<div align="center">**Detailed Description of Proposed Research:**</div>

Project: Quantifying the response of maritime shipping CO_2 emissions to economic shocks

Objective: There are three goals. First, we quantify weekly, fleet-level CO_2 emissions from worldwide maritime shipping activity before and during the COVID pandemic. Second, we examine the change in CO_2 emissions from maritime shipping during the COVID pandemic in terms of changes in bilateral trade volumes and provide a decomposition analysis. Third, we estimate the heterogenous elasticities of CO_2 emissions from maritime shipping with respect to international trade using the COVID pandemic demand shock as a source of significant variation, which may be used for conducting a counterfactual analysis of future change in international trade on CO_2 emissions.

Context: Global trade is intricately linked with maritime shipping, which transports over 80% of the volume of all traded goods and around 70% of their value (United Nations Conference on Trade and Development, 2017). At the same time, ships contribute about 3% of global CO_2 emissions, roughly equal to the total emissions of Germany (Faber et al., 2020). These emissions lie outside the scope of national emissions tallies, and fall instead under the jurisdiction of the International Maritime Organization (IMO), which has set a target of a 50% reduction by 2050. The stringency of abatement actions required to meet this goal clearly depends on how trade will evolve over the coming decades, and a thorough understanding of this relationship is essential for effective policy.

While trade volumes typically vary slowly, the COVID pandemic induced substantial variation over a short period: World merchandise trade decreased by more than 10 percent in the first three months of the pandemic before recovering over the following two years (Arriola et al., 2021). We first measure the change in shipping emissions before and during this period using high-frequency data of ships' movements, which we then relate to the change in bilateral trade volumes between country pairs. By exploiting the large variation in shipping, we estimate the short- to medium-run elasticity of CO_2 emissions from maritime shipping with respect to international trade. In doing so, we provide an important quantitative analysis to inform policymakers in assessing the effectiveness of emissions regulations.

Quantifying the elasticity of shipping emissions to trade is challenging for a number of reasons. A ship's fuel consumption depends on many factors, including its size and age, with newer and larger ships typically more efficient. The existing fleet is

extremely heterogeneous: Figure 1 illustrates the large variation across both dimensions in just a subset of ships, namely small to medium bulk carriers (This excludes the largest class up to 400'000 deadweight tonnes (DWT)). Furthermore, new ships have become larger over time. Ship size is related to the volume of trade, the type of products shipped, and port and canal infrastructure. As such, different bilateral trade relationships involve different sizes of ships and hence different fuel efficiency, leading to heterogenous emissions–trade elasticity across different country pairs. In addition, the presence of trade imbalances means ships often travel without cargo on certain routes. Finally, fuel consumption depends roughly cubically on speed, meaning that the short-run elasticity of emissions to shipping demand may be quite large and may fluctuate over time with the price of fuel.
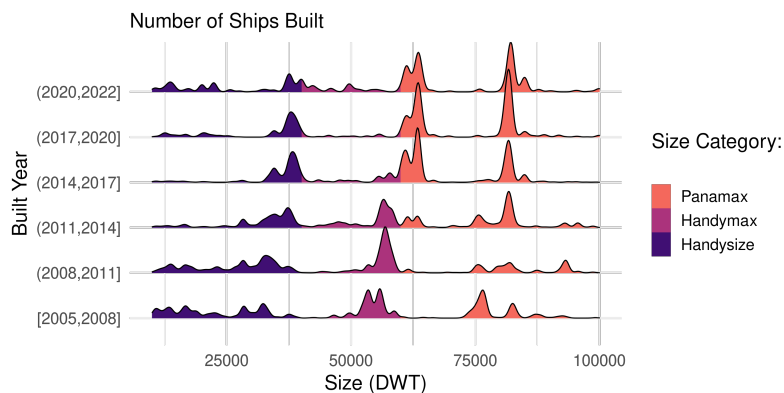

Figure 1: Existing fleet of bulk carriers between 10'000–100'000 by size and built year.

The most extensive existing literature quantifying shipping emissions comes from the IMO itself, in cooperation with a handful of related organizations: The Fourth IMO GHG Study 2020 (Faber et al., 2020) details both bottom-up and top-down methodologies for calculating emissions. Their bottom-up approach employs data collected from ships' automatic identification systems (AIS) which transmit the location and speed of each ship every few minutes. This approach has been developed by various authors, including Jalkanen et al. (2009), Olmer et al. (2017), and Johansson et al. (2017). In order to estimate CO_2 emissions, they combine AIS data with ship fuel consumption ratings and aggregate. Our approach is similar, but leverages actual emissions reports to estimate fuel efficiencies.
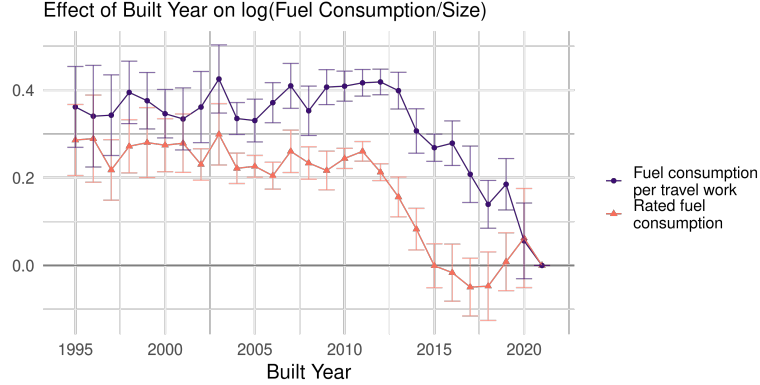
Effect of Built Year on log(Fuel Consumption/Size)

