and kept the ones that led to balanced treated and control groups while resulting in enough matched pairs. We found that a maximum discrepancy of around half a standard deviation often yields a good balance. We match exactly for the East and West wind directions because they play an important role in the dispersion of air pollutants.

At the daily level, we create similar pairs of treated and control units over the current and previous day before the treatment occurred (i.e., 0 and 1 lags). We relax some of the constraints from the hourly level to have enough matched pairs. We strictly match on the day of the week, bank days, and holidays over the two days of the series. We allow treated and control units to have up to two years of difference, but with a maximum of three months difference (for example, a Monday in December 2008 can be matched to a Monday in March 2010, but not to a Monday in July 2008). For weather parameters, we match exactly on the rainfall indicator and the wind direction on days $t$ and $t-1$, and we allow a small discrepancy threshold for temperature and wind speed on $t$ and $t-1$.

Based on these thresholds, each treated unit is matched to its closest control unit using a maximum bipartite matching algorithm (Micali and Vazirani 1980). If no control unit is available to match a treated unit, it is discarded. We thus approximate the design of a pair randomized experiment where the assignment mechanism is a Bernoulli trial with a treatment probability of 0.5. Given this design, for each
hypothesised experiment, the number of possible permutations is \(2^P\), with \(P\) being the number of matched pairs.

**Table 1:** Maximum Discrepancies allowed for each Covariate between Treated and Control Units.

| Calendar Indicators          | Hourly | Daily |
|------------------------------|--------|-------|
| Distance in days             | 30     | 720   |
| Hour of the day in \(t\)     | 0      |       |
| Weekday, Bank Days and Holidays in \(t\) | 0 | 0   |
| Weekday, Bank Days and Holidays in \(t-1\) | 0 | 0 |
| Weekday, Bank Days and Holidays in \(t-2\) | 0 |     |
| Month in \(t\)               | 3      |       |

| Weather Parameters           | Hourly | Daily |
|------------------------------|--------|-------|
| Average Temperature (°C) in \(t\) | 4    | 4     |
| Average Temperature (°C) in \(t-1\) | 4 | 4   |
| Average Temperature (°C) in \(t-2\) | 4 |     |
| Rainfall Dummy in \(t\)      | 0      | 0     |
| Rainfall Dummy in \(t-1\)    | 0      | 0     |
| Rainfall Dummy in \(t-2\)    | 0      |       |
| Average Humidity (%) in \(t\)| 9      |       |
| Average Humidity (%) in \(t-1\)| 9 |     |
| Average Humidity (%) in \(t-2\)| 9 |     |
| Wind direction in two categories (East/West) \(t\) | 0 | 0   |
| Wind direction in two categories (East/West) \(t-1\) | 0 | 0   |
| Wind direction in two categories (East/West) \(t-2\) | 0 |     |
| Wind speed (m/s) in \(t\)    | 1.8    | 2     |
| Wind speed (m/s) in \(t-1\)  | 1.8    | 2     |
| Wind speed (m/s) in \(t-2\)  | 1.8    |       |

*Notes:* This table displays the maximum distance allowed for each covariate in the pair matching algorithm. Distances between treated and control units are presented for hourly and daily experiments. For example, it means that, for each matched pair, treated and control units must have the same values for weekday, bank days and holidays indicators in \(t\). If a discrepancy value is missing, it means that the associated covariate was not used in the matching procedure.

