Detailed Description of Proposed Research:

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

Objective: First, we quantify monthly, 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 model the heterogenous elasticities of CO_2 emissions from maritime shipping with respect to international trade, which in turn are used to conduct a counterfactual analysis of potential emissions policies.

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 (UNCTAD, 2017). At the same time, maritime shipping contributes just under a third of CO_2 emissions from all trade-related activities (Shapiro, 2016), which corresponds to about 3% of global CO_2 emissions, roughly equal to the total emissions of Germany (Faber et al., 2020). The International Maritime Organization (IMO) has set a target of a 50% reduction by 2050 and introduced a minimum efficiency requirement for new ships in 2013, with stringency increasing over time and future levels yet to be determined. 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 elasticities across 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.

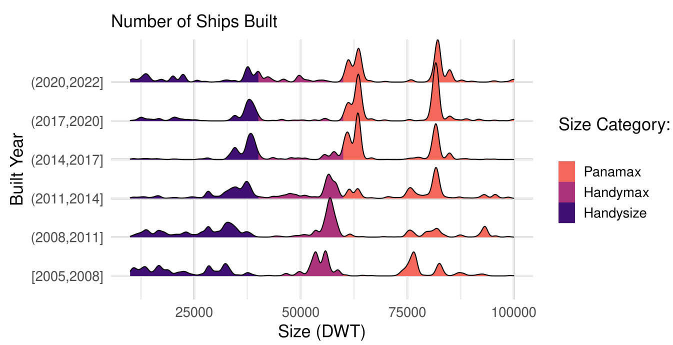

Figure 1: Existing fleet of bulk carriers by size and built-year.

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 transportation modes involved 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, accounting for its speed and draft, is determined by its observed technical 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, 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 port calls 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—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 traveled at each speed s_x, Z_i is a vector of ship 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). The current specification does not include the effects of laden status or weather but we plan to include the draft 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

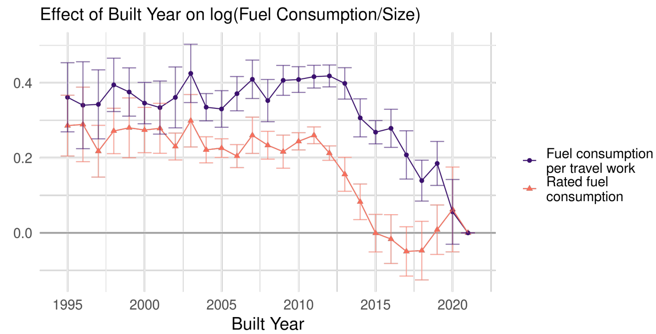

Figure 2: Built-year fixed effects from efficiency regression (1). Error bars represent 95% confidence intervals, with errors clustered at the individual ship level.

time period. We partially mitigate this by using only observations for which reported distance traveled closely matches the distance from tracking data. On the other hand, the advantage with regards to the approach of Faber et al. (2020) is that it relies less on theoretical assumptions. Figure 2 provides a preliminary indication of the difference between using nominal versus actual fuel efficiencies. 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–destination port pair by aggregating all trips taken from the origin port to the destination port 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 draft from AIS data. For validation, we use monthly product-level bilateral trade data from UN Comtrade, Eurostat, and the US census to examine how the directional trade volumes estimated using AIS data correspond to the reported monthly bilateral trade volumes between country pairs, where the proportion of seaborne trade is taken into account.

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 each ship category and origin-destination 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 observed empirical shipping weights.

Specifically, we create multiple categories of ships based on ship type (containerships, bulk carriers, and tankers), size, and age. 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 draft for each category of ships traveling from each origin country to each destination country. This will allow us to compute the elasticity of fuel consumption (and CO_2 emissions) with respect to an increase in trade volume shipped from an origin country to a destination country. Note that these elasticities are different across ship categories; furthermore, they depend on the average speed and the average draft. The route-specific draft is also used to indicate the utilization of ship capacity to account for trade imbalances. For example, the flow of dry bulk goods between Australia and China is highly directional so that using solely ship movements from China to Australia would vastly overestimate the flow of dry bulk goods in that direction.