Figure 2: update, tidy, fix labels Error bars represent 95% confidence intervals for errors clustered at the individual ship level.

A small number of authors have explored the relation between trade and shipping. Cristea et al. (2013) and Shapiro (2016) take macroeconomic approaches to look broadly at emissions from all transporation modes invovled in trade. Focusing on maritime shipping, van der Loeff et al. (2018) and Liu et al. (2019) link AIS data with granular indicators of trade volumes to create region-specific estimates. Most closely related to our work, Wang et al. (2021) calculate bilateral seaborne trade volumes and link them with shipping emissions estimated from AIS data. They provide a snapshot of values for the year 2018 and develop a model based on nominal efficiencies for exploring counterfactuals. With a more empirical approach Brancaccio et al. (2018) explore the elasticity of trade with respect to ship fuel costs. Our work will be among the first to seriously explore the relationship in the opposite direction — from trade to emissions — on a global scale. We borrow from the methods of Wang et al. (2021), but we propose a novel empirical method to estimate efficiencies using reported fuel consumption from the European Union's Monitoring, Reporting, and Verification (MRV) program. Furthermore, we leverage COVID-related variations to calibrate and validate our model. The use of actual reported emissions allows us to capture more of the previously discussed adjustment channels, and the large cross-sectional/time-series variation in shipping activity during the COVID pandemic aids identification.

Methodology: We first estimate how a ship's fuel consumption efficiency is determined by ship's speed, location, draft, and ship's observed characteristics. Then we

compute high-frequency emissions estimates for each ship's voyages between ports. This first stage relies on three key datasets that we have obtained: (i) AIS tracking data, (ii) the World Fleet Register, and (iii) the MRV data.

We have obtained hourly AIS tracking data for the entire fleets of bulk carriers and containerships from the beginning of 2019 to the end of 2021. This includes information on speed, location, and draft (the vertical distance between the waterline and the bottom of the hull), which can be used to determine whether a ship is carrying cargo or not. This data is then matched to the World Fleet Register from Clarksons Research, which is a virtually complete listing of all large merchant ships. It includes basic information on each ship, including built year, size, and type, and for many ships includes highly detailed technical characteristics such as hull dimensions, engine power, propeller details, etcetera. Finally, this can be further linked to publicly available data collected through the European Union's Monitoring, Reporting, and Verification (MRV) regulation, which provides annual fuel consumption and emissions for trips into and out of the EU ("EU trips," hereafter). This data begins in 2018 and naturally includes only ships with portcalls in the EU.

Our methodology of estimating the fuel efficiency builds on that of the IMO as detailed in Faber et al. (2020) and follows closely the data cleaning and matching procedures described therein. However, whereas they use theoretical fuel consumption values corresponding to rather coarse ship size- and age-bins, we propose to empirically estimate more ship-specific fuel efficiencies. In particular, we use actual fuel consumption data from the MVR data while Faber et al. (2020) does not use any fuel consumption data by themselves— rather, fuel consumption is computed using pre-determined formula based on theoretical assumption on specific types of ships. By using actual fuel consumption data, we hope to better estimate how fuel consumption is determined under actual operating conditions.

Our procedure consists of following steps. First, we estimate how fuel efficiency is determined by operating conditions (speed, draft) and ship characteristics (age, deadweight tonnage etc.) using the data on EU trips reporting in the MRV dataset. Then, we extrapolate these efficiencies to non-reporting ships, i.e., ships that never stopped at any EU ports, based on their operating condition and ship characteristics. Given ship efficiencies, we can calculate a monthly emission estimate for each ship. Finally, these estimates can be aggregated at any desired level. To our knowledge, this will be the first work to employ the MRV data to estimate fuel efficiency. Ugé et al. (2020) also link MRV data with AIS data, but they use it in the opposite sense,

namely to validate reported emissions in the MRV.

We detect trips between ports from the tracking data. We detect stops based on a ship speed threshold and a location near to land and denote a trip as a trip between any two stops. To ensure the accuracy of our data, we then use data only for ship-year observations for which the total distance of detected trips to/from the EU agrees closely with the distance reported in the MRV data.