### 2.2.3 Stage 3: Analyzing the Experiments using Randomization-based Inference

**Point estimate.** As a point estimate of a Fisherian interval, we take the observed value of the average of pair differences in a pollutant concentration, which is also our test statistic. As argued by Keele et al. (2012), if the assumption of a constant additive treatment effect is true, this difference in means is an unbiased estimator.
Randomization-based quantification of uncertainty. We carry out a test-inversion procedure to build 95% Fisherian (also called “Fiducial”) Intervals (FI) for the constant unit-level treatment effect. We closely follow the procedure detailed by T. Dasgupta and D.B. Rubin in their forthcoming book (Dasgupta and Rubin 2021). Instead of gauging a null effect for all units, we test $J$ sharp null hypotheses $H_{0j}^i$: $Y_{ij}(1) = Y_{ij}(0) + \tau_j$ for $j = 1, \ldots, J$, where $\tau_j$ represents a constant unit-level treatment effect size. We test 201 sharp null hypotheses of constant treatment effects ranging from -10 µg/m$^3$ to +10 µg/m$^3$ with an increment of 0.1 µg/m$^3$. For each constant treatment effect $j$, we calculate the upper $p$-value associated with the hypothesis $H_{0j}^i$: $Y_{ij}(1) - Y_{ij}(0) > \tau_j$ and the lower $p$-value for $H_{0j}^i$: $Y_{ij}(1) - Y_{ij}(0) < \tau_j$. We run 100,000 permutations for each hypothesis to approximate the null distribution of the test statistic. Running the exact number of possible allocations is computationally too intensive given the number of matched pairs we found. The sequence of $J$ hypotheses $H_{0j}^i$: $Y_{ij}(1) - Y_{ij}(0) > \tau_j$ forms an upper $p$-value function of $\tau$, $p^+(\tau)$, while the sequence of alternative hypotheses $H_{0j}^i$: $Y_{ij}(1) - Y_{ij}(0) < \tau_j$ makes a lower $p$-value function of $\tau$, $p^-(\tau)$. To calculate the bounds of the 100(1-\alpha)% Fisherian interval, we solve $p^+(\tau) = 0.025$ for $\tau$ to get the lower limit and $p^-(\tau) = 0.025$ for the upper limit. We set our $\alpha$ significance level to 0.05, and thus calculate two-sided 95% Fisherian intervals. This procedure allows us to get the range of constant treatment effects consistent with our data (Rosenbaum et al. 2010, Dasgupta and Rubin 2021), and the hypothetical assignment mechanism we posit.

In SI Appendix, Section 6.1, we provide a detailed toy example for understanding each step of our procedure.
2.2.4 Stage 4: Interpreting the Results

The causal interpretation of our results relies on the plausibility of the hypothetical experiment and of the unconfoundedness assumption (Rubin 1991). This is a strong assumption as it states that the treatment assignment probability is not a function of potential outcomes given observed and unobserved confounding factors (Sekhon 2009).

In the case of the effect of cruise vessel traffic on ambient pollution, we also note that our causal estimates could capture the road traffic induced by cruise vessel passengers. This is part of the causal effect that we want to capture. We however note that road traffic flow appear to be relatively balanced across treated and control units in the matched samples of the three experiments (See SI Appendix, Section 5).

Finally, we insist that our results apply to our matched sample rather than to the full initial sample.

3 Results

We first present covariate balance diagnostics on how our matching performed. At the hourly level, we take the experiment for cruise vessel arrivals as a representative example. The matching performances of the other experiments at the hourly and daily levels are similar, as discussed in SI Appendix, Section 5. We then display results for the effects of hourly and daily cruise vessel traffic on air pollutant concentrations.

3.1 Matching Results

As shown in Table 2, our matching procedure at the hourly level results in few matched treated units, with less than 4% of treated units matched to similar control
Table 2: Number of Matched Pairs by Experiment.

|                      | Hourly cruise arriving | Hourly cruise departing | Daily cruise |
|----------------------|------------------------|-------------------------|--------------|
| $N_{\text{Total}}$  | 96,432                 | 96,432                  | 4,018        |
| $N_{\text{Treated}}$| 4,034                  | 4,037                   | 2,485        |
| $N_{\text{Control}}$| 92,396                 | 92,393                  | 1,532        |
| $N_{\text{Pairs}}$  | 138                    | 123                     | 285          |

Notes: This table displays the total number of observations, $N_{\text{Total}}$ for each experiment, the number of potential treated and controls units before matching, $N_{\text{Treated}}$ and $N_{\text{Control}}$, and the number of matched pairs, $N_{\text{Pairs}}$.

