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 a change in the worldwide CO_2 emissions from maritime shipping before and during the COVID pandemic. Second, we examine a source of a change in the worldwide CO_2 emissions from maritime shipping during the COVID pandemic in terms of a change in different 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 the worldwide CO_2 emissions.

Context: Global trade is intricately linked with maritime shipping, which carries 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, maritime ships contribute about 3% of global CO_2 emissions, roughly equal to the total emissions of Germany (Faber, Hanayama, Zhang, Pereda, Comer, Hauerhof, and Yuan, 2020). These emissions lie outside the scope of national emissions tallies, and fall instead under the jurisdiction 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. A continuation of the trend of increasing trade would make this goal much more difficult to hit. Faced with this uncertainty, the IMO and its consituent countries are developing and implementing policies to reduce shipping emissions, with new efficiency regulations being phased in this year.

The trade volumes substantially fluctuated during the COVID pandemic, where world merchandise trade decreased by more than 10 percent in the first three months of COVID pandemic and then slowly recovered over next two years (Arriola et al., 2021). In this project, we measure a change in the worldwide CO_2 emissions before and during the COVID pandemic using the detailed high-frequency satellite data of ships' movements and analyze the source of a change in in the worldwide CO_2 emission, i.e. a change in bilateral trade volumes across different bilateral relationships as well as across different traded products. Furthermore, by exploiting a large variation in international shipping that resulted from the COVID pandemic, we estimate the elasticity of of CO_2 emissions from maritime shipping with respect to international trade, and quantitatively examine how a change in trade volumes affects the CO_2 emission from maritime shipping to inform policy makers.

Quantifying this elasticity of CO_2 emissions with respect to trade volumes is important for predicting how an increase in international trade affects CO_2 emissions in future. Yet, it is challenging for a number of reasons. A ship's fuel consumption depends on various factors, including its size and age (newer and larger ships tend to be more efficient) and the existing fleet is extremely heterogeneous. As an illustration, Figure 1 shows the existing fleet size distribution measured by deadweight tonnage (DWT) for bulk carriers below 100,000 DWT in size (this excludes the largest classes up to just over 400,000 DWT). Is this a good figure to include? Is it better to use MRV emissions plots instead? Because ship sizes are related to types of products shipped as well as port infrastructures, different bilateral trade relationships involves different sizes of ships and hence fuel efficiency, leading to heterogenous trade elasticity across different country pairs. Furthermore, fuel consumption per tonnage depends roughly cubicly on speed, meaning that the short run elasticity of emissions to demand may be quite large and may fluctuate over time as fuel cost or other factors changes. Finally, the presence of trade imbalance leads to ship travels without cargo, making it complicated to estimate the relationship between fuel consumption and trade volumes from the data on ship movements.

The most extensive existing literature regarding shipping emissions comes from the IMO itself, in cooperation with a handful of related industry organizations. In particular, 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 relies on high frequency tracking data and has been developed and employed by various authors (e.g. Olmer et al. (2017); Johansson et al. (2017); Jalkanen et al. (2009); van der Loeff et al. (2018)). All ships are equipped with automatic identification system (AIS) transceivers which transmit information about the location and speed of each ship every few minutes. In order to estimate emissions, this information is combined with ship fuel consumption ratings and aggregated.

With regards to relating trade to shipping activity, Brancaccio et al. (2018) explore the elasticity of trade with respect to ship fuel costs. Our work will be some of the first to seriously explore the relationship in the opposite direction - from trade to emissions. To the best of our knowledge, our work will be the first to utilize actual reported emissions to empirically estimate ship efficiencies on a large scale, which allows for more of the previously mentioned channels to be captured. In addition, our

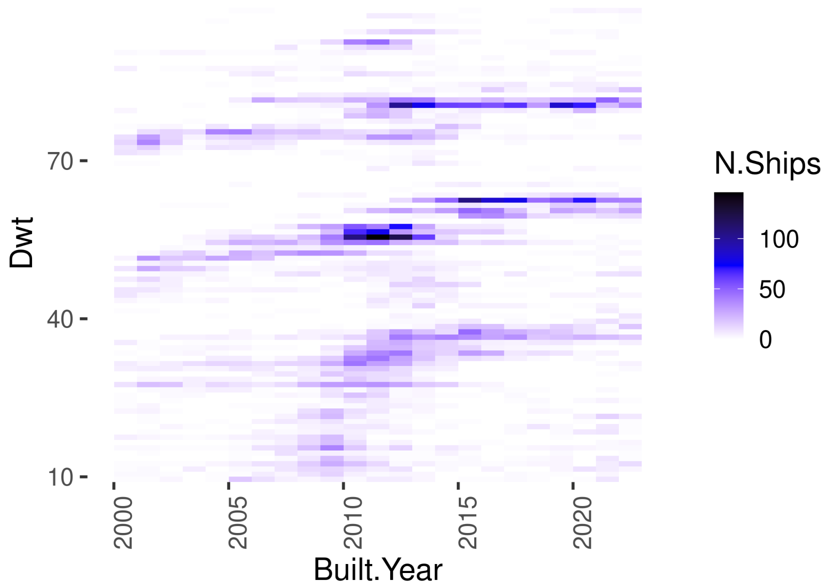

Figure 1: Number of new ships by size (Dwt) and built year fix labels

approach is novel in its use of machine learning to extrapolate efficiencies for ships without reported emissions. Furthermore, we are not aware of any literature yet that exploits the large variation in shipping activity due to COVID to explore emissions. With these contributions, we hope to provide important quantitative estimates to help inform policy makers in assessing the effectiveness of emissions regulations and setting their stringency levels going forward.