As a preliminary investigation, we have estimated fuel efficiencies for bulk carriers, regressing fuel efficiency on a set of ship characteristics (using logs of all variables) as well as built-year fixed effects.

$$\log \left(\frac{fuel\ consumption}{size \cdot \sum_{x \in X} \cdot s_x^2 \cdot x} \right)_{it} = \delta age_{it} + \boldsymbol{\beta} f(Z_i) + \varepsilon_{it}, \tag{1}$$

where $fuel\ consumption$ is an observed annual consumption, $size$ is the ship's capacity in deadweight tonnage, s_x and x are the average speed and distance of each trip [check if this is a correct description], Z_i is a vector of ship's characteristics (including $size$), and $f(\cdot)$ is an unknown function, which we use semi-parametric sieve method using B-splines as well as machine learning tools (e.g., random forest, deep neural network) to estimate.

Figure 2 plots the coefficients for the built-year fixed effects for our preliminary estimation based on log-linear specification and indicates that efficiency after controlling for size is surprisingly flat for ships built before roughly 2013, after which efficiency improved. fairly sharply and significantly. Importance of age. Difference between rated and actual! This agrees well with the analysis of evolution of new ship efficiency from Faber et al. (2015, Figure 15). The current specification does not include the effects of laden status or weather but we plan to include the draft level in the AIS data as well as wind/wave speeds using detailed weather data.

A limitation of our proposed approach is that the fuel consumption data is annual and there may be significant error in calculating the travel work over such a long time period. On the other hand, the advantage of this approach over that used by Faber et al. (2020) is that it relies less on theoretical assumptions. We plan to compare our CO_2 emission estimate with the estimate from Faber et al. (2020).

Second, using the estimated fuel consumption for each ship's trip, we compute the worldwide CO_2 emissions within each month of the years from 2017 to 2022 by aggregating fuel consumptions across all trips. Furthermore, we identify fuel consumption at port level, i.e., the fuel consumption associated with maritime shipping

from port A to port B by aggregating all trips taken from port A to port B in each month. Then, by aggregating all ports within each country for source and destination country, we estimate the monthly CO_2 emission associated with maritime shipping from country A to country B. This allows us to analyze the source of a change in the worldwide CO_2 emission by decomposing it as the sum of a change in (directional) bilateral trade flows across different countries and direction. Here, we take into account of trade imbalance by identifying ship loading and unloading at each port using the high frequency data on the level of draft, where 42% of ships are found to be travelling without cargo (Brancaccio et al., 2020).

Finally, we model the elasticity of CO_2 emissions from maritime shipping with respect to the trade volume from country A to country B for any country pair that involves maritime shipping. The idea is that we estimate the elasticity of CO_2 emission that are specific to ship categories (type, size, age) and shipping route (different directional trade involves different utilization of ships due to trade imbalance) and then compute the elasticity of CO_2 emission with respect to trade volume from country A to country B by aggregating the elasticities across different ship categories using their observed empirical weights for shipping from country A to B.

Describe trade data, seaborne trade calculation as per Wang et al. (2021), and use

Specifically, we create multiple categories of ships based on ship types (containerships, bulk carriers, and tankers), sizes, and ages. For each category, we estimate a version of the fuel efficiency equation (1). As a benchmark, we evaluate the equation at the observed average speed and the average level of draft for each category of ships travelling from country A to B. This will allow us to compute the elasticity of fuel consumption (and CO_2 emission) with respect to an increase in trade volume shipped from country A to B. Note that these elasticities are different across ship categories; furthermore, it depends on the average speed and the average level of draft. The route-specific level of draft is also used to adjust the utilization of ship capacity to take into account of trade imbalance so that, for some ship route (e.g., shipping from China to Australia), the amount of traded goods shipped is much less than what the observed ship movements from China to Autrlia imply because many ships are near empty.

The elasticity of CO_2 emission with respect to trade volume depends on shipping speed, capacity utilization, and ship size. The required fuel consumption and, hence, the CO_2 emission is less if the slower the speed, the higher the capacity uti-

lization, and the larger the size of ships. Using the estimated elasticities, we plan to evaluate the impact of implementing the following two policy regulations on CO_2 emissions. First, we evaluate the effect of regulating the maximum speed of ships on CO_2 emissions. Second, we evaluate the effect of regulating the minimum capacity utilization of ships. The proposed analysis has two important limitations. First, our analysis abstract away from the general equilibrium effect. Second, our project has limited scope in that we don't analyze the CO_2 emission from production of trade goods. Nonetheless, we hope that our analysis will provide an important stepping stone for future, more comprehensive quantitative analyses. think about these counterfactuals need to include mention of existing regulations if discussing regulation counterfactuals?

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