Can targeted disclosure regulations facilitate the environmental transition of the shipping sector?

A study on the effect of the EU MRV Regulation on ship emissions

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Abstract

This research examines the impact of the EU Monitoring, Reporting, and Verification (MRV) regulation on ship emissions when calling at EU ports. The main question is whether ships that are required to report their emissions emit less due to the regulation. The study utilizes Automatic Identification System (AIS) data on distance sailed, fuel consumption, deadweight tonnage, and gross tonnage to calculate each ship's Annual Efficiency Ratio (AER) value. The value is an index used to describe a ship’s carbon intensity per carrying capacity and distance traveled. An empirical analysis is conducted using the Regression Discontinuity Design (RDD) method to clarify the question. By limiting the analysis to ships with a gross tonnage just above 5,000 and ships with a gross tonnage just below 5,000, the effect of MRV regulation on emissions is isolated. According to the result estimates, it appears that the MRV regulation does not have a significant impact on ship emissions. In fact, if any effect exists, it might be positive. Nevertheless, it is essential to note that the results are not statistically significant.

Keywords: environmental disclosure regulation, maritime sector, shipping, targeted transparency, MRV regulation, EU, Regression Discontinuity Design (RDD)

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Abbreviations

AER	Annual Efficiency Ratio
AIS	Automatic Identification System
ATE	Average Treatment Effect
BAU	Business-as-usual
DCS	Data Collecting System
DWT	Deadweight ton
EC	European Commission
EID	Environmental Information Disclosure
ETS	Emission Trading System
EU	European Union
GHG	Green House Gas
GT	Gross tonnage
IMO	International Maritime Organization
LATE	Local Average Treatment Effect
MRV	Monitoring, Reporting, and Verification
PTTI	Pollutant Information Transparency Index
UN	United Nations

1. Introduction

The shipping sector is crucial to world trade and operates under complex international and national regulations. Over 80% of the world's traffic in goods is carried by the global shipping sector (ECSA, 2017), with more than 50,000 cargo ships currently in service (Smart Freight Centre, 2019), and 40% of the world's merchant fleet is under the hands of European shipowners (ECSA, 2017). Moreover, the EU economy depends heavily on the shipping industry, supporting over 2 million jobs and generating EUR 149 billion in EU GDP (Oxford Economics, 2020). At the same time, global greenhouse gas (GHG) emissions continue to increase, and the shipping sector contributes to around 2 – 3% of total emissions (Ritchie & Roser, 2020). At the EU level, maritime transportation contributes to about 4% of the EU's overall CO2 emissions (Smart Freight Centre, 2019). In addition, shipping is one of the industries with the fastest-growing GHG emissions (Winnes et al., 2015). In 2015, the International Maritime Organization (IMO) forecasted that if no abatement actions were done, CO2 emissions related to the maritime sector would increase by up to 250% between 2014 and 2050. In addition, it is considered a politically prioritized issue to increase the proportion of goods transported by sea. Therefore, it is essential to create a marine transportation system that is both sustainable and effective in the long run (Styhre et al., 2019).

In order to reduce CO2 emissions from shipping within the EU, the European Council and Parliament adopted a directive regarding the monitoring, reporting, and verification (MRV) of carbon dioxide emissions from maritime transport. The directive applies to ships with a Gross Tonnage (GT) of over 5,000 in 2015. The directive's goal is to help remove market barriers that limit the adoption of cost-effective initiatives that would cut greenhouse gas emissions from maritime transport by allowing the public access to emissions data. By providing comparable and trustworthy information on fuel consumption and energy efficiency, the introduction of a Union MRV system is anticipated to contribute to an emission reduction of up to 2% compared to business-as-usual (BAU), for example, by reducing the ship's speed and using more efficient routes (Winnes et al., 2015; Regulation 2015/757). In addition, the regulation is also predicted to reduce the aggregated net cost of up to EUR 1,2 billion by 2030 (Regulation 2015/757). This paper investigates the impact of the EU MRV regulation on ship emissions, applying a sharp regression discontinuity design (RDD) surrounding the implementation of the regulation on 1 January 2018. The study utilizes Automatic Identification System (AIS) data on distance sailed, fuel consumption, deadweight tonnage, and gross tonnage to calculate each ship's Annual Efficiency Ratio (AER) value. The value is an index used to describe a ship’s carbon intensity per carrying capacity and distance traveled. The treatment group in the study consists of vessels just above 5,000 gross tons that call on EU ports. The control group comprises vessels just below 5,000 that call on the same ports. The research question is: *What is the effect of the EU MRV Regulation on CO2 emissions from ships subject to the regulation?*

Given that a variety of stakeholder groups, such as clients, employees, and investors, view corporate emissions as a negative “firm feature,” it makes sense that a disclosure requirement could result in the “pillory” of a company’s carbon footprint (Drucker, 1954). Further, according to stakeholder theory arguments, companies tend to respond to external stakeholder pressure to report GHG emissions. Hence, mandatory reporting could entail a real GHG emission reduction effect on carbon emissions (Downar et al., 2021; Liesen et al., 2015, Shi, D et al., 2021). In addition, a transparent system is expected to mobilize the power of public opinion, inform choice, and help markets operate more effectively (Fagotto & Graham, 2007). Moreover, targeted transparency policies are a well-visited topic in previous research. Many of these find that environmental disclosure policies significantly decrease corporate emissions (Downar et al., 2021; Shi et al., 2021; Salman, 2022; Zhang et al., 2020), while other findings demonstrate that targeted transparency policies have no appreciable impact on pollutant concentration levels (Kasim, 2017; Poulsen et al., 2021). Panagakos et al. (2019) find that the geographic coverage limitations of the MRV Regulation introduce a considerable bias, preventing the intended purpose of the regulation. Nevertheless, companies may hide information about their sustainability efforts, emphasizing transparency policies’ importance (Linares-Rodríguez et al., 2022).

This study investigates and contributes to the research on the relationship between environmental disclosure regulation and CO2 emissions. To enhance the research on MRV policy evaluation, this study employs an econometric model that examines the efficacy of the EU MRV policy using empirical data, which has not been done before. In addition, since this study has access to AIS data, the dataset is unique and detailed. Previous studies employ qualitative and inductive approaches, such as semi-structured interviews, publicly available data (Poulsen et al., 2021), literature reviews (Fedi, 2017; Deane et al., 2019), grounded theory (Olczak. et al., 2022) or best practices (Poulsen & Johnson, 2016). However, quantitative studies within the field use machine learning models comparing the annual fuel consumption of ships from external databases (Yan et al., 2023) or investigating the value of the published data rather than the effect on emissions (Panagakos et al., 2019). This work contributes to the literature on principal-agent interactions in transportation science and provides an empirical measurement of the effect of disclosure within the industry. Additionally, it adds to the sustainable operations literature on determinants in shipping emissions. However, according to the outcome estimates, it appears that the MRV regulation does not have a significant impact on ship emissions. In fact, if any effect exists, it might be positive. Nevertheless, it is essential to note that the results are not statistically significant.

This study is organized as follows: The next section provides a background to increase the understanding of the topic. Section 3 provides the theoretical framework. Section 4 contains a summary of relevant previous research. Section 5 includes a description of the data and the variables and a presentation of the descriptive statistics. Section 6 explains the econometric method and the delimitations necessary in the study. Section 7 presents the results, which will be discussed in Section 8. Finally, the conclusion is presented in section 9.

2. Background

The first part of this section explains the EU rules and regulations in the maritime freight transport sector, emphasizing the 2015/757 regulation on monitoring, reporting, and verification (MRV) of CO_2 emissions. The second part provides some background information regarding the international regulatory regime within the maritime sector. Finally, the third part provides an overview of AIS.

2.1 The Union Context

The MRV Regulation's immediate objective is to produce precise statistics on the CO_2 emissions of large ships using EU ports and encourage emission reduction breakthroughs by making this data accessible to the public. Furthermore, given that the EU is a sizable shipping market, the MRV regulation is believed to affect the entire shipping sector (Regulation 2015/757). The Regulation (EU) 2015/757 was adopted by the European Council and Parliament and entered into force on 1 July 2015. Beginning on January 1, 2018, companies with ships subject to EU MRV regulation must monitor the required parameters. The regulation applies to all passenger and freight ships above 5,000 gross tons (GT) that call on EU ports, regardless of flag. This covers ports in the member states and some ports independent and foreign territories, such as Açores, Madeira, Canarias, Guadeloupe, French Guiana, Martinique, Mayotte, Saint Martin, and Reunion. It also includes ports in Iceland and Norway (except Svalbard). The monitoring is on a per-voyage and annual basis (Regulation 2015/757).

All CO_2 emissions from the ship must be reported; the primary engines, auxiliary engines, gas turbines, boilers, and inert gas generators are among the sources of these pollutants. According to the regulation, reported emissions must consider the distance traveled between two port calls and the time spent in the port. In addition, the emission report must undergo third-party verification before being submitted to the European Commission (EC). As Article 21 of Regulation (EU) 2015/757 requires, the EC makes the information publicly available once confirmed. This is done using the THETIS-MRV platform, where emissions reported from 2018 to 2022 are now accessible.

In addition, the EU has introduced a scheme that uses emission allowances to encourage companies to reduce their emissions. The scheme requires companies to reduce their emissions each year or buy more allowance to compensate for the shortfall in emissions reductions. However, shipping is currently not included in the scheme. Still, since ship owners must report their emissions from vessels to the EU, they are expected to be included in the EU's so-called Emission Trading System (ETS) by 2024 (European Commission, 2021).

2.2 The International Context

The International Maritime Organization (IMO) governs international shipping under the UN and has developed and introduced instruments to regulate and reduce shipping's total environmental impact for decades (IMO, 2021). In 2016, the IMO implemented its own Data Collection System (DCS), which came a year after the introduction of the EU MRV Regulation. This was the first step in a three-step process that included data collection, data analysis, and decision-making about whether additional measures were necessary. However, the IMO method uses different indicators for measuring emissions, and the data are not made public (MEPC, 2021c).

The IMO DCS requires ships in international traffic with a gross tonnage (GT) of 5,000 or more to collect and report data on fuel consumption, distance, and journey time annually from 1 January 2019. In June 2021, the IMO's Maritime Environmental Protection Committee (MEPC) decided to introduce a Carbon Intensity Indicator (CII) directive that entered into force on 1 November 2022. The regulation will cover all merchant ships of 5,000 GT and above. The decision introduces CII as regulation 28 in Annex VI of the International Convention for Preventing Pollution from Ships (MARPOL). CII is a rating system where a ship's carbon intensity annually is assessed with a grade. The assessment is based on the ship's total carbon dioxide emissions concerning its carrying capacity and distance traveled. The emissions data collection will be done through the IMO DCS (MEPC, 2021c).

The IMO has set different targets in its efforts to reduce maritime emissions. By 2030, carbon dioxide emissions per transport operation should be reduced by at least 40%. Furthermore, annual greenhouse gas emissions should be reduced by at least 50% by 2050 compared to 2008 (IMO, 2018).

2.3 Overview of AIS

To calculate each ship's AER value, this study utilizes AIS data on distance sailed, estimated fuel consumption, deadweight tonnage, and gross tonnage. Over the past ten years, AIS data has become popular as satellite-based receivers have enabled extensive coverage and increased data quality. In addition, the system provides information-rich vessel movement data. From purely navigation-focused research, trade flow estimation, pollution accounting, and vessel performance monitoring are now included in the applications of AIS data. Combined with additional databases, the AIS currently provides high-frequency, real-time positioning and sailing patterns for the entire globe’s commercial fleet. It is possible to argue that this has marked the beginning of an era of digitalization in the shipping sector (Yang et al., 2019).

In addition to the information that may be gathered directly from AIS data, AIS data can be combined with data from other sources to generate additional information. For example, with the IMO number[1], one can access fleet databases like Clarkson’s World Fleet Register (n.d.) to find technical ship specifications like a deadweight ton (DWT), capacity, design speed, and design drought. Then, port-to-port bunker consumption can be predicted based on the speed, the distance between the ports, and technical ship data like DWT and capacity (Yang et al., 2019).

Further, satellite-based AIS ship tracking creates new opportunities for precise environmental accounting and shipping effect modeling (Mjelde et al., 2014). Using AIS data, numerous research has established techniques for creating assessment indices that measure the performance of shipping activities (Hansen et al., 2013; Li et al., 2018; Eide et al., 2007; Jia et al., 2017). The AIS data has also been extensively used to track ship emissions. The determination of emission inventories has been considered in most studies in this field (Windmark et al., 2017), and ship operators are frequently determined using AIS data (Winther et al., 2014; Kivekäs et al., 2014).

[1] Every ship is assigned with a permanent number for identification purposes (IMO, n.d.)