units for the experiments at the hourly level. Two main reasons explain this result. First, cruise vessel traffic is regular over time (see SI Appendix, Figure 2), so that it is hard to find similar hours with and without traffic. Second, even if we relax our matching constraints, it is difficult to find treated and control units with similar weather covariates. In Figure 2, Panel A displays the average increase in cruise vessel arrivals at hour 0. The average difference in gross tonnage between treated and control units is about 65,000 for the hourly cruise experiment, which is the average gross tonnage of one cruise vessel. Panel C shows that, on average, treated and control units have similar vessel traffic for other vessel types and flows. Overall, the matching improves the balance of calendar and weather covariates. In Panel B of Figure 2, we plot the distribution, before and after matching, of the standardized mean difference between treated and control units for all continuous covariates: standardized mean differences are clearly lower after matching for the cruise vessels’ arrivals experiment (See the SI Appendix, Sections 5.2 and 5.3 for similar figures for the other experiments).

At the daily level, we found 285 matched pairs, which means that 12% of the treated units were matched to similar control units. The average difference in gross tonnage between treated and control units is around 200,000. This amounts to a shock of approximately three cruise vessels of an average size. The variation in gross tonnage for other vessel types is similar across treated and control units (SI
Appendix, Panel B of Figure 37). Again, our matching procedure resulted in similar covariates. The balance of covariates not used as matching constraints also improved, including road traffic and pollutant concentrations at $t-1$ (SI Appendix, Figures 42-48).
Figure 2: Matching Diagnostics for the Experiment on Cruise Vessels’ Arrivals

Notes: All figures are based on the hourly experiment on cruise vessels’ arrivals. Panel A shows the average hourly total gross tonnage for matched treated and control units. Panel B displays the improvement in continuous covariates balance, measured as the standardized difference in means. Panel C plots the average difference in total gross tonnage between treated and control units by vessel type and flow.
3.2 The Effects of Cruise Vessel Traffic on Air Pollutants

In Figure 3, we plot the point estimates and the 95% Fisherian intervals of the constant treatment effects on concentrations of NO$_2$, SO$_2$, and particulate matter that are consistent with our data for the two hourly experiments (see SI Appendix, Figures 59 and 66 for results for ozone).

For NO$_2$, results for experiments on cruise arrivals and departures are mixed. When ships dock, there is no clear pattern for NO$_2$ measured at Saint-Louis. We observe a clearer trend for Longchamp station, which is further away from the cruise terminal. At hour 0, the point estimate is 4.7 µg/m$^3$ (95% FI: [1.4, 8.0]). There is, however, also a positive treatment effect before the treatment occurs: this could be consistent with the maneuvering phase of the ship as it enters the port or reveal the difficulty to obtain close pre-treatment outcomes. When vessels leave the port, we observe a decrease in NO$_2$ concentrations at Saint-Louis: this could be consistent with vessels starting their engines a few hours before leaving. The pattern is less clear for NO$_2$ concentrations at Longchamp.

For SO$_2$, we observe an increase in concentrations at hours 0, 1, and 2 following the arrival of cruise ships, with an increase in concentrations of 1.2 µg/m$^3$ at hour 0 (95% FI: [-0.1, 2.5]). There is not a clear variation of SO$_2$ concentrations when cruise ships leave the port: data are consistent with small negative, null, and positive effects that are relatively high compared with the average hourly concentration of SO$_2$. For particulate matter, we see an increase in PM$_{10}$ by 4.6 µg/m$^3$ measured at Saint-Louis when cruise ships dock (95% FI: [0.9, 8.3]). We cannot distinguish a particular trend for PM$_{10}$ and PM$_{2.5}$ measured at Longchamp station, although PM$_{2.5}$ concentrations seem to increase following the departure of cruise ships.
Figure 3: Effects of Cruise Vessel Traffic on Pollutant Concentrations at the Hourly Level.

Notes: The treatment occurs at hour 0. Dots represent the point estimate of the unit-level treatment effect on a pollutant concentration. Lines are 95% Fisherian intervals of constant treatment effects consistent with the data. The effects are plotted from the third lag to the third lead.