The elasticity of CO_2 emissions with respect to trade volume depends on shipping speed, capacity utilization, and ship size. The fuel consumed and, hence, the CO_2 emitted is less if the speed is slower, ships are more fully loaded, and larger ships are used. Using the estimated elasticities, we plan to evaluate the impact of 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 unloaded trips in the context of trade imbalance. The proposed analysis has two important limitations. First, our analysis abstracts away from the general equilibrium effect (e.g., Shapiro, 2016). Second, our project has limited scope in that we don't analyze the CO_2 emission from production of trade goods (e.g., Cristea et al., 2013). Nonetheless, we hope that our analysis will provide an important stepping stone for future, more comprehensive quantitative analyses.

References

Arriola, C., Kowalski, P., and van Tongeren, F. (2021), "The impact of COVID-19 on directions and structure of international trade," *OECD Trade Policy Papers, No. 252, OECD Publishing, Paris.*

Brancaccio, G., Kalouptsidi, M., and Papageorgiou, T. (2018), "The impact of oil prices on world trade," *Review of International Economics.*

— (2020), "Geography, transportation, and endogenous trade costs," *Econometrica*, 88, 657–691.

Cristea, A., Hummels, D., Puzzello, L., and Avetisyan, M. (2013), "Trade and the greenhouse gas emissions from international freight transport," *Journal of Environmental Economics and Management*, 65, 153–173.

Faber, J., Hanayama, S., Zhang, S., Pereda, P., Comer, B., Hauerhof, E., and Yuan, H. (2020), "Fourth IMO greenhouse gas study," Online, accessed 11. Jul. 2021.

Faber, J., Hoen, M., Vergeer, R., and Calleya, J. (2015), "Historical trends in ship design efficiency," Tech. rep., CE Delft.

Jalkanen, J.-P., Brink, A., Kalli, J., Pettersson, H., Kukkonen, J., and Stipa, T. (2009), "A modelling system for the exhaust emissions of marine traffic and its application in the Baltic Sea area," *Atmospheric Chemistry and Physics*, 9, 9209–9223.

Johansson, L., Jalkanen, J.-P., and Kukkonen, J. (2017), "Global assessment of shipping emissions in 2015 on a high spatial and temporal resolution," *Atmospheric Environment*, 167, 403–415.

Liu, H., Meng, Z.-H., Lv, Z.-F., Wang, X.-T., Deng, F.-Y., Liu, Y., Zhang, Y.-N., Shi, M.-S., Zhang, Q., and He, K.-B. (2019), "Emissions and health impacts from global shipping embodied in US–China bilateral trade," *Nature Sustainability*, 2, 1027–1033.

Olmer, N., Comer, B., Roy, B., Mao, X., and Rutherford, D. (2017), "Greenhouse gas emissions from global shipping, 2013–2015 Detailed Methodology," *International Council on Clean Transportation: Washington, DC, USA*, 1–38.

Shapiro, J. S. (2016), "Trade Costs, CO¡sub¿2¡/sub¿, and the Environment," *American Economic Journal: Economic Policy*, 8, 220–54.

Ugé, C., Scheidweiler, T., and Jahn, C. (2020), "Estimation of worldwide ship emissions using AIS signals," in *2020 European Navigation Conference (ENC)*, IEEE, pp. 1–10.

United Nations Conference on Trade and Development (2017), "Review of Maritime Transport 2017," United Nations Geneva.

van der Loeff, W. S., Godar, J., and Prakash, V. (2018), "A spatially explicit data-driven approach to calculating commodity-specific shipping emissions per vessel," *Journal of Cleaner Production*, 205, 895–908.

Wang, X.-T., Liu, H., Lv, Z.-F., Deng, F.-Y., Xu, H.-L., Qi, L.-J., Shi, M.-S., Zhao, J.-C., Zheng, S.-X., Man, H.-Y., et al. (2021), "Trade-linked shipping CO2 emissions," *Nature Climate Change*, 11, 945–951.