3. Theoretical framework

The causal effect of disclosure policies is relatively well-researched. From studies carried out in the past, two main theories can be distinguished: the principal-agent theory and the targeted transparency theory. Below is a presentation of the study's theoretical starting points and how these are intended to be operationalized.

3.1 Principal-Agent theory

By providing comparable and reliable information on fuel consumption and energy efficiency, implementing a Union MRV system is predicted to help remove market obstacles, such as a lack of information about ship efficiency and emissions. Thus, the hope is that shipping companies may act differently when forced to share more details (Regulation 2015/757).

Numerous theoretical and empirical papers published in recent years have shown that even relatively minor informational imperfections can have a significant impact on the actions of businesses (Fung et al., 2007; Longarela-Ares et al., 2020); consumers; workers; and other economic actors (Fagotto & Graham, 2007), leading to inefficiencies that undermine the neat predictions of social welfare economics (Johnson & Andersson, 2016). Moreover, participants in private markets will either generate less information than ideal or try to restrict access to it to profit economically. In any case, private incentives transmit too little information. Therefore, policies promoting its more extensive availability, e.g., the EU MRV regulation, should benefit society (Arrow, 1974; Fung et al., 2007).

Agents in agency theory are presumed to be autonomous and have the propensity to maximize their interests at the principal's expense, which can result in conflicts of interest or split incentives: split incentives and asymmetric information result in the principal-agent problem. The market fails because verifying the agent's behavior, as emissions, may be impossible or prohibitively expensive (Longarela-Ares et al., 2020).

The market in the shipping sector demonstrates a specific kind of a principal-agent issue resulting from information asymmetries between the charterer and shipowner.

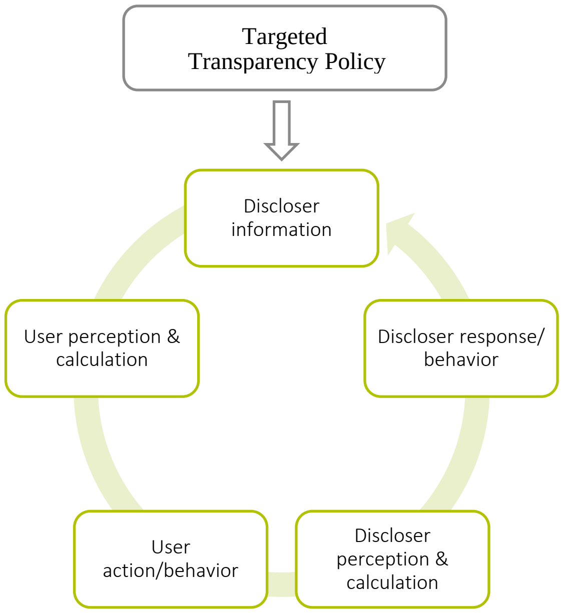
For example, in an agency relationship, the principal hires the agent to carry out a service on their behalf and thus delegates specific authority to the agent. In the shipping sector, a charter party agreement governs the relationship between the shipowner and the charterer, i.e., the transport buyer (Dirzka & Acciaro, 2021). The most typical agreement for shipping is a time charter. The time-charter contracts can be compared to a traditional tenant-landlord deal. In the shipping sector, the shipowner acts as the agent since, like a landlord, it is assumed that the shipowner is more knowledgeable of the ship's energy-efficiency baseline. Therefore, the time-charter contract could lead to an efficiency issue because the shipowner chooses the baseline technology installed on the vessel. At the same time, the charterer pays the operations costs, i.e., transactions where the entity responsible for making investment decisions is not the party responsible for paying future operating fees caused by that investment. As a result, split incentives emerge due to contractual agreements, reducing the adoption of green technologies, i.e., failing to reduce ship emissions. (Dirzka & Acciaro, 2021; Longarela-Ares et al., 2020).

3.2 Targeted transparency

Targeted transparency constitutes a distinctive public policy category requiring businesses or other actors to disclose standardized, comparable, and disaggregated information. Targeted transparency policies aim to create incentives for change and often assume that there is some information asymmetry between suppliers and customers. The information must alter the user's behavior or the disclosure of the data to achieve anything beyond words or numbers on a piece of paper. Users change their behavior through activities, whereas disclosers alter it through their answers (Fung et al. 2007). According to Fagotto & Graham (2007), once made public, emissions data could be used by authorities and other actors to develop and implement emission-reduction plans, and business owners would be encouraged to act pragmatically to reduce greenhouse gas emissions.

If the given information alters users' (for example, shipping buyers') perspectives, this may cause a change in their behavior, such as deciding to change shipping companies or require higher standards. In this way, a transparency policy may start a chain reaction. The disclosures (such as shipping companies) must then assess if it is in their best interest to address the buyers' concerns and determine what action would maximize their anticipated net advantages while considering the buyers' demand. Figure 1 demonstrates how regulation transparency may impact business conduct (Fung et al. 2007).

Figure 1: The targeted transparency action cycle. Source: Fung et al. (2007, p. 54)



In addition to implementing policies, Styhre et al. (2019) find that transport purchasing companies that set environmental requirements for shipping companies and show a willingness to pay more for transport with fewer emissions could influence shipping companies' ability to sustainability efforts. However, concerning the purchase of maritime transport, previous research also shows that specific environmental requirements have been lacking (Styhre et al., 2019).

Moreover, Hombach and Sellhorn (2019) claim that reporting will not have any effect unless a system of standards is in place. First and foremost, it is crucial to have correctly detailed reporting standards and compliance requirements. Second, the reporting variables under consideration (such as emissions) must produce new public data or, at the very least, promote transparency on the reporting variable under consideration. Third, the provided information must also be considered valuable and pertinent. The MRV Regulation is viewed as a first step in assisting the EU in meeting its GHG reduction targets by including maritime transport emissions in its commitments, i.e., providing new public data. In addition, the emission report must undergo third-party verification before being submitted to the EC for confirmation and publication on the THETIS-MRV platform. Considering this, it seems that the MRV regulation meets the requirements mentioned by Hombach and Sellhorn (2019).

4. Previous research

It is evident from earlier research that current political efforts to slow down environmental deterioration are a vital topic to investigate and that using real-world policy and robust econometric methods is an effective approach to do it. However, to the best of my knowledge, the EU MRV Regulation has not yet been subject to this. This paper hence adds to the research investigating real-world policy using econometric analysis. I also address the gap in knowledge about how the EU MRV Regulation has affected ship emissions. This section investigates the research fields to which the thesis subject belongs. The first section will cover previous research on MRV regulation. Thereafter, following the theoretical framework, previous research concerning stakeholder theory (e.g., principal-agent theory) and targeted transparency will be presented.

4.1 MRV Regulation

Transparency and information disclosure have received much attention as governance tools that can alter environmental practices in emission-intensive sectors. Moreover, the circumstances in which transparency and information can reduce the environmental impact of business operations are crucial topics in the academic fields of environmental governance (Poulsen et al., 2021). One of the regulations debated and researched in the literature is the EU MRV Regulation. Although early research produces intriguing findings, few have examined the actual effects of the regulation on emissions using real-world data. Previous studies on the EU MRV Regulation focus on analyzing the strengths and weaknesses of the regulation, gathering viewpoints from stakeholders in order to identify improvements to future EU legislation on MRV (Olczak et al., 2022), as well as its *potential* impact on ship emissions (Fedi, 2017; Rony et al., 2019; Poulsen et al., 2021), rather than its actual effects.

Moreover, a few examples exist, however. Panagakos et al. (2019) use data on all 2018 voyages by a fleet of 1041 dry bulk vessels managed by a prominent Danish shipping company to examine the value of published MRV data. The effectiveness of the regulation was evaluated using updated calculations of the MRV indicators; the Energy Efficiency Operational Indicator (EEOI), the Annual Efficiency Ratio (AER), the Individual Ship Performance Indicator (ISPI), and the Energy Efficiency per Service Hour (EESH). The paper mainly focuses on how the restrictions were supposed to help sector operators "make more informed decisions and be more conscious of the environment." However, according to the authors, the aim of restricting carbon emissions from ships and increasing funding for developing low-carbon technologies could not be evaluated when the report was produced. The key findings of their analysis are that the disclosed indicator values are insufficient to fill the information gap on the energy efficiency of ships and that the geographic coverage limitations of the MRV Regulation introduce a considerable bias, preventing the intended purpose of the regulation. Thus, the authors conclude that the monitoring, reporting, and verifying CO2 emissions required by the EU MRV Regulation cannot help market actors make better decisions.

Moreover, Poulsen et al. (2021) aim to examine how transnational environmental governance (TEG) and global value chains (GVCs) interact in order to show how mandatory disclosure might reduce the environmental impact of business operations. To do this, they investigate the case of the EU MRV Regulation and its application in tanker shipping using a qualitative, inductive research approach. Semi-structured interviews, publicly available data, and ethnographic observations on board a tanker and at industry conferences are the three data sources used in this study. The sources are used to examine how many circumstances may affect tanker shipping GVC actors' fuel consumption choices. The authors find that the MRV Regulation does not allow charters, shipping management, other GVC actors, or the public to distinguish between the most and least energy-efficiency ships. They believe this is the main factor preventing the MRV regulation from producing appreciable fuel savings. Moreover, while the public and civil society benefits more from the MRV's normative effect (the right to know), the MRV's procedural and substantive effects are relatively small. As a result of the regulations' inability to shed light on the underlying variables that influence fuel usage during tanker operations, the authors particularly demonstrate substantial opposition to adopting MRV's main performance measures (Poulsen et al., 2021).

4.2 Stakeholder pressure

Making companies report their emissions is one way to encourage them to adopt more environmentally friendly practices by giving stakeholders insight into company operations. Regulations requiring environmental disclosure are therefore expected to lead to a decrease in business emissions (Downar et al., 2021; Drucker, 1954; Liesen et al., 2015; Shi, D et al., 2021; Saka et al., 2014; Matsumura E.M. et al., 2014).

Liesen et al. (2015) explore whether stakeholder pressure influences corporate greenhouse gas (GHG) emissions reporting among 431 European companies. The authors carry out a logistic regression analysis to examine if concerns regarding climate change from stakeholders affect the existence of quantitative GHG emissions revelation. Drawing on the frameworks of stakeholder theory and legitimacy theory, Liesen et al. (2015) hypothesize that stakeholder exposure positively correlates with companies' choice to disclose GHG emissions information but negatively correlates with the completeness of the GHG emissions information. The data is collected from companies' reports and websites and Disclosure Insight Action (CDP), a non-profit charity with a global disclosure system for actors to manage their environmental impacts. The paper focuses on four corporate stakeholders and creates stakeholder proxy variables for each: the state, NGOs, providers of capital, and the public. The dependent variable is a binary dummy equal to one if the company discloses most of its activities in tests of reporting existence. The authors conclude that stakeholder pressure is a factor in the presence of GHG emissions disclosure but not in its completeness. The findings are consistent with stakeholder theory arguments that companies respond to external stakeholder pressure to report GHG emissions, but also with legitimacy theory claims that firms can use carbon disclosure, in incomplete reporting, as a symbolic act to address legitimacy exposures.

Further contributions to this area of research are from a study conducted by Villena and Dhanorkar (2020). The study examines the impact of institutional pressures for driving supplier carbon transparency depending on the presence of climate change incentives. The authors focus on three institutional forces (i) coercive, (ii) mimetic, and (iii) normative, and develop different hypotheses based on transparency literature, institutional theory, and insights gained from interviews with CDP officials (both supplier firms and buyers). They hypothesize that all institutional pressures mentioned above will respectively result in higher carbon transparency. The study uses data from the Carbon Disclosure Project's supply chain program (CDP-SCP). The dependent variable is transparency which they treat as a formative construct caused by comprehensiveness, accuracy, and public disclosure. They use explanatory factor analysis (EAF) to obtain transparency as a single factor constructed from the three indicators. The independent variables used are coercive, mimetic, and normative pressure. A binary variable for climate change incentives is also included, equal to one if the supplier provided incentives for managing climate change issues. According to the findings, suppliers with climate change incentives respond more to normative pressure regarding their carbon transparency level. In contrast, suppliers without climate change incentives are more vulnerable to coercive and mimetic pressures.

4.3 Targeted transparency

As mentioned above, studying transparency and information disclosure regulations is a popular topic in the literature (Poulsen et al., 2021). In addition, it has become popular within environmental economics to identify these policies' causal effects (Wuepper & Finger, 2023).