Figure 4 also shows mixed results for the daily experiment on cruise ships. For the two pollutants measured at Saint-Louis, NO$_2$ and PM$_{10}$, we observe a small increase in their concentrations. The point estimate of the 95% Fisherian interval for the effect of NO$_2$ in Saint-Louis at day 0 is equal to 1.2 µg/m$^3$ (95% FI: [-0.5, 3.0]). For PM$_{10}$, the point estimate is 1.3 µg/m$^3$ (95% FI: [-0.3, 3.0]) at day 0 but the range of consistent effects with the data was similar on the previous days. We do not observe any clear increase in pollutant concentrations measured at Longchamp station.

In the SI Appendix, Section 8.1, we report results for an alternative experiment where we compare short-time series of two days with an increase in cruise vessel traffic between Lag -1 and Lag 0 to short-time series with a stable cruise vessel traffic. The resulting traffic shock is 25% higher, and we observe a stronger increase by 2.9 µg/m$^3$ in NO$_2$ measured at Longchamp (95% FI: [-0.6, 6.3]) and by 1.1 µg/m$^3$ in SO$_2$ (95% FI: [0.0, 2.2]) concentrations on the treatment day. We however do
not see an impact for pollutants measured at Saint-Louis station for this alternative experiment.

**Figure 4:** Effects of Cruise Vessel Traffic on Pollutant Concentrations at the Daily Level.

![Graph showing effects of cruise vessel traffic on pollutant concentrations]

*Notes:* The treatment occurs at Day 0. Dots represent the point estimate of the unit-level treatment effect on a pollutant concentration. Lines are 95% Fisherian intervals of constant treatment effects consistent with the data. The effects are plotted from the first lag to the first lead.

We run two sensitivity analyses (see SI Appendix, Sections 7.2 and 7.3). First, because the pair differences in pollutant concentrations were particularly disperse, we use the Wilcoxon signed-rank test statistic, known to be less sensitive to outliers. The 95% Fisherian intervals obtained with this test statistic are similar to those obtained with the average of pair differences. Second, we reproduce the analysis on non-missing concentrations because up to 20% of pollutant concentrations were imputed in our matched data. We find similar results with slightly wider 95% Fisherian intervals.
4 Discussion

We start by discussing our results in view of the environmental science literature. We then reflect on the new statistical method used for our analyses. Finally, we suggest paths for future research assessing the causal impact of maritime traffic on air pollution.

4.1 Putting our Results into Perspective

Our results point to a potential short-term effect of cruise traffic on the concentrations of NO$_2$, SO$_2$, and PM$_{10}$. For the hourly experiment on cruise ships’ arrivals, our estimates for NO$_2$, SO$_2$, and PM$_{10}$ on the hour of treatment represent, respectively, 16% of the average NO$_2$ concentrations at Longchamp, 52% of the average SO$_2$ concentrations at Longchamp, and 15% of the average PM$_{10}$ concentrations at Saint-Louis. For the daily experiment, our estimates for NO$_2$ and PM$_{10}$ on the day of treatment represent 3% of the average daily NO$_2$ concentrations and 4% of the average daily PM$_{10}$ concentrations at Saint-Louis. However, our 95% Fisherian intervals are often wide, and the implied degree of randomization-based uncertainty can be quite large relative to the average concentration of these pollutants.

Directly comparing our results to those found in the atmospheric science literature is difficult for several reasons. First, they are based on other methods - either source apportionment techniques or dispersion modeling - and usually only report average effects without comparable measures of uncertainty. Second, they often consider the entire traffic of vessels rather than isolating the impact of a pre-defined treatment focusing on one vessel type, as we do. Third, recent literature reviews have shown that contribution of vessel emissions to local air pollution depends highly on the port-city considered and the procedure carried out by researchers (Viana et al. 2014, Murena et al. 2018). We can nonetheless assess whether our
causal estimates are of the same order of magnitude as estimates from the atmospheric sciences literature.

