Detailed Description of Proposed Research:

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 cubicly 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.

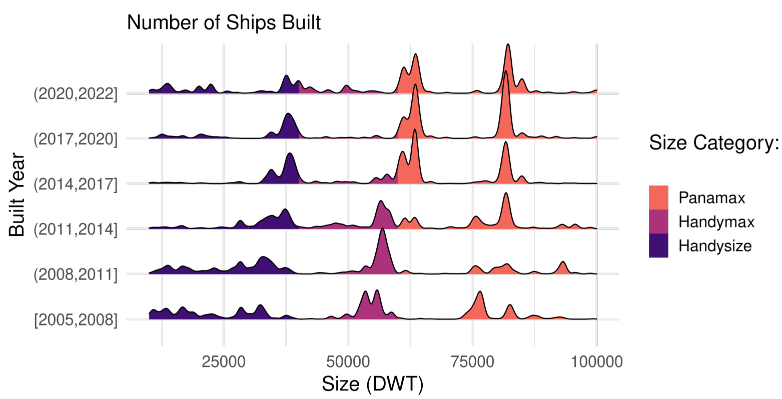

Figure 1: Existing fleet of bulk carriers between 10'000–100'000 by size and built year.

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.

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 (EU) 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. We match this data to the World Fleet Register from Clarksons Research, which is a virtually complete listing of all large merchant ships that 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 we further link this to publicly available data from the EU's 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 for estimating fuel efficiency builds on that of the IMO as detailed in Faber et al. (2020). However, whereas they use theoretical fuel consumption values corresponding to rather coarse ship size- and age-bins, we empirically estimate ship-specific fuel efficiencies using actual fuel consumption data and all available ship characteristics.

Our procedure is as follows. First, we identify trips from the AIS data as between two stops of a sufficient length in proximity to land, and flag EU trips as those with at least one stop within the EU. To ensure the accuracy of our data, we 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. Next, we estimate how fuel efficiency, accounting for the detected EU trip operating conditions (speed, draft), is determined by ship characteristics (age, size, etc.) using the fuel consumption data for EU trips from the MRV dataset. Then, we extrapolate these efficiencies to non-reporting ships — ships that did not stop at an EU port — based on their operating conditions and ship characteristics. 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.

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.

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

where $fuel\ consumption$ is reported annual consumption, $size$ is the ship's capacity in deadweight tonnage, x is the distance travelled at each speed s_x, Z_i is a vector of ship's characteristics (including $size$), and $f(\cdot)$ is an unknown function, which we use semi-parametric sieve methods using B-splines as well as machine learning tools (e.g., random forest, deep neural network) to estimate.

Figure 2 plots the built-year fixed effects for our preliminary estimation based on a log-linear specification. Efficiency is surprisingly flat for ships built before roughly 2013, after which it improved sharply. This agrees well with the analysis of evolution of new ship efficiency from Faber et al. (2015, Figure 15). We also include estimates using the rated, rather than the actual fuel consumption, which illustrates the difference between these approaches. 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.

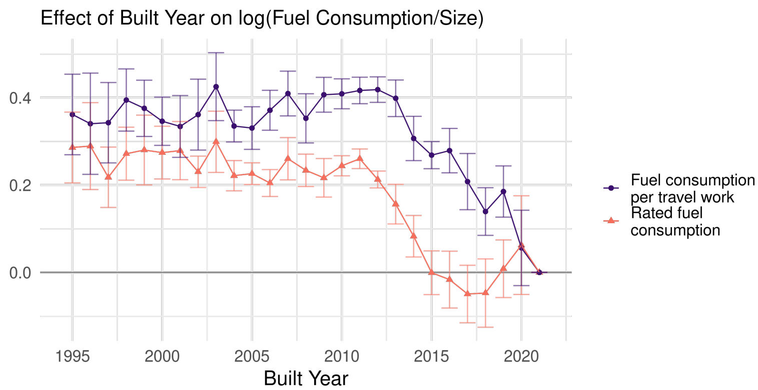

Figure 2: Built year fixed effects from efficiency regression (1). Error bars represent 95% confidence intervals, with errors clustered at the individual ship level.

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 with regards to the approach of Faber et al. (2020) is that it relies less on theoretical assumptions. For CO_2 emissions estimates, we plan to compare our estimate with that of Faber et al. (2020).

Using the estimated fuel efficiency for each ship and its travel history, it is straightforward to compute the worldwide CO_2 emissions within each month of the years from 2017 to 2022 by aggregating fuel consumptions across all ships. This allows us to identify fuel consumption for each origin-port – destination-port pair by aggregating all trips taken from port A to port B in each month. Further aggregating all ports within each country, we estimate the monthly CO_2 emissions associated with maritime shipping from each origin country to each destination country. 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 directions. We emphasize the importance of directionality — around 42% of bulk carriers travel without cargo due to trade imbalances (Brancaccio et al., 2020) — and account for it by identifying ship loading and unloading at each port using the level of draft from AIS data.

Finally, we model the elasticity of CO_2 emissions from maritime shipping with respect to the trade volume from origin country to destination country for any country pair that involves maritime shipping. The idea is that we estimate the elasticity of CO_2 emissions specific to ship categories (type, size, age) and origin-desination pair and then compute the elasticity of CO_2 emissions with respect to trade volume from each origin country to each destination country by aggregating the elasticities across different ship categories using their corresponding observed empirical shipping weights.

Are we using actuall trade data or implied trade volumes from AIS? If former, describe trade data, seaborne trade calculation as per Wang et al. (2021), and use

Specifically, we create multiple categories of ships based on ship type (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 Australia 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 utilization, 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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