Downar et al. (2021) examine if obligatory reporting impacts reducing GHG emissions, possibly due to stakeholder pressure on firms to subsequently "manage" their carbon emissions. The Companies Act 2006 (Strategic Report and Director's Report) Regulations 2013, which mandate that publicly traded UK-incorporated enterprises declare their GHG emissions as part of their annual financial reports, serve as the central framework for the study. Installations in the UK or another European country ultimately held by UK-incorporated, publicly traded enterprises make up the treatment group. The control group comprises facilities that are ultimately controlled by businesses not governed by the 2013 legislation, i.e., publicly traded companies in other EU countries. The authors formulate hypotheses relating to changes in GHG emissions and changes in the financial operating performance of the enterprises subject to the UK disclosure mandate and use a difference-in-difference (DiD) approach to test the impact. They differ the variation between pre- and post-mandate (from 2009-2018) emission data for affected enterprises with emission data and the control firms. The authors find that firms belonging to UK companies subject to the disclosure mandate show significant reductions in GHG emissions compared to firms in the control group. Compared to pre-treatment emission levels, the treated enterprises reduced their emissions by 8% after the disclosure. Further, they find that multinational companies with more complicated operations tend to cut their emissions by a lower proportion than their less complex peers. Finally, regarding the economic effects, they discovered that the treated firm's production costs and sales increased somewhat but were statistically insignificant in the years after the mandate. This is consistent with the idea that firms' public perception of customers has improved due to an improvement in a key CSR variable (Downar et al., 2021).

Moreover, Shi et al. (2021) conduct a firm-level empirical study to test whether environmental information disclosure (EID) policies influence pollution control and improve environmental performance. The authors use the Pollutant Information Transparency Index (PTTI), released in China in 2008, in a quasi-natural experiment to estimate the emissions reduction effect of EID on SO2 emissions of firms. A treatment group (firms located in the EID pilot city) and a control group (firms located outside the EID pilot city) are included in the sample. They hypothesize that EID reduces pollution emissions of firms through both reducing capital factor input in polluting industries and through innovative mechanisms. The method they use to test the effect is a difference-in-difference approach and a matched dataset from the Chinese industrial firm database and the Chinese industrial firm pollution database from 2003 to 2012. The findings demonstrate that EID may significantly lower SO2 emissions from industrial firms. Moreover, the results show that local governments may influence how EID regulations affect business emission reduction. They also confirm methods by which EID affects company emissions. EID can lower firms' emissions by enhancing their energy structures and modifying their capital factor structures, although the importance of their innovation and end-governance mechanisms is insignificant (Shi et al., 2021).

In addition, the RDD has been used in previous research to investigate the impact of transparency policies on emissions. For example, Zhang et al. (2020) applies an RDD to evaluate the reduced SO2 emissions effectiveness of an Emission Control Area (ECA) policy in Shanghai port. By the use of AIS data, it was revealed that ship pollutants accounted for 12% of the city of Shanghai's SO2 concentration in 2010. As a result, Shanghai Port became a pioneer by adopting a strict ECA policy on 1 April 2016 that forbids bunker fuels on board with a sulfur concentration over 0,5% in the waters of Shanghai Port. The authors adopt a sharp RDD, which implies that a sharp discontinuity in Shanghai city's SO2 concentration exists at the cutoff point of the ECA policy in Shanghai port, to detect if the ECA policy has a causal effect on the SO2 concentration reduction. The estimated results demonstrate a discontinuity where the ECA policy terminates and that, on average, Shanghai's SO2 concentration was decreased by at least 0,229 g/m3 per day due to implementing the policy. Moreover, Salman et al. (2022) also employ an RDD and use the Paris Agreement as a quasi-natural experiment. The authors assess the impact of the agreements' policy changes on environmental performance and GHG emissions in 162 countries from 1990 to 2020. To assess the effectiveness of the global environmental system, the authors use a global Malmquist-luenberger productivity (GML) index. The study employs a fuzzy RDD and assumes that the probability of getting treated by the Paris Agreement increases discontinuously once a member country's initial level of environmental efficiency is lower than a specific value. According to the findings, industrialized countries' environmental efficiency increased while emerging and less developed countries deteriorated.

However, like Poulsen et al. (2021) and Panagakos et al. (2019), Kasim (2017) does not find that transparency-targeted policies lead to lower emissions. The author aims to estimate the impact of an environmental disclosure policy on air pollution.

The policy of interest in the study is the *Requirement for Publishing Pollution Monitoring Data* in New South Wales (NSW). All NSW Environmental Protection License (EPL) holders must make monitoring data stored under each EPL they had available to the public beginning on July 1, 2012. The study's identifying assumption is that the pollution measure discontinues on the day the environmental information disclosure policy is enforced. Utilizing a sharp RDD, the exogenous shock caused by the policy is identifiable. However, the findings demonstrate that the policy's implementation had no appreciable impact on pollutant concentration levels.

5. Data

This section provides an overview of the data construction and reliability used in the study. First, section 5.1 presents the outcome variable's data, an Annual Efficiency Ratio (AER) measure from 1 January to 31 December 2018. After that, the data on which the running variable, GT, is described. Lastly, the descriptive statistics are presented.

5.1 Data Construction and Reliability

The paper aims to answer whether the EU regulation on MRV has any real effects on ship emissions. Fuel consumption by ship type is the foundation for calculating CO2 and other GHG emissions. However, multiple factors and variables affect the quantity and composition of CO2 emissions from ships, according to reports from the International Council on Clean Transport (ICCT) from June 2014 (IMO, 2015) and October 2017 (Olmer et al., 2017). Factors such as ship type, size, precise distance traveled, the total cargo carried, and time spent traveling must also be accounted for. Additionally, fuel consumption while the ship is in port for loading, unloading, and associated operations is a factor that should be considered when estimating emissions (Olmer et al., 2017), which is the case of this study.

Therefore, the outcome variable of interest in capturing ship emissions will be an *Annual Efficiency Ratio* (AER) measure rather than just total CO2 emissions. The calculation will gain the grams of CO2 emitted per cargo-carrying capacity and nautical miles in a year and is presented in Equation (1) below. Moreover, a ship's maximum weight is expressed in *Deadweight Tons* (DWT). The measurement of *DWT* contains the weight of the cargo and summarized weights of the fuel, freshwater, provisions, ballast water, crew, and passengers (Morgan, 1943). Finally, the *Distance sailed* is calculated as the sum of the nautical miles the ship has sailed in a year.

$$AER = \frac{Annual\ CO2\ emissions}{Deadweight \times Distance\ sailed} = \frac{\Sigma_j FC_j \times C_{Fj}}{DWT \times D} = \frac{gco_2}{DWT\ mile} \qquad (1)$$

The *Annual CO2 emissions* of a ship are calculated as the sum of fuel consumption times the emission factor[2], demonstrated in Equation (2). The combined use of the main engine, auxiliary engine, and boiler represents fuel consumption.

$$Annual\ CO2\ emissions = \Sigma fuel\ consumption \times emission\ factor \qquad (2)$$

The variable that determines whether the MRV regulation is active or not for the ship is called the running variable. The running variable, *Gross Tons* (GT), measures a ship's internal volume. It does not consider the cargo and only applies to the vessel itself. Therefore, a ship's GT value should be interpreted as a volume rather than weight. To calculate it, the enclosed space of the vessel's contents in cubic feet is divided by 100 (Morgan, 1943).

To generate the AER variable described above, detailed ship-level data is needed. The DNV NPS database serves as the primary repository for ship statistics. With a focus on the performance of the global marine industry in terms of quality, energy efficiency, safety, and the environment for all types of ships, DNV is considered a trusted advisor and a global leader in classification societies for the maritime industry (DNV, n.d.). Data from the DNV NPS database is communicated with, created, stored, and retrieved using Structured Query Language (SQL). Specifically, data on the *Annual CO2 emissions*, *GT*, and *Distance sailed* was collected from the DNV NPS database, which applies AIS data to provide the vessel data. However, although the *GT* data is complete, data regarding *Distance Traveled* and *Annual CO2 Emissions* is incomplete. This is because there was variance in the ships calling at EU ports between 2017 and 2019, with some vessels going out of service and others coming into service. It is also possible that the *AER* metric is invalid because one of the metrics, such as Distance Sailed, has missing data (making the *AER* equal to zero). Consequently, when the GT and AER are matched, a small share of the ships has missing values. Fortunately, the method adopted ensures that attrition is random; and that the outcome is not biased due to selection issues.

The collection of *DWT* was downloaded from Sea-web, the largest marine internet database in the sector (S&P Global, n.d.). The data on *DWT* is complete. The MarineTraffic Ports Database is used to locate all ports that are part of the EU and subject to EU MRV regulation. There is no indication on the database website that the port data needs to be completed. I, therefore, rely on including all ports subject to the EU MRV regulation. A list of the ports included in the study can be found in

[2] The emission factor is expressed in relation to energy output (t CO2/t fuel) (IMO, 2020).

Appendix Table 6. MarineTraffic is the world's leading provider of ship tracking, using AIS data and maritime intelligence (MarineTraffic, n.d.).

The data is collected for 2017, 2018, and 2019 since it allows for comparisons before and after the EU MRV Regulation was implemented. Furthermore, ships with a GT between 4,500 and 5,500 are included. A trade-off between variance and bias explains why not all data is used (i.e., ships with GT far from the cutoff). The data must be as closely confined to the cutoff where ships are most comparable to one another as possible to minimize the impact of confounding factors. However, by reducing the number of available observations, estimates, and casual inferences become less precise, making it harder to evaluate the actual effect of the EU MRV Regulation. As a result, choosing a bandwidth around the cutoff that balances variation and bias in the best way is necessary (Wuepper & Finger, 2023; Calonico et al., 2014; Calonico et al., 2017). This will be further discussed in section 6.2.

5.2 Descriptive statistics

The summary statistics of this study are presented in Table 1. The ships that had missing AER values are not included. The outcome variables demonstrate the AER for all ships included in the study for each year, where the AER in 2018 is the outcome variable of interest. A list of the vessels included in the study can be found in Table 7 in the Appendix. The AER mean is consistent between the years. However, it peaked in 2019 after reaching its lowest point in 2018. In addition, the treatment group, which consists of ships subject to the EU MRV legislation, has consistently higher AER values than the control group. The number of vessels in the control and treatment groups is relatively evenly distributed. Nevertheless, it is essential to note that the treatment group has an additional 45 ships compared to the control group. Since the sample size is relatively small, the differences in AER can be explained by the different sizes of the control and treatment groups.

Table 1: Summary statistics by treatment and control group

	Control group			*Treatment group*		
Outcome variables	Obs	Mean	St.dev	Obs	Mean	St.dev
AER2017	235	25.51	28.01	280	26.53	27.33
AER2018	235	25.39	24.77	280	26.28	26.84
AER2019	235	27.54	43.19	280	28.69	56.59
Running variable						
GT	235	4799	144	280	5199	142

Furthermore, because both groups' standard deviations are roughly equal, there is approximately equal variation in the ships' GT around the mean GT. Considering that the RDD method implies that the ships are randomly distributed around the threshold, and hence that the control group is a legitimate counterfactual to the treatment group (Lee & Lemieux, 2010), it is a good thing that there are not any noticeable systematic differences between the ships AER 2017 (i.e., before the treatment) and GT on average (Wuepper & Finger, 2023). The identifying assumptions of the RDD will be explained in section 6.

6. Empirical method

This study addresses whether the EU MRV regulation translates into an effect on ships' CO_2 emissions. I use the Regression Discontinuity Design (RDD) to achieve this. Section 6.1 presents the RDD and its identifying assumptions. Section 6.2 presents the econometric specification for this study. Finally, in section 6.3, a discussion regarding the strengths and limitations of the methodology is made.

6.1 Regression Discontinuity Design

RDD is a quasi-experimental method similar to a randomized controlled experiment, but with the difference that the treatment allocation is not controlled but instead the result of some exogenous factor and is therefore referred to as a natural experiment (Hahn et al., 2001). Applying an RDD as a methodology is based on using a threshold as a clearly defined boundary, in which only units on one side of the threshold are subjected to treatment. Sorting the units by treatment status requires that the treatment is a deterministic function of some underlying variable, i.e., the exogenous factor whose value determines whether the unit is assigned to the treatment or not (Pettersson-Lindbom, 2008). The treatment status of the units is thereby determined according to the following function:

$$D_{it} = \begin{cases} 1 \ if \ X_{it} \geq c_0 \\ 0 \ if \ X_{it} \leq c_0 \end{cases} \tag{3}$$

The variable X_{it} in equation (1) is the underlying assignment (i.e., running variable) whose value determines whether unit i is assigned to treatment in period t, c_0 represents the cutoff that sorts the units into two separate groups based on treatment status (treatment group and control group). D_{it} is a binary variable indicating the treatment status of the units. Hence, the treatment assignment is denoted by $D \in \{0,1\}$. If the probability of being assigned treatment changes discontinuously, from 0 to 1, at the threshold, it implies that units whose observed value of the running variable exceeds the threshold ($X_{it} \geq c_0$) are permanently assigned to the treatment ($D_{it} = 1$). On the other hand, units whose observed value of the running variable is below the threshold ($X_{it} < c_0$) are never assigned to the treatment ($D_{it} = 0$). In this situation, a sharp discontinuity in the treatment allocation at the threshold is generated as a function of the running variable; the assignment rule is deterministic, making it possible to apply a *sharp RDD*. The alternative design is called *fuzzy RDD*, where the probability of treatment discontinuously *increases* at the cutoff (Cunningham, 2021), and the assignment rule is probabilistic (Hahn et al., 2001).