For gaseous pollutants such as NO$_2$ and SO$_2$, the atmospheric science literature has mostly used approaches starting with emission inventories and inferring how emissions turn into concentrations using dispersion modeling (Viana et al. 2014). The few studies on ports from the Mediterranean area find different contributions of maritime traffic to city-level concentrations depending on the size of the city, the location of the monitoring stations, the prevailing wind patterns, the type of boat considered and the assumptions used in the emissions inventory (Murena et al. 2018). These estimates typically take into account all the phases where a vessel may contribute to pollution, in particular the hotelling phase, while our experiment focuses on the navigation phase when vessels enter or leave the port. For NO$_2$, estimates range from 1.2-3.5% for the contribution of cruise ships in summer in Naples, a city three times more populated than Marseille, to 32.5% for the contribution of all types of ships in the Italian city of Brindisi, much smaller than Marseille (Merico et al. 2016). Our estimated contribution of a positive cruise traffic to NO$_2$ concentrations is close to the estimates for the study in Naples which also focuses on cruise traffic. The estimates for SO$_2$ range from 1.5% for Naples in winter to 46% for Brindisi in summer. In contrast, we do not observe an impact of cruise vessel traffic on daily SO$_2$ for the main daily experiment. We however find a positive contribution of cruise traffic to SO$_2$ concentrations, when we consider an alternative experiment with a higher treatment intensity, comparing days with an increase in cruise traffic to days with a stable cruise traffic.

For particulate matter, atmospheric science studies often use source apportionment methods, consisting in monitoring particles near the port for a few months and tracing back the origin of different particles based on the statistical decomposition of chemical data acquired at monitoring sites (Sorte et al. 2020, Viana et al.
Our estimated contribution of cruise traffic to daily PM$_{10}$ concentrations are broadly consistent with such studies on other Mediterranean ports: estimates for the contribution of vessels to PM$_{10}$ concentrations range from 1.1% for Rijeka in Croatia up to 11% for Genoa in Italy (Merico et al. 2016, Bove et al. 2014).

The media and non-governmental organizations have insisted on the high contribution of vessel traffic, and in particular cruise vessel traffic, to city-level emissions as measured by emission inventories (de la rédaction 2019, Environment 2019). According to emission inventories, vessel traffic contributes to 40% of NO$_2$ emissions in Marseille in 2018 (AtmoSud 2020). Our estimates, based on the specific impact of cruise vessels during the maneuvering phase (and the hotelling phase on the day of arrival for the daily experiment), may imply a lower contribution of cruise vessel traffic to concentrations compared to its contribution to total emissions. Inferring the responsibility of different sources over pollution based on emission inventories only could hide important disparities in how sectoral emissions translate into city-level concentrations. We contrast the relatively small contribution of cruise ships to NO$_2$ concentrations in our estimates with the contribution of road traffic, which can be inferred from a simple comparison between weekdays and weekends (see SI Appendix, Section 8.2). Because they are balanced in terms of weather covariates, the difference in observed concentrations between weekdays and weekends can be attributed to differences in economic activity only, and in particular to differences in road traffic. Road traffic decreases by 20% on average on Saturdays and Sundays. In parallel, NO$_2$ concentrations decrease by 20% of their average level at the Saint-Louis station. Although other sources of pollution may be less intense on weekends, the road traffic and NO$_2$ time series follow an extremely similar pattern, suggesting a strong contribution of road traffic to ambient concentrations compared to maritime traffic. More systematic assessments are needed to understand the relative contribution of different sources to ambient concentrations in order to estimate the
benefits of abatement in each sector and prioritize policies.

4.2 Reflection on the Methods

The causal inference pipeline we follow helps to clearly distinguish the design stage of our study — where we create hypothetical experiments — from its statistical analysis. Our pair-matching procedure has two notable advantages. First, it prunes treated units for which we cannot find a similar control unit, and thereby avoids extrapolating treatment effects for units without any empirical counterfactuals. In a way, a matching procedure reveals the common support available in the data from which we can draw our statistical inference. Second, our approach adjusts for covariates in a nonparametric way and achieves balance between treated and control units on observed covariates. This is another advantage, as it is often hard to guess what functional forms are needed to adjust for confounding factors (Cochran and Rubin 1973, Ho et al. 2007, Imbens 2015).