Methodology: We first estimate how ship's fuel consumption efficiency is determined by ship's speed, location, draft, and ship's observed characteristics and compute the high-frequency disaggregated emissions estimates for each ship's trip between two 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 that reports individual emissions.

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 European Union in a given year.

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 *nominal* 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 prior experiments 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 four steps: First, we estimate 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 operating condition and ship characteristics. Given ship efficiencies, we can calculate a high frequency emissions 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.

To date, we have estimated fuel efficiencies using this procedure for bulk carriers. We have further constructed a predictive model for efficiency extrapolation, regressing fuel efficiency on a set of ship characteristics (using logs of all variables) as well as built-year fixed effects.

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

where Z_i is a vector of ship's characteristics 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, XGboost, deep neural network) to estimate. The coefficients for the built-year fixed effects for our preliminary estimation based on log-linear specification are plotted in Figure 2 and indicate that efficiency after controlling for size is surprisingly flat for ships built before roughly 2013, after which efficiency improved. This agrees qualitatively with the analysis of evolution of new ship efficiency from Faber et al. (2015) (see Figure 15). The current specification does not include the effects of laden status or weather but we plan to include the draft level as well as wind and wave speeds using detailed weather data like that used by Brancaccio et al. (2020b).

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).

After estimating fuel consumption for each ship's trip, we estimate the worldwide CO_2 emission within each month of the years from 2017 to 2022 by aggregating fuel consumptions from all trips. Furthermore, we identify fuel consumption at more disaggregated 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 bilateral trade flows across different countries and direction. Here, we take into account of imbalance in trade volumes 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., 2020b).

Because the MRV data encompasses only trips in and out of the EU, in order to estimate fuel efficiency, we must first detect trips from the tracking data and identify those that involve a portcall in the EU. 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. In order 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. With this travel history constructed, we calculate a proxy for the travel work performed by a ship in a given year as the sum of its speed squared multiplied by the distance travelled between every pair of observations in the AIS data. The fuel efficiency is then calculated as the reported annual fuel consumption divided by the inferred annual travel work. .

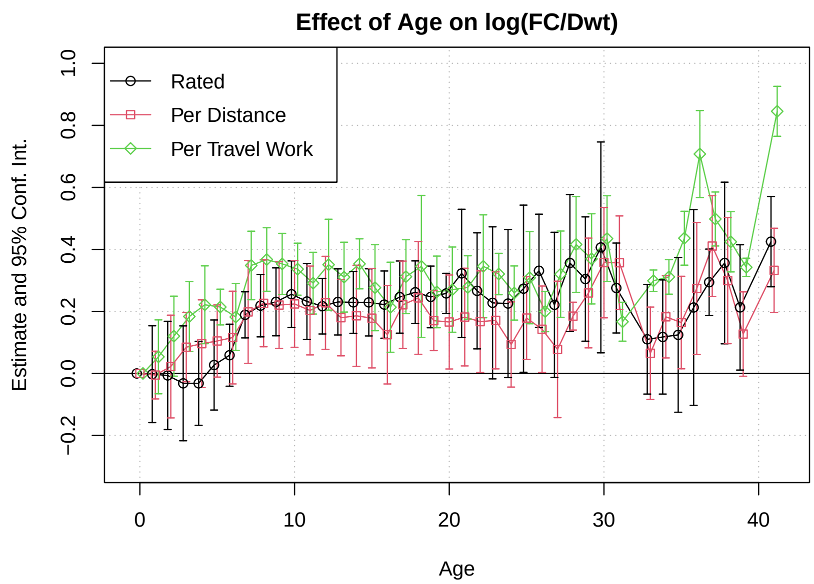

Figure 2: update, tidy, fix labels

Our next step is to assess the quality of extrapolation in a more systematic manner using cross-validation on randomly selected training and testing subsets. We are also developing an alternative, more flexible neural network model for efficiency extrapolition, and will compare its performance to the simple linear model. Finally, this exercise will be repeated for containerships.

COVID variation **Trade data** Bilateral trade data from...

Method of linking to emissions to trade Begin with global, then incorporate geographical variation

Potential data purchases:

- expand time series of AIS tracking data beyond 2021
- AIS tracking data for tankers
- bilateral trade

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