The methodology assumes that units sufficiently close to the threshold are randomly distributed. Comparing outcomes just above and below the threshold allows for identifying the average causal effect of treatment (Wuepper & Finger, 2023), known as the local average treatment effect (LATE). Technically, we are identifying an average casual effect for the units near the cutoff because identification in an RDD is a limiting situation (Cunningham, 2021). By initially assuming that the relationship between the outcome variable and the running variable is linear, it is possible to illustrate the impact of the treatment by estimating the following regression:

$$Y = \alpha + \tau D + \beta_1 X^{above} + \beta_2 X^{below} + \varepsilon \tag{4}$$

where τ represents the average effect of the treatment (D_{it}) on the relevant outcome (Y_{it}), α is a constant, β_1 and β_2 smoothly control for the distance to the cutoff from above and from below, and ε is an error term (Wuepper & Finger, 2023). The identifying assumption for τ corresponds to the causal effect of the treatment is that all the relevant underlying factors are a continuous function of the running variable at the threshold. If the continuity assumption is fulfilled, the treatment is the only reason the outcome variable is a discontinuous function of the running variable at the threshold. There should not be any indication that units are trying to manipulate their probability of being eligible for the treatment. This means that the vertical distance at the cutoff between the two groups can be considered to correspond to the causal effect of the treatment effect. The vertical distance, often called "the jump," can be observed when the data is plotted (Wuepper & Finger, 2023).

According to Lee and Lemieux (2010), through the "potential outcomes framework," the necessity of the continuity assumption is more formally understood. Often, it is assumed that there are two possible outcomes for each individual: Y_i (1) for what would happen if the unit was subjected to the treatment, and Y_i (0) for what would happen if it were not. The difference $Y_i(1) - Y_i(0)$ represents the treatment's casual effect. However, the main issue with casual inference is that we cannot simultaneously see the pair Y_i (1) and Y_i (0). As a result, instead of concentrating on impacts at the unit level, we usually concentrate on average treatment effects, i.e., the subpopulation's average effect $Y_i(1) - Y_i(0)$. Nevertheless, the RDD design dictates that everyone to the right of the cutoff receives treatment, while everyone to the left is not. Due to the underlying functions' $E[Y_i(1)|X]$ and $E[Y_i(0)|X]$ continuity, the following inference is possible:

$$B - A = \lim_{\varepsilon \downarrow 0} E[Y_i|X_i = c + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[Y_i|X_i = c + \varepsilon] \tag{5}$$

where the left-hand side of Equation (5) illustrates the inference between *(B)efore* and *(A)fter* the treatment, and the right-hand side equals the average treatment effect (ATE):

$$E[Y_i(1) - Y_i(0)|X = c] \tag{6}$$

In essence, the continuity condition allows us to utilize the average outcome of units who fall just below the cutoff and are not given treatment as a legitimate counterfactual for individuals who fall just above the cutoff and were given treatment (Lee & Lemieux, 2010).

6.2 Econometric specification

In the case of the EU MRV Regulation, implementing an RDD as a method is relatively straightforward, and the constituent variables are easy to define. Below, the main design for this study will be described.

The units, ships, can be linearly sorted along the running variable as ship GT. Every ship that calls on EU ports and has a GT of 5,000 or more is subject to the MRV regulation, which is considered a clear cutoff value. The treatment group consists of ships with a GT of 5,000 or higher, whereas the control group consists of ships with a GT of 5,000 or less. Hence, the running variable X (i.e., the GT of a ship) is a deterministic function of the treatment (i.e., the MRV regulation) (Cunningham, 2021; Regulation 2015/757).

In order to estimate the causal effect of the EU MRV Regulation, a sharp RDD is applied by implementing the following local linear regression for all ships with a GT between 4,500 – 5,500 that have been calling on EU ports in the treatment year 2018. In addition, for comparison reasons, estimates of the AER of 2017 and 2019 will also be included.

$$AER_{i,t} = \alpha + \tau D_i + \beta_1(GT_i - c_0) + \gamma D_i(GT_i - c_0) + \varepsilon_i \tag{7}$$

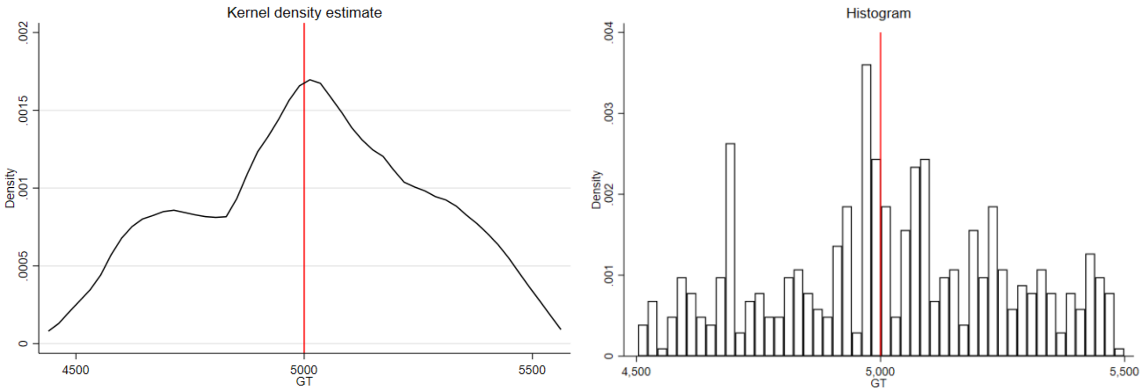
where τ represents the "MRV-Regulation effect," which will measure the average difference in AER outcomes, depending on the GT of a ship, GT has been normalized to the distance from the threshold ($GT_i - c_0$) to provide a more intuitive and consistent interpretation. The inclusion of the interaction term [$D_i(GT_i - c_0)$] allows for the slope of the regression line to vary on either side of the threshold (c_0) in order to minimize the risk of biasing the estimated effect, where β corresponds to the slope of the regression line below the threshold, GT < 5,000, ($D_i = 0$) and where γ is added to the slope of the regression line above the threshold, GT ≥ 5,000, ($D_i = 1$) (Lee & Lemieux, 2010). The coefficient α represents the intercept, and $\varepsilon_{i,t}$ is the error term which is expected to be uncorrelated with (D_i) since all variation in (D_i) is explained by the GT of a ship, and thus (GT_i) is the only variable to be controlled for in the regression (Lee & Lemieux, 2010).

6.3 Strengths and limitations

RDD has gained popularity during the past 20 years (Cunningham, 2021), and it is more frequently used in environmental economics to identify causal effects (Wuepper & Finger, 2023). The RDD's capacity to successfully eliminate selection bias is one reason it appeals to many. By making selection bias powerless, the method can recover a subset's average treatment effects (ATE) (Cunningham, 2021). Moreover, the identifying assumptions can be transparently tested, and instructive plots of the data can visibly support arguments. The transparency of the research design is improved by the disclosure of the "raw data." For example, if "the jump" in the outcome variable at the cutoff is graphically exceptionally large compared to the bumps in the regression curve, it is possible to establish an early opinion on the existence and magnitude of the effect of the treatment. The issue with graphical presentations, however, is that there is some room for the researcher to construct graphs that appear to show effects when none exist or conceal effects that do. (Cunningham, 2021). Later in the study, I discuss methods for reducing such presentational biases.

In contrast to other quasi-experimental approaches, the method's identifying assumptions are less stringent (Lee & Lemieux, 2010). On the contrary, it has been demonstrated that assuming that the treatment is randomly distributed around the threshold is unnecessary since the local random variation follows when the continuity assumption is met. For a proper RDD, the running variable GT cannot be accurately manipulated around the 5,000 GT threshold, i.e., "bunching" behavior right before the cutoff. A lack of systematic selection around the cutoff is compatible with a continuous density of the running variable near the cutoff. Because ships cannot modify their GT after they have been constructed, there is little probability of such manipulation occurring in the context of this thesis. However, it is conceivable that new ships will be designed just below 5,000 GT to avoid the policy. Presenting a histogram of the running variable GT with many bins is the most straightforward way to check for manipulation at the cutoff. The bin width should be as narrow as it can be without impairing the ability to visualize the overall shape of the distribution (Lee & Lemieux, 2010). I also carry out a kernel density estimate of the running variable GT to gain as much understanding of the distribution of the running variable as feasible.

Figure 2: Density distribution



Notes: The left figure displays an RDDensity plot for the running variable GT including the entire sample. The right figure displays a histogram of the aggregate distribution of the number of ships (i) for different values of the running variable GT around the threshold (5,000 GT) for each ship, where the threshold is normalized to the value 5,000 GT. Bars to the left of the threshold represent ships below 5,000 GT and are not obligated to the MRV regulation. In contrast, bars to the right represent ships equal to and above 5,000 GT, which is obligated to the MRV regulation.

Figure 2 shows that the GT distribution is a bit "bumpy" around the threshold. Ideally, we would see a plateau near the 5,000 GT cutoff point in the kernel density estimate, and now a small peak is visible. Moreover, the histogram would ideally not have any discontinuity around the cutoff. I thus conducted a manipulation test based on density discontinuity using the local polynomial to rule out the possibility that this is the result of bunching. The assumption that no discontinuity is close to the cutoff is thereby formally tested in this experiment. The test contrasts the observations with a 0.5 binomial random distribution. According to Table 2, there was no indication of manipulation at the threshold of 5,000. The null hypothesis is not rejected because the p-value is 0.1588, indicating that there is no self-selection of ships into or out of the treatment of the policy. It is important to note that there is still almost a 16 percent probability that the ships may manipulate themselves around the cutoff, and the effective number of observations could be viewed as relatively low. Nevertheless, because the binominal test is not statistically significant, the distribution of ships at the cutoff is assumed to be as good as random.

Table 2: Manipulation Testing

Bandwidths		**Eff. n**		**Test**
left	right	left	right	P>|T|
26	26	22	35	0.1112
36	37	48	35	0.1875
46	47	53	37	0.1133
56	58	53	48	0.6908
66	68	59	62	0.8558
76	79	69	76	0.6184
86	90	75	94	0.166
96	100	85	101	0.2714
106	111	88	105	0.2494
116	122	90	108	0.2269
P-value				0.1588

P-values of binomial tests. (H0: prob = .5)

Notes: Columns under "Bandwidths" report estimated bandwidths, columns under "Eff. n" report effective sample size on either side of the cutoff, and columns under "Test" report the value of the p-value for each density estimator. The last row, labeled "P-vale," corresponds to the unrestricted test with 515 observations, 90 effective observations to the left of the cutoff and 108 effective observations to the right of the cutoff, and a bandwidth estimator between 116.056 – 121.595.

As in a randomized controlled experiment, it is possible to test whether the treatment can be considered randomly distributed by determining whether there is a balance of underlying factors between ships on each side of the threshold. This is considered a strength of this approach (Pettersson-Lindbom, 2008). However, since local randomization implies that the distribution of treatment is independently related to the underlying characteristics of the ships, satisfying the continuity assumption has important implications, including the fact that it is not necessary to control for observable underlying factors by including them in the regression. Suppose the running variable's value determines the ships' treatment status. In that case, it is the only variable that needs to be considered in the regression because it captures the correlation between the explanatory variable (D_{it}) and the error term (Pettersson-Lindbom, 2008). Nevertheless, it is essential to consider how the running variable should be controlled and, as a result, how the RDD as a method should be implemented.

Two basic techniques have dominated the prior literature in this regard. One option is to use a non-parametric technique and estimate a local linear regression using observations in an area sufficiently close to the threshold where the local randomization occurred. (Hahn et al. 2001; Lee & Lemieux 2010). Using a local linear regression implies a trade-off between bias and precision. Theoretically, it would be preferable to minimize the distortion of the estimated effect by reducing the so-called bandwidth, i.e., the window size around the threshold that determines how many observations are used. The issue is that the estimated effect's precision decreases when the bandwidth is restricted since fewer observations can still be used. Expanding the bandwidth is required to achieve appropriate precision, which comes with the cost of increased risk of bias.