Yet, drawing randomization-based inferences from high-frequency observational data also poses inherent difficulties. Finding comparable treated and control units is challenging. At the hourly level, it is difficult to match a treated unit with a control unit because vessel traffic is very regular within different periods of the year. For instance, cruise vessels nearly always dock in the port at particular hours and days of the week—leaving few control hours without any cruise traffic. In addition, obtaining days with close weather patterns over several consecutive days is extremely difficult: at the hourly level, it was nearly impossible to find similar pairs over three lags of covariates.

Surprisingly, even if we strive to find similar pairs of treated and control units, we observe a wide heterogeneity in pair differences in pollutant concentrations, which makes it difficult to precisely estimate the potential contribution of vessel emissions. In our study, we are therefore confronted with a trade-off between the
comparability of units within pairs and the sample size on which we base our statistical analysis. Analyzing the full sample using a multivariate regression model delivers more precisely estimated effects and, for hourly experiments, point estimates closer to 0 (see SI Appendix, Section 7.4). This regression-based approach however does not provide an explicit imputation of the missing potential outcomes. It also relies on its ability to correctly model the functional form to adjust for confounders and to extrapolate treatment effects outside the support of the data. In the context of cruise-ship port traffic, we believe that the assumptions underlying our pair matching algorithm are more plausible than those necessary for multivariate regression.

Regarding the statistical inference procedure, randomization-based inference allows us to avoid large-sample approximations and makes no assumption on the distribution of our test statistic under the sharp null hypothesis (Rosenbaum et al. 2010, Bind and Rubin 2020). Given that we deal with small sample sizes and provided that our treatment effect assumptions are correct (e.g., constant and additive causal effect, unconfoundedness of the treatment), we believe that our procedure offers a more appropriate quantification of uncertainty in our estimates. However, randomization-based inference, as any inference mode, does not overcome issues implied by having a low statistical power to detect plausible effect sizes of cruise traffic on air pollution. In the SI Appendix, Section 7.5, we carry out a post hoc design analysis for each experiment (Gelman and Carlin 2014, Gelman et al. 2020). Given the size of our matched sample, we would have a low statistical power if the true effect of cruise vessel traffic on pollutant concentrations was low: estimated effects that are “statistically significant” would overestimate the true effect of vessel traffic on pollutants. Simulations should be implemented to better guide future research on this specific issue.

Last, our randomization-based inference procedure relies on the stringent as-
sumption that the treatment is constant, while it might have been of interest to estimate the average treatment effect and quantify its uncertainty for each hypothetical experiment. We therefore provide results from a Neymanian inference perspective (Imbens and Rubin 2015, Splawa-Neyman et al. 1990). In the SI Appendix, Section 7.3, we calculate for each experiment the estimates of the average treatment effects and their associated 95% confidence intervals. Although based on a different interpretation of the data, results from Fisherian and Neymanian inference are substantively similar. We could also have implemented a Bayesian model-based approach, which explicitly imputes the missing potential outcomes given the observed data and can target a variety of estimands (Bind and Rubin 2019, Imbens and Rubin 2015, Rubin 1978).

4.3 Potential Paths for Future Research

We see at least three main improvements for future research on the effects of maritime traffic on air pollution. First, it would be useful to exploit data on the duration vessels keep their engines running while docked at the port, as several studies indicate that a large share of air pollutant emissions occur during this phase (project 2015, Murena et al. 2018). Second, monitoring stations in Marseille only measure some pollutants and are located relatively far away from the port. It would be useful to carry out similar analyses as ours in a port city where pollutants such as ultrafine particles are monitored and with receptors located in the port at different heights (Viana et al. 2014, Mocerino et al. 2020). Third, several areas have implemented regulations to decrease the sulfur content of vessel fuel. This type of policy is particularly well-suited for causal inference methods such as interrupted-time series, difference-in-differences, and synthetic control (Kotchenruther 2017, Grange and Carslaw 2019, Zhu and Wang 2021). Researchers could estimate how pollutant concentrations evolved before and after the policy was implemented by comparing
the treated area to control areas.

4.4 Concluding Remarks

Our study is a complementary approach to current source-apportionment and dispersion modeling methods. We provide very detailed replication materials in the hope that researchers could implement our method for other ports. We believe that well-designed observational studies relying on a causal inference pipeline could bring new insights on the environmental and health consequences of maritime activities.

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