The second option is to use all observations and estimate a parametric regression instead of a local linear regression, which is done by controlling for the running variable with different degrees of higher polynomials to determine the extent of the discontinuity at the threshold. The parametric technique has frequently been chosen in earlier research because it permits more data, which increases precision and is thought to yield accurate estimations if an appropriate polynomial degree is utilized. However, a correct polynomial function can be challenging to specify, and using observations far from the local randomization seems contradictory (Lee & Lemieux, 2010). It has also been demonstrated to offer less accurate predictions than when local regressions are used (Gelman & Imbens, 2019). Given that the first technique is now regarded as the preferred and most widely used approach in more recent applied literature (Gelman & Imbens, 2019; Wuepper & Finger, 2023; Calonico et al., 2014; Calonico et al., 2017), the decision is made to implement an RDD through local linear regression, where data-driven (automated) bandwidths are used to optimize the balance between bias and precision in a transparent and non-arbitrary manner. Nonetheless, it is advised to allow the bandwidth to vary and to include a lower-order polynomial function as a specification test to determine whether the estimated effects are stable and whether the functions are correctly specified (Lee & Lemieux, 2010; Calonico et al., 2014; Calonico et al., 2017). Hence, this will be done through sensitivity tests in the result section.

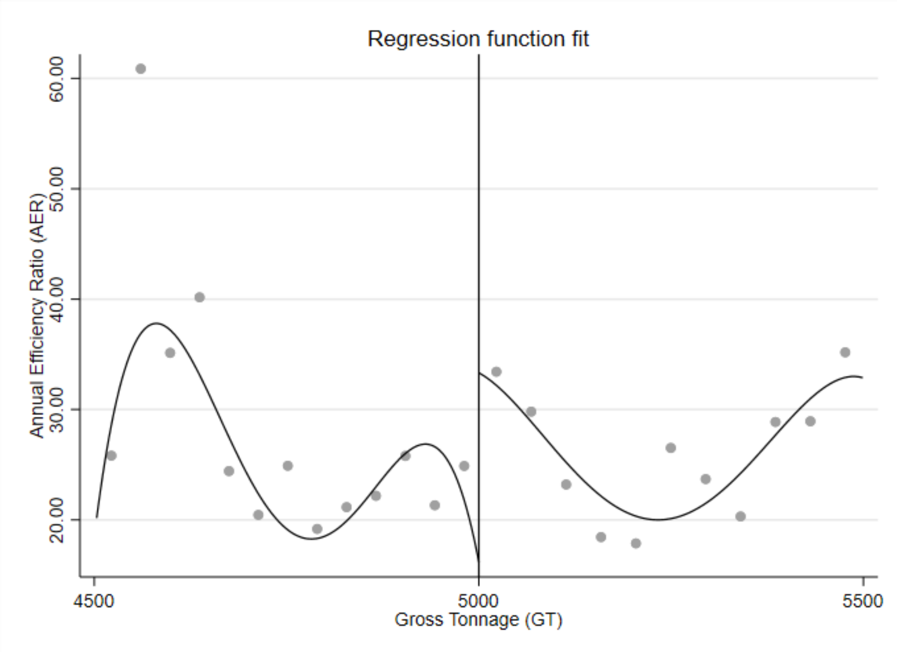
7. Results

This section presents the results of the study. First, section 7.1 displays the RDD's graphical representation, focusing on AER2018 as the variable of interest. Next, section 7.2 provides the regression results. Finally, section 7.3 conduct sensitivity tests.

7.1 Graphical Results

The results of the graphical analysis are presented in Figure 3. The graph illustrates the relationship between the running variable GT for each vessel and the AER2018 outcome. The non-overlapping intervals correspond to different values of the running variable, and the grey dots indicate the average value of the outcome measure for vessels inside each point interval. The dots allow for more local comparisons of means between different intervals in order to analyze the discontinuities both right at and further away from the threshold, while the solid black regression lines on either side of the threshold aim to illustrate a more flexible and smoothed approximation of the running function globally across the entire distribution (Lee & Lemieux, 2010; Calonico et al., 2015).

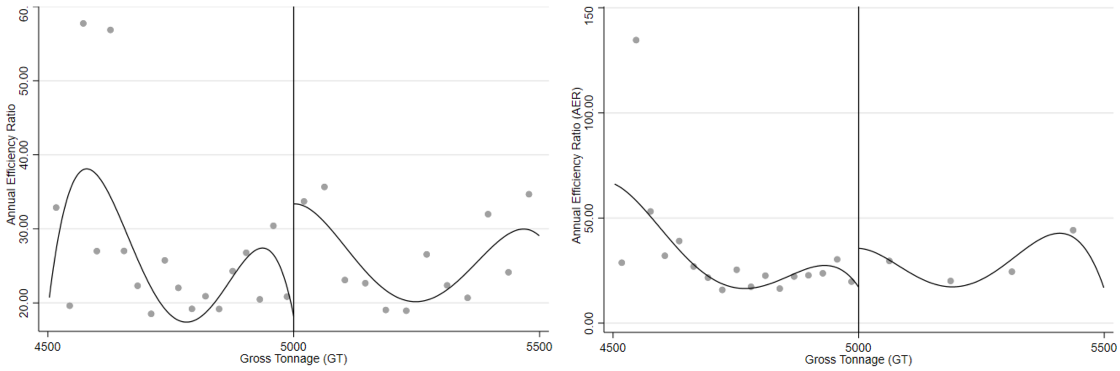
Figure 3: Graphical presentation of the RDD analysis for outcome AER2018



Notes: Data-driven RDD graph following Calonico et al. (2015) with the dependent variable in the form of the outcome measure (AER2018) on the y-axis and the running variable (GT) around the threshold value (5,000 GT) on the x-axis, where the x-axis is divided into non-overlapping intervals for different values of the running variable. The grey dot intervals represent the mean of the outcome measure for ships within each interval weighted by a uniform kernel. The solid black lines represent fitted regressions estimated with fourth-degree polynomials separately for vessels on each side of the threshold.

By analyzing the graphical result for AER2018, it can be seen from the regression line to the left of the threshold that the AER of the vessels seems to decrease discontinuously as the GT of the vessel increases. The underlying variable appears relatively discontinuous regarding the average value of the outcome variable between the different ranges of GT. At the threshold, it looks like a sharp increase in the outcome's value, indicating a discontinuity. However, it is essential to acknowledge that the effect looks more extensive since the polynomial goes down right before the threshold. Regardless, the graph demonstrates how the policy positively impacts AER2018. This indicates that the ships that must report their emissions emit more than those exempt from reporting, which is the opposite of what the policy aims to achieve. However, it is possible to distinguish a relatively large spread in the point intervals in the form of apparent discontinuities set over the entire distribution. This raises caution in interpreting a possibly significant estimate as a causal effect.

Figure 4: Graphical presentation of the RDD analysis for AER2017 and AER2019



Notes: Data-driven RDD graphs. The outcome of AER2017 is presented to the left, and the outcome of AER2019 is presented to the right.

Figure 4 presents the relationship between the running variable GT for each vessel and the AER outcome for 2017 and 2019, respectively. The graphs are included for comparison. The graphical outcome for AER2017 and AER2018 are comparable. Additionally, the AER2017 illustrates discontinuities in the mean value of the outcome variable across the whole distribution of point intervals. A discontinuity that denotes an increase in a ship's emissions as its GT rises can be seen at the threshold. However, it is worth mentioning that considering its magnitude in relation to the discontinuities in the point intervals further from the threshold, a significant effect should not be expected. As for AER2019, the graph in Figure 4 shows that the shape of the regression line to the left of the threshold is not as volatile as it is for AER2017 and AER2018. Instead, the shape of the regression line to the left of the threshold shows how the ship's AER decreases successively the larger GT they have. Further, the running variable appears relatively continuous and without any distinct discontinuities in the average value of the outcome variable between the different point intervals, which, however, become smaller on the regression line to the right. It is essential to mention that the smoother lines could be because the scales differ due to higher extreme values in AER2019. This will be clearer to interpret in the regression results. We still observe a positive effect at the cutoff value, which is smaller in magnitude than for AER2017 and AER2018.

7.2 Regression Results

This section presents the results for the estimated effect of the EU's MRV regulation (τ) on the respective outcome measures for the Annual Efficiency Ratio ($AER_{i,t}$) from the local linear regressions estimated with equation (7). The result is presented in tabular form in Table 3 below, with an optimal data-driven bandwidth for all outcome metrics. The primary regression of interest is presented in column (2) in Table 3, representing the outcome of AER2018.

Table 3: Regression results

	(1)	(2)	(3)
	2017	*2018*	*2019*
RD Estimate	8.429	10.19	10.78
	(10.09)	(8.633)	(10.93)
Robust 95% CI	[-11.817 ; 32.709]	[-6.622 ; 31.121]	[-11.952 ; 40.447]
Kernel Type	Triangular	Triangular	Triangular
BW Type	MSE-optimal	MSE-optimal	MSE-optimal
Observations	515	515	515
Conventional p-value	0.404	0.238	0.324
Robust p-value	0.358	0.203	0.286
Order Loc. Poly. (p)	1	1	1
Order Bias (q)	2	2	2
BW Local. Poly. (h)	204.795	185.353	225.9
BW Bias (b)	219.055	209.436	250.656

* p<0.05, ** p<0.01, *** p<0.001. Robust standard errors in parentheses

Notes: The columns report the RD estimates from local linear regressions weighted with a triangular kernel, with standard errors given in parentheses. The output includes two confidence intervals. The second one is called the robust confidence interval, accounting for the fact that the RDD uses polynomials to approximate the underlying mean outcome functions. The variance is corrected for the misspecification error or smoothing bias in the other confidence interval. The authors of this command suggest that the robust confidence interval should have good statistical properties, especially in relatively small samples. They should be used for statistical inference to test a policy impact's statistical significance. Bandwidth = Optimal data-driven bandwidth (mean squared error (MSE) following Calonico et al. (2014; 2017).

Column (2) of Table 3 shows that ships with a GT of 5,000 or higher are associated with an increase in AER of 10.19 index points. This means that ships that, according to the EU's MRV regulation, are obliged to report their emissions on average have an AER that is 10.19 index points higher than ships that do not have this obligation. In addition, since the average AER2018 for the treatment group is 26.28, presented in section 5.2, the difference could be considered relatively large. The estimate is, however, not statistically significant from zero. Hence it is not possible to identify any effect on this measure. In addition, the standard errors are too large in relation to the size of the estimate. Columns (1) and (3) of Table 3 show the regression estimates for AER2017 and AER2019, respectively. The regressions are included for comparison purposes. According to the RD estimates, the average difference between ships in the treatment and control groups appears to grow over time. The results confirm what we saw in the graphical findings, namely that the regulation positively impacts emissions, as seen by the fact that ships that are required to report their emissions emit more than ships that are not required. Additionally, given that the point estimation in columns (1) and (3) is similar, it is confirmed that scale adjustments can explain the smoother lines in Figure 4 of AER2019. However, like the main regression in column (2), neither of the regressions in columns (1) and (3) are statistically significant.

7.3 Sensitivity tests

When implementing an RDD, it is advisable to implement some sensitivity tests. The general objective is to illustrate to what extent the results are sensitive to alternative specifications. One of these specification checks is the manipulation test conducted in section 6.2. In addition, this section will implement specification checks such as higher-order polynomial tests and placebo tests.

Table 4: Sensitivity test – different polynomials

	(1) *Second-order local polynomial*	(2) *Third-order local polynomial*	(3) *Fourth-order local polynomial*
RD Estimate	14.89 (9.397)	21.24 (12.257)	14.89 (9.397)
Kernel Type	Triangular	Triangular	Triangular
BW Type	MSE-optimal	MSE-optimal	MSE-optimal
Observations	515	515	515
Eff. Number of observations	106 / 133	109 / 133	129 / 151
Conventional p-value	0.113	0.083	0.097
Robust p-value	0.085	0.094	0.112
Order Loc. Poly. (p)	2	3	4

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses

Notes: RD estimates.

Table 4 estimates the RDD treatment effect with different polynomial orders. Exploring whether the RD estimate is robust to different higher-order polynomials is essential. The results are too sensitive and unreliable if the treatment effect vanishes using a different polynomial (Lee & Lemieux, 2010). However, in this case, the results were insignificant in the main regression in Table 3 column (2). Remarkably, the RD estimate becomes somewhat near statistical significance when changing to a higher polynomial order; see Table 4 columns (1)-(3). There are, however, valid reasons to avoid using the higher-order polynomial approach, as pointed out by Gelman and Imbens (2019). When a high-order polynomial is fitted, the weighted average can be influenced by observations that are distant from the threshold, causing the estimate to be highly sensitive to the degree of the polynomial used. Consequently, confidence intervals may be too narrow, resulting in a bias toward discovering a significant effect where none exists.

However, the robust results to a range of specifications are more compelling. Thus, one should not rely on one specification when using local linear regression because there are also bias issues to consider. Lee & Lemieux (2010) suggest that the amount of data near the threshold is crucial. If there is an extensive dataset, it may be better to focus on local regression and disregard distant data. However, if the sample is small, utilizing as much data as possible is more important, even if it results in greater dependence on the functional form. The sample for this thesis is considered relatively small. Therefore, it seems feasible to take notice of the higher-order polynomial estimations.

Table 5: Sensitivity test - placebo cutoff

	(1)	(2)
	Placebo cutoff 4600	*Placebo cutoff 5400*
RD Estimate	-13.05	23.56
	(21.65)	(14.69)
Robust 95% CI	[-72.251 ; 29.66]	[-10.551 ; 85.63]
Kernel Type	Triangular	Triangular
BW Type	mserd	mserd
Observations	515	515
Conventional p-value	0.547	0.109
Robust p-value	0.413	0.126
Order Loc. Poly. (p)	1	1
Order Bias (q)	2	2
BW Local. Poly. (h)	58.852	67.722
BW Bias (b)	81.633	88.010

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in parentheses

Another type of sensitivity robustness check consists of testing if jumps of the outcome variable occur at other placebo cutoffs, i.e., artificial cutoffs. There should be a treatment effect at the policy participation cutoff, but there should be no similar jumps at other levels of the running variable without reason. Placebo tests can help detect potential discontinuities over the support of the running variable (Lee & Lemieux, 2010). Table 5 presents two different placebo cutoffs, one below (4,600) and one above (5,400), with the actual cutoff value of 5,000. As seen in Column (1), there is a negative RD estimate effect, which results in an average 13,05 index point decrease in AER2018 for ships over 4,600. The positive RD estimate effect in Column (2) indicates that ships above 5,400 tons have an average AER2018 of 23,56 index points higher. None of the estimates, however, are statistically significant. The fact that the placebo point estimates are of similar magnitudes as the main estimation does give some evidence for the absence of any actual effect of the MRV regulation.

Making RDD estimations based on placebo outcomes is another sensitivity test. The foundation of this falsification test is the notion that results for which the treatment is known to have no effect should display a zero RDD treatment effect (Lee & Lemieux, 2010). This was done in Table 3, columns (1) and (3), when running regressions for the outcomes of AER2017 and AER2019, respectively. However, the results were not statistically significant.

8. Discussion

The results of this study are discussed and compared with the findings of previous research and established theories in this section. The objective of this paper is to assess whether the EU MRV Regulation led to a reduction in emissions from ships. In concrete terms, the issue has been to find out whether ships that are forced to report their emissions as a result of the regulation have a lower Annual Efficiency Ratio (AER), i.e., if they have a lower carbon intensity, than ships that do not have to account for their emissions. The results indicate the opposite, however, as the point estimates suggest that the effect of the MRV regulation, if any, might be positive. Nevertheless, the result is not statistically significant. This could be attributed to either the lack of a noticeable impact or the complexity of measuring the possible effect due to the diverse outcomes of the AER, combined with data limitations. The lack of significance in the point estimates, along with similar point estimates the year before the MRV regulation was enforced and similar magnitude in point estimates for placebo treatments, indicate that the MRV regulation might not have affected carbon intensity.

The nonsignificant estimates of this study could be explained by the fact that the regulation did not provide enough incentives for ship operations to change their BAU operations. Hombach and Sellhord (2019) suggest that reporting would only be effective if all parties perceived the information provided as valuable and distinctive. Similar to the findings in the studies conducted by Panagakos et al. (2019) and Poulsen et al. (2021), the EU MRV Regulation does not seem to satisfy the expectations regarding transparency between the actors in the shipping sector. One of the key findings from Poulsen et al. (2021) is that the MRV Regulation does not enable shipping actors to differentiate between the most and least energy-efficient ships, failing to aid the market in making better decisions. Similarly, Shi et al. (2021) did not find any significant effect of an EID on innovation and end-governance mechanisms. Given this, it is unsurprising that this study did not discover a significant impact of the MRV Regulation on ship emissions. Another reason for the insignificant results could be the complexity of measuring the possible effect with an index value such as AER. Adding up different variables will sum up each variable’s measurement error. This can distort the coefficient and result in insignificant results. However, as discussed in section 5.1, it would not be accurate to only look at total emissions since that would not account for influential factors, such as ship type, which is essential when interpreting a ship's energy efficiency.

Even though the primary regression estimation in Table 3 column (2) was statistically insignificant, it is worth acknowledging that it shows a positive effect of the AER from the MRV Regulation. This means that ships forced to report their emission also have a higher carbon intensity. A result that is the opposite of the purpose of the regulation. The result is also the opposite of what some previous studies about targeted transparency policies have found (Downar et al., 2021; Shi et al., 2021; Salman, 2022; Zhang et al., 2020). Nevertheless, the aforementioned studies also find that multinational companies with "complicated operations" did not cut their emissions as much as their "less complex" peers. It could be argued that the shipping industry consists of relatively complex contracts, described in section 3.1 and that this - combined with the fact that the MRV regulation was the first policy to regulate emissions for ships in the EU - is a contributing factor to the result. Among the studies analyzed in this thesis, Kasim's (2017) findings align most closely with the result of this study. Kasim aim to estimate the effect of an environmental disclosure policy on air pollution and concludes that the policy's implementation does not significantly impact pollutant concentration levels. However, transitioning the shipping sector faces a challenging task as its operations involve traveling great distances without refueling, which requires much energy. Furthermore, ships have exceptionally long lifespans (IMO, 2015). Therefore, it is essential to note that it may take time for ships to adjust their emissions with actions such as re-routing or reducing speed, possibly creating an effect lag, which could explain the ineffectiveness of the MRV regulation. It could be argued that the EU needs to take more concrete actions to reduce emissions in the shipping sector.

In addition to above, it is possible that the lack of a significant effect in the results is due to an anticipation effect. It is plausible that ships had higher AERs before the EU decided on the regulation in 2015 and might have decreased their emissions before being required to report them in 2018. Unfortunately, this cannot be confirmed as the collected data only covers the years 2017 to 2019. However, based on the descriptive statistics in section 5.2, AER2017 only had a slightly higher value than AER2018.

Finally, section 6.2 discussed the strengths and limitations of this study. One of the threats to the validity of an RDD is bunching, i.e., if the ships can manipulate themselves around the cutoff value at 5,000 GT. As Figure 2 shows, the GT distribution is more discontinuous than what can be considered optimal. Notably, if the apparent discontinuity results from manipulation, this implies that ships emitting lesser pollutants have deliberately positioned themselves beneath the threshold. Such action could be interpreted as counterproductive since, as Liesen et al. (2015) argue, ships that emit less will see the opportunity to disclose for legitimacy purposes from stakeholders. Furthermore, as the sensitivity tests show, there is more reason to interpret the results cautiously. Indeed, the continuity assumption seems to be fulfilled. However, the sensitivity tests show that the results are sensitive to the type of specification model used. The fact that results are not stable across different specifications indicates there may be limitations in the internal validity of the results. However, this is not unexpected, given the lack of significance in the main regression.

9. Concluding remarks

This research aims to examine the impact of the EU MRV regulation on ship emissions when calling at EU ports. The main question is whether ships that are required to report their emissions emit less due to the regulation. The study utilizes AIS data on distance sailed, fuel consumption, deadweight tonnage, and gross tonnage to calculate the AER value of each ship. This value is an index used to describe a ship's carbon intensity per carrying capacity and distance traveled. An empirical analysis is conducted using the RDD method to clarify the question. By limiting the analysis to ships with a GT just above 5,000 and ships with a GT just below 5,000, the effect of MRV regulation on emissions is isolated. However, based on the estimations, the MRV regulation seems to have little to no influence on ship emissions. If there is any impact, it could potentially be positive. However, it is crucial to mention that the outcomes are not statistically significant.

Further research is necessary to determine the impact of MRV on emissions in the EU, as the outcome of the current study was inconclusive. It is recommended that future investigations consider area-specific characteristics that influence the relationship between ship emissions and transparency policies. Additionally, the study highlights the need to consider other variables that could affect the AER, such as completeness of reporting. To increase the explanatory power of future studies, collecting more data from additional ports and using a method that can track changes in ship emissions over time would be beneficial. Furthermore, it would be interesting to include more time periods before and after the treatment to enhance the comprehension of ship operations and emissions. Lastly, this study did not explore the regulations' anticipated aggregated net cost reduction, which is still an intriguing and unexplored subject for future research.

References

Arrow, K. J. (1974). Essays in the theory of risk-bearing (Vol. 121). Amsterdam: North-Holland.

Calonico, S., Cattaneo, M. & Titiunik, R. (2014). Robust data-driven inference in the regression discontinuity design. *The Stata Journal*, 14(4): 909–946.

Calonico, S., Cattaneo, M. & Titiunik, R. (2015). Optimal data-driven regression discontinuity plots. *Journal of the American Statistical Association*, 110(512): 1753–1769. https://doi.org/10.1080/01621459.2015.1017578

Calonico, S., Cattaneo, M., Farrell, M. & Titiunik, R. (2017). Rdrobust: software for regression discontinuity designs. *The Stata Journal*, 17(2): 372–404.

Clarkson Research Services (n.d.). Limited, World Fleet Register. https://www.clarksons.com, [Downloaded 2023-04-20]

Cunningham, S. (2021). Causal inference: The mixtape. Yale university press.

Deane, F., Huggins, A., & Karim, M. S. (2019). Measuring, monitoring, reporting and verification of shipping emissions: Evaluating transparency and answerability. Review of European, Comparative & International Environmental Law, 28(3), 258-267. https://doi.org/10.1111/reel.12308

Dirzka, C., & Acciaro, M. (2021). Principal-agent problems in decarbonizing container shipping: A panel data analysis. *Transportation Research Part D: Transport and Environment*, 98, 102948. https://doi.org/10.1016/j.trd.2021.102948

DNV (n.d.), About DNV – Maritime, https://www.dnv.com/about/maritime/index.html, [Downloaded 2023-04-27]

Downar, B., Ernstberger, J., Reichelstein, S., Schwenen, S., Zaklan, A. (2021) The impact of carbon disclosure mandates on emissions and financial operating performance. Rev Account Stud 26, 1137–1175. https://doi.org/10.1007/s11142-021-09611-x

Drucker, P.F. (1954). The practice of management. Harper Business.

ECSA – European Community Shipowners' Associations. (2017). Shipping and Global Trade. Towards an EU external shipping policy.

Eide, M. S., Endresen, Ø., Breivik, Ø., Brude, O. W., Ellingsen, I. H., Røang, K., Brett, P. O. (2007). Prevention of oil spill from shipping by modeling of dynamic risk. *Marine Pollution Bulletin*,54(10), 1619–1633.

European Commission, (n.d.), Climate Action, Reducing emissions from the shipping sector. https://climate.ec.europa.eu/eu-action/transport-emissions/reducing-emissions-shipping-sector_en, [Downloaded 2023-05-05]

European Commission, Joint Research Centre, Istrate, I., Iribarren, D., Dufour, J., et al. (2022) Quantifying emissions in the European maritime sector: a review on life cycle assessments of maritime systems combined with an analysis of the THETIS-MRV portal. Publications Office of the European Union. https://data.europa.eu/doi/10.2760/496363,[Downloaded 2023-05-05]

European Commission (2021), Questions and Answers: Taxonomy Climate Delegated Act and Amendments to Delegated Acts on fiduciary duties, investment, and insurance advice. https://ec.europa.eu/commission/presscorner/detail/en/qanda_21_1805, [Downloaded 2023-05-05]

Fagotto, E., & Graham, M. (2007). Full disclosure: using transparency to fight climate change. *Issues in Science and Technology, 23*(4), 73–79.

Fedi, L. (2017). The Monitoring, Reporting and Verification of Ships' Carbon Dioxide Emissions: A European Substantial Policy Measure towards Accurate and Transparent Carbon Dioxide Quantification. *Ocean Yearbook Online*. 31. DOI: 10.1163/9789004347137_015

Fung, A., Graham, M., & Weil, D. (2007). *Full disclosure: The perils and promise of transparency*. Cambridge University Press.

Gelman, A., & Imbens, G. (2019). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, 37(3), 447-456. https://doi.org/10.1080/07350015.2017.1366909

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1), 201-209. http://www.jstor.org/stable/2692190

Hansen, M. G., Jensen, T. K., Lehn-Schiøler, T., Melchild, K., Rasmussen, F. M., & Ennemark, F. (2013). Empirical ship domain based on AIS data. *The Journal of Navigation*, 66(6), 931-940.

Hombach, K., & Sellhorn, T. (2019). Shaping corporate actions through targeted transparency regulation: A framework and review of extant evidence. *Schmalenbach Business Review*, 71, 137-168. https://doi.org/10.1007/s41464-018-0065-z

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

IMO (International Maritime Organization) (2021a) IMO AND THE ENVIRONMENT, IMO's response to current environmental challenges. https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/IMO%20and%20the%20Environment%202011.pdf [Downloaded 2023-04-27]

IMO (International Maritime Organization) (2018). Resolution MEPC.304(72) (Adopted on 13 April 2018): Initial IMO Strategy on Reduction of GHG Emissions from Ships. London: International Maritime Organization.

IMO (International Maritime Organization) (2015) Third IMO GHG Study 2014, Executive Summary and Final Report.

IMO (International Maritime Organization) (2020) Fourth IMO GHG Study 2020 Executive-Summary.

IMO (International Maritime Organization) (n.d.) IMO Ship Numbering FAQ. https://wwwcdn.imo.org/localresources/en/OurWork/IIIS/Documents/IMO%20Ship%20Number%20&%20Extension%20FAQs.pdf [Downloaded 2023-04-27]

Jia, H., Adland, R., Prakash, V., & Smith, T. (2017). Energy efficiency with the application of Virtual Arrival policy. *Transportation Research Part D: Transport and Environment, 54*, 50-60.

Johnson, H., & Andersson, K. (2016). Barriers to energy efficiency in shipping. *WMU Journal of Maritime Affairs*, 15, 79-96. https://doi.org/10.1007/s13437-014-0071-z

Kasim, M. T. (2017). Evaluating the effectiveness of an environmental disclosure policy: An application to New South Wales. *Resource and Energy Economics*, 49, 113-131. https://doi.org/10.1016/j.reseneeco.2017.04.003

Kivekäs, N., Massling, A., Grythe, H., Lange, R., Rusnak, V., Carreno, S., Kristensson, A. (2014). Contribution of ship traffic to aerosol particle concentrations downwind of a major shippinglane. *Atmospheric Chemistry and Physics*,14(16), 8255–8267. https://doi.org/10.5194/acp-14-8255-2014

Lee, D. S., & Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of economic literature*, 48(2), 281-355. DOI: 10.1257/jel.48.2.281

Li, L., Lu, W., Niu, J., Liu, J., & Liu, D. (2018). AIS data-based decision model for navigation risk in sea areas. *The Journal of Navigation*,*71*(3), 664–678.

Liesen, A., Hoepner, A., Patten, D., Figge, F. (2015). Does Stakeholder Pressure Influence Corporate GHG emissions reporting? Empirical Evidence from Europe. *Accounting, Auditing & Accountability Journal* Vol. 28 No.7 pp. 1047-1074. DOI 10.1108/AAAJ-12-2013-1547.

Linares-Rodríguez, M.C., Gambetta, N., García-Benau, M.A. (2022). Carbon management strategy effects on the disclosure and efficiency of carbon emissions: A study of Colombian companies' context and inherent characteristics, *Journal of Cleaner Production*, Volume 365, 132850, ISSN 0959-6526. https://doi.org/10.1016/j.jclepro.2022.132850.

Longarela-Ares, Á., Calvo-Silvosa, A., & Pérez-López, J. B. (2020). The influence of economic barriers and drivers on energy efficiency investments in maritime shipping, from the perspective of the principal-agent problem. *Sustainability*, *12*(19), 7943. https://doi.org/10.3390/su12197943

MarineTraffic, (n.d.), About us. https://www.marinetraffic.com/en/p/company, [Downloaded 2023-04-27]

Matsumura, E.M., Prakash, R., & Vera-Munoz, S.C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review*, 89(2), 695-724. DOI: 10.2308/accr-50629

MEPC. (2021c). Resolution MEPC.336(76) – 2021 Guidelines on operational carbon intensity indicators and the calculation methods. IMO.

Mjelde, A., Martinsen, K., Eide, M., & Endresen, Ø. (2014). Environmental accounting for Arctic shipping–a framework building on ship tracking data from satellites. *Marine pollution bulletin*, 87(1-2), 22-28.

Morgan, F. W. (1943). Tonnage. *Royal United Services Institution. Journal*, *88*(551), 215-217. https://doi.org/10.1080/03071844309419526

Olczak, M., Piebalgs, A., Balcombe, P. (2022) Methane regulation in the EU: Stakeholder perspectives on MRV and emissions reductions, *Environmental Science & Policy*, Volume 137, Pages 314-322, ISSN 1462-9011. https://doi.org/10.1016/j.envsci.2022.09.002

Oxford Economics (2020) The economic value of the EU shipping industry – 2020 update. A report for the European Community Shipowners' Associations (ECSA).

Panagakos, G., Pessôa, T. D. S., Dessypris, N., Barfod, M. B., & Psaraftis, H. N. (2019). Monitoring the carbon footprint of dry bulk shipping in the EU: An early assessment of the MRV regulation. *Sustainability*, 11(18), 5133.

Poulsen, R. T., Ponte, S., van Leeuwen, J., & Rehmatulla, N. (2021). The potential and limits of environmental disclosure regulation: A global value chain perspective applied to tanker shipping. *Global Environmental Politics*, *21*(2), 99–120. https://doi.org/10.1162/glep_a_00586

Regulation (EU) 2015/757 of the European Parliament and of the Council of 29 April 2015 on the monitoring, reporting and verification of carbon dioxide emissions from maritime transport, and amending Directive 2009/16/EC.

Rony, A. H., Kitada, M., Dalaklis, D., Ölçer, A. I., & Ballini, F. (2019). Exploring the new policy framework of environmental performance management for shipping: a pilot study. *WMU Journal of Maritime Affairs*, 18, 1-24. https://doi.org/10.1007/s13437-019-00165-z

Pettersson-Lidbom, P. (2008). Do parties matter for economic outcomes? A regression-discontinuity approach. *Journal of the European Economic Association*, 6(5), 1037-1056. https://doi.org/10.1162/JEEA.2008.6.5.1037

Ritchie, H., Roser, M. (2020). CO2 and Greenhouse Gas Emissions. Our World In Data. https://ourworldindata.org/co2-and-greenhouse-gas-emissions [Downloaded 2023-04-27]

Saka, Chika & Oshika, Tomoki. (2014). Disclosure effects, carbon emissions and corporate value. *Sustainability Accounting*. 5. 10.1108/SAMPJ-09-2012-0030

Salman, M., Long, X., Wang, G., & Zha, D. (2022). Paris climate agreement and global environmental efficiency: new evidence from fuzzy regression discontinuity design. *Energy Policy*, 168, 113128. https://doi.org/10.1016/j.enpol.2022.113128

Shi, D., Bu, C., Xue, H. (2021) Deterrence effects of disclosure: The impact of environmental information disclosure on emission reduction of firms, *Energy Economics*, Volume 104, 105680, ISSN 0140-9883. https://doi.org/10.1016/j.eneco.2021.105680

Smart Freight Centre (2019). Global Logistics Emissions Council Framework for Logistics Emissions Accounting and Reporting. ISBN 978-90-82-68790-3.

Styhre, L., Rogerson, S., Santén, V., Green, L. (2019). Transportköparens roll för ökad och hållbar sjöfart. IVL Svenska Miljöinstitutet. https://www.diva-portal.org/smash/get/diva2:1701289/FULLTEXT01.pdf

S&P Global Market Intelligence, (n.d.), Sea-web™: The ultimate marine online database. https://www.spglobal.com/marketintelligence/en/mi/products/sea-web-maritime-reference.html, [Downloaded 2023-04-27]

Poulsen, R., & Johnson, H. (2016). The Logic of Business vs. the Logic of Energy Management Practice: Understanding the Choices and Effects of Energy Consumption Monitoring Systems in Shipping Companies. *Journal of Cleaner Production*, *112*(5), 3785–3797. https://doi.org/10.1016/j.jclepro.2015.08.032

Villena, V. H., & Dhanorkar, S. (2020). How institutional pressures and managerial incentives elicit carbon transparency in global supply chains. *Journal of Operations Management*, *66*(6), 697-734.

Windmark, F., Jakobsson, M., & Segersson, D. (2017). Modellering av sjöfartens bränslestatistik med Shipair. *SMHI Rapport*, (2017-10).

Winnes, H., Styhre, L., Fridell, E. (2015). Reducing GHG emissions from ships in port areas. *Research in Transportation Business & Management* Vol. 17, 73-82 pp. ISSN 2210-5395. https://doi.org/10.1016/j.rtbm.2015.10.008

Winther, M., Christensen, J. H., Plejdrup, M. S., Ravn, E. S., Eriksson, Ó. F., & Kristensen, H. O. (2014). Emission inventories for ships in the Arctic based on satellite sampled AIS data. *Atmospheric Environment*, 91, 1–14. https://doi.org/10.1016/j.atmosenv.2014.03.006

Wuepper, D., & Finger, R. (2023). Regression discontinuity designs in agricultural and environmental economics. *European Review of Agricultural Economics*, 50(1), 1-28. https://doi.org/10.1093/erae/jbac023

Yan, R., Mo, H., Wang, S., & Dong Yang (2023) Analysis and prediction of ship energy efficiency based on the MRV system, *Maritime Policy & Management, 50*:1, 117-139. https://doi.org/10.1080/03088839.2021.1968059

Yang, D., Wu, L., Wang, S., Jia, H., & Li, K. X. (2019). How big data enriches maritime research–a critical review of Automatic Identification System (AIS) data applications. *Transport Reviews*, 39(6), 755-773. https://doi.org/10.1080/01441647.2019.1649315

Zhang, Q., Zheng, Z., Wan, Z., & Zheng, S. (2020). Does emission control area policy reduce sulfur dioxides concentration in Shanghai?. *Transportation Research Part D: Transport and Environment*, *81*, 102289. https://doi.org/10.1016/j.trd.2020.102289

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Appendix

Table 6: Alphabetical order of ports with port code in the study

Port	Port code	Port	Port code	Port	Port code
Aalborg	DKAAL	Hanko	FIHKO	Piraeus	GRPIR
Aarhus	DKAAR	Hanstholm	DKHAN	Ponta delgada	PTPDL
Agioi theodori	GRAGT	Hansweert	NLHAN	Port de bouc	FRPDB
Ajaccio	FRAJA	Hardinxveld	NLHGS	Port du crouesty	FRRZN
Alblasserdam	NLABL	Harlingen	NLHAR	Port jerome	FRPJE
Alcaidesa	ESLLI	Hasselt	NLHAS	Portals nous	ESPNX
Alcudia	ESALD	Heeg	NLHEG	Portimao	PTPRM
Algeciras	ESALG	Heilbronn	DEHEN	Porto	PTOPO
Alicante	ESALC	Heilgenhafen	DEHHF	Potsdam	DEPOT
Alimos	GRAIO	Hel	PLHEL	Povoa de varzim	PTPDV
Alkmaar	NLALK	Helgoland	DEHGL	Prague	CZPRG
Almeria	ESLEI	Hellevoetsluis	NLHSL	Premia de mar	ESZJP
Alphen aan den rijn	NLAPN	Helsingborg	SEHEL	Preveza	GRPVK
Altea	ESAQA	Helsinki	FIHEL	Puerto calero	ESPRE
Ameland	NLAML	Hemiksem	BEHEX	Puerto deportivo alm	ESEEJ
Amsterdam	NLAMS	Hendaye	FRHEN	Puerto rico	ESPGC
Antibes	FRANT	Hendrik ido ambracht	NLHIA	Regensburg	DEREG
Antwerp	BEANR	Hengelo	NLHGL	Ridderkerk	NLRID
Arcachon	FRARC	Herne	DEHEE	Riga	LVRIX
Arenys de mar	ESARN	Heusden	NLHES	Rijeka	HRRJK
Arnhem	NLARN	Hindeloopen	NLHLP	Roda de bara	ESROD
Arrecife	ESACE	Hirtshals	DKHIR	Rodbyhavn	DKROD
Aveiro	PTAVE	Hoorn	NLHRN	Roenne	DKRNN
Aviles	ESAVS	Horta	PTHOR	Roermond	NLOMD
Badalona	ESBAD	Huelva	ESHUV	Roscoff	FRROS
Baiona	ESZHR	Huizen	NLHUI	Roses	ESZKQ
Bandol	FRXBD	Husum	DEHUS	Rostock	DERSK
Barcelona	ESBCN	Hvide sande	DKHVS	Rota	ESROT
Beaulieu-sur-mer	FRBZM	Ibiza	ESIBZ	Rotterdam	NLRTM
Berlin	DEBER	Ijmuiden	NLIJM	Rotterdam Botek	NLBOT
Bermeo	ESBRM	Isla cristina	ESZGA	Rotterdam Maasvlakte	NLMSV
Bilbao	ESBIO	Javea	ESJAV	Rotterdam Vondeling	NLZBW
Bingen	DEBIN	Kalmar	SEKLR	Rotterdam Waalhaven	NLWAL
Bonneuil	FRHRE	Kalundborg	DKKAL	Rouen	FRURO
Bordeaux	FRBOD	Kampen	NLKAM	Rozenburg	NLROZ
Bottrop	DEBOT	Karlshamn	SEKAN	Ruse	BGRDU
Boulogne billancourt	FROGB	Karlskrona	SEKAA	Sada	ESSAD
Boulogne-sur-mer	FRBOL	Karlsruhe	DEKAE	Sagunto	ESSAG

Braila	ROBRA	Keizersveer	NLKZV	Saint gratien	FRSGO
Brake	DEBKE	Kiel	DEKEL	Saint Malo	FRSML
Brandenburg	DEBBG	Killybegs	IEKBS	Saint Mandrier	FRLU2
Braskens	NLBRS	Klaipeda	LTKLJ	Saint quay portrieux	FRSQ2
Bratislava	SKBTS	Koblenz	DEKOB	San adrian de besos	ESSAB
Bremen	DEBRE	Koeln	DECGN	San carlos	ESSCR
Bremerhaven	DEBRV	Kokkola	FIKOK	San vicente barquera	ESSVB
Brest	FRBES	Kolobrzeg	PLKOL	Santa pola	ESSPO
Breukelen	NLRUK	Koper	SIKOP	Santander	ESSDR
Brugge	BEBGS	Korsor	DKKRR	Santona	ESSNN
Bruinisse	NLBSE	Kos	GRKGS	Sas van gent	NLSVG
Brunsbuettel	DEBRB	Kotka	FIKTK	Sassnitz	DESAS
Brussels	BEBRU	La Ciotat	FRLCT	Scheveningen	NLSCE
Budapest	HUBUD	La cotiniere	FRLC5	Schiedam	NLSCI
Buesum	DEBUM	La gomera	ESSSG	Schwelgern	DESGW
Burgas	BGBOJ	La grande motte	FRGDM	Sesimbra	PTSSB
Burriana	ESBRX	La pallice	FRLPE	Sete	FRSET
Cadiz	ESCAD	La seyne-sur-mer	FRYNE	Setubal	PTSET
Calais	FRCQF	La turballe	FRTBE	Sevilla	ESSVQ
Cambrils	ESCBL	Laboe	DELAB	S-gravendeel	NLGRA
Canet en roussillon	FRPYO	Lagos	PTLOS	Sibenik	HRSIB
Cannes	FRCEQ	L'ametlla de mar	ESKLL	Simrishamn	SESIM
Cap dail	FRCPA	Langedrag	SELGD	Sines	PTSIE
Capelle aan ijssel	NLCPI	Larnaca	CYLCA	Sint annaland	NLSNN
Cartagena	ESCAR	Las palmas	ESLPA	Skagen	DKSKA
Cascais	PTCAS	Lauwersoog	NLLAN	Sliedrecht	NLSLD
Castellon	ESCAS	Lavrio	GRLAV	Sluiskil	NLSLU
Castletown bearhaven	IECSW	Le cap d'agde	FRAGK	Sneek	NLSNK
Cernavoda	ROCEV	Le grau du roi	FRLGR	Sodersalje	SESOE
Ceuta	ESCEU	Le havre	FRLEH	Sozopol	BGSOZ
Chalkis	GRCLK	Leer	DELEE	Speyer	DESPE
Charleroi	BECRL	Leewarden	NLLWR	Split	HRSPU
Cherbourg	FRCER	Leiden	NLLID	St nazaire	FRSNR
Cleopatra	GRAKT	Leimuiden	NLLMU	Stavoren	NLSTA
Concarneau	FRCOC	Leixoes	PTLEI	Stellendam	NLSTD
Conflans	FRCSH	Lelystad	NLLEY	Stockholm	SESTO
Constanta	ROCND	Lemmer	NLLMR	Stralsund	DESTL
Copenhagen	DKCPH	Les sables d olonne	FRLSO	Strandby	DKSTD
Corfu	GRCFU	Liepaja	LVLPX	Strasbourg	FRSXB
Coruna	ESLCG	Limassol	CYLMS	Stromstad	SESMD
Cuxhaven	DECUX	Lindoe	DKLIN	Stuttgart	DESTR
Delfzijl	NLDZL	Linz	ATLNZ	Sulina	ROSUL
Den helder	NLDHR	Lisboa	PTLIS	Svendborg	DKSVE
Den oever	NLWRG	Lobith	NLLOB	Swinoujscie	PLSWI
Denia	ESDNA	Lorient	FRLRT	Szczecin	PLSZZ
Deventer	NLDEV	Lubeck	DELBC	Tarifa	ESTRF
Dieppe	FRDPE	Ludwigshafen	DELUH	Tarragona	ESTAR
Dinteloord	NLDIN	Lyon	FRLIO	Tenerife	ESSCT
Dordrecht	NLDOR	Maasbracht	NLMSB	Terneuzen	NLTNZ
Douarnenez	FRDRZ	Maassluis	NLMSL	Terschelling	NLTSL
Dresden	DEDRS	Maastricht	NLMST	Thessaloniki	GRSKG
Drimmelen	NLDRM	Mahon	ESMAH	Tholen	NLTHO

Druten	NLDRU	Mainz	DEMAI	Thorsminde	DKTMD
Dublin	IEDUB	Makkum	NLMAK	Thyboron	DKTHN
Duisburg	DEDUI	Malaga	ESAGP	Torrevieja	ESTOR
Dun laoghaire	IEDLG	Malmo	SEMMA	Toulon	FRTLN
Dunkirk east	FRDKK	Mangalia	ROMAG	Travemunde	DETRV
Dusseldorf	DEDUS	Mannheim	DEMHG	Trogir	HRTRO
Eemshaven	NLEEM	Mariehamn	FIMHQ	Turku	FITKU
El ferrol	ESFRO	Marin	ESMPG	URK	NLURK
El masnou	ESMSN	Marina frapa	HRRGN	Utrecht	NLORJ
Elburg	NLELB	Marsamxett	MTMSX	Vaasa	FIVAA
Elefsis	GREEU	Marsaxlokk	MRMAR	Valencia	ESVLC
EMDEN	DEEME	Marseille	FRMRS	Valletta	MTMLA
Empuriabrava	ESEMP	Medemblik	NLMDM	Varberg	SEVAG
Enkuizen	NLENK	Meppel	NLMEP	Varna	BGVAR
Esbjerg	DKEBJ	Merksem	BEMRK	Vassiliko	CYVAS
Everingen	NLANK	Midia	ROMID	Velez	ESVMG
Figueira da foz	PTFDF	Minden	DEMID	Ventspils	LVVNT
Fiskeback	SEFIS	Moerdijk	NLMOE	Viana do castelo	PTVDC
Flensburg	DEFLF	Monnickendam	NLMNN	Vigo	ESVGO
For sur mer	FRFOS	Montoir	FRMTX	Vilanova	ESVLG
Franeker	NLFRK	Motril	ESMOT	Vlaardingen	NLVLA
Frankfurt am main	DEFRA	Muiden	NLMUD	Vlissingen	NLVLI
Frederikshavn	DKFDH	Neeltje jans	NLNTJ	Volendam	NLVOD
Fredricia	DKFRC	Nekso	DKNEX	Volos	GRVOL
Freudenau	ATFNA	Neuss	DENSS	Wageningen	NLWGW
Fuengirola	ESFGL	Neustadt	DENDT	Wandre	BEWND
Funchal	PTFNC	Nice	FRNCE	Warmond	NLWRM
Galati	ROGAL	Niehl	DENHL	Wemeldinge	NLWED
Gavle	SEGVX	Nieuwegein	NLNWG	Werkendam	NLWKD
GDANSK	PLGDN	Nieuwpoort	BENIE	Wessem	NLWSM
Gdynia	PLGDY	Nijmegen	NLNIJ	Westknollendam	NLWAM
Geesthacht	DEGET	Norddeich	DENOE	Wien	ATVIE
Gelsenkirchen	DEGEK	Nord-Ostee-kanal	DECKL	Wijk bij duurstede	NLWBD
Genk	BEGNK	Norrkoping	SENRK	Wijnegem	BEWJG
Ghent	BEGNE	Numansdorp	NLNUD	Wilhelmshaven	DEWVN
Gijon	ESGIJ	Nynashamn	SENYN	Willemstad	NLWIS
Gilleleje	DKGLE	Ockero	SEOCO	Wintham	BEWTH
Giurgiu	ROGRG	Oldenburg	DEOLO	Wismar	DEWIS
Glyfada	GRGFD	Oostende	BEOST	Wladyslawowo	PLWLA
Godorf	DEGDO	Oosterhout	NLOOS	Workum	NLWKU
Golfe Juan	FRGJU	Oss	NLOSS	Wormerveer	NLWRV
Gorinchem	NLGOR	Oudeschild	NLOHI	Worms	DEWOR
Goteborg	SEGOT	Palamos	ESPAL	Woudrichem	NLWCM
Gouda	NLGOU	Paljassaare	EEPAS	Woudsend	NLWSD
Granville	FRGFR	Palma de Mallorca	ESPMI	Yerseke	NLYSK
Grenaa	DKGRE	Paloukia	GRPAO	Ystad	SEYST
Groningen	NLGRQ	Papendrecht	NLPAP	Zaandam	NLZAA
Haarlem	NLHAA	Paris	FRPAR	Zadar	HRZAD
Halmstad	SEHAD	Patra	GRGPA	Zea	GRMAZ
Hamburg	DEHAM	Peniche	PTPEN	Zeegrugge	BEZEE
Hamm	DEHMM	Peniscola	ESPNL	Zoutkamp	NLZOT
				Zwartsluis	NLZWS

		Zwijndrecht	NLZWI
		Zwolle	NLZWO

Table 7: IMO numbers in the sample

IMO numbers							
9034731	9698355	9279628	8025898	8652201	9175200	9167057	9817157
9867293	9789532	9365269	7636614	9523457	9175195	9676230	9817169
9522403	9383326	9378022	9571105	9523469	9175236	9735335	7926095
8322844	9371933	9365245	9851933	9147136	9175224	7910888	9130468
9109940	9371957	9658109	9823039	9507984	8821759	9480409	9130456
9085479	9371907	9613642	9823065	9507972	7917006	9480382	9053842
9045651	9371969	9658094	9645035	9468516	7922166	9235945	9053830
9185346	9371971	9613628	9640580	8420359	8821761	9519614	9053828
8206533	9430791	9363986	9645009	9077587	7391422	9014286	9011519
9671486	9434759	9364007	9804239	9077563	9381952	9426491	9263930
9671462	9434761	9281504	9813565	9077575	9809265	9518880	9200029
9671474	7724253	9364019	9640528	7725374	9811189	9426489	9224142
9671450	9174127	9281487	9804241	9448889	9200093	9354222	9229075
9671448	8884555	9281499	9645114	9452256	9814947	8755699	9263540
9671436	9354571	9281516	9640542	9452268	7915541	9101534	9224154
9045728	9344174	9363974	9683740	9455985	9565467	9101546	9323132
8204157	9519535	9363998	9823821	8420361	9556038	9014298	9323144
9658367	9519523	9588122	9645011	9517288	9556040	9599353	9148738
9658355	9612844	9360221	9645023	9517290	8610667	9679373	9189718
9304318	7726847	9795244	9645059	9263552	9600372	9687992	9381811
8418253	9388479	9482017	9645073	8866840	9600360	9687980	8857772
8418265	9428437	9541150	9645102	9266891	7528790	9344344	9177404
9116084	9396529	9361392	9640566	8871508	9335707	9673214	9269295
9308900	9464285	9781528	9645097	9141687	9503914	9224130	9188752
9404625	9064281	9314442	9640504	8963181	9503902	9480992	9213131
9350898	9260366	9350006	9804215	7725386	8219932	9428889	9133903
9350886	9418286	9517331	9655470	9610614	8807636	9305362	9001148
9100774	8125454	9624316	9683726	9343065	9133575	9358503	9045687
9526071	8411243	9624304	9777656	9408712	9164732	9599341	9034092
9532812	9173032	9526758	9777670	9421087	9164718	9566708	9140607
9526083	9202039	9274537	9638783	9421051	9164720	9260407	9083134
9532824	9215141	9255799	9638769	9213882	9191656	9433561	8959192
9526095	8601408	9260835	9638795	9215658	9191668	9343950	8954946
8121020	9356646	9260847	9219862	9180865	9598684	9299109	8959180
9427445	9823390	9255816	9219874	9180877	9554121	9396969	8959219
8203660	9648178	9255828	8308288	9229049	9268277	9040883	8728828

9045704	9797319	9274549	9317212	8834691	9435337	9232840	8728490
9526100	9797333	9255804	9640499	9263966	9435363	7434949	8829294
9610341	9236133	9602825	9683738	9148336	9435349	9540302	8848408
9143506	9352743	9616955	9683714	9333577	9435375	9480980	1012957
9131096	9378230	9228332	9645061	9297199	9327346	9481001	9277307
9131101	9442914	9235684	9640530	9314612	9435351	9540340	9358278
9481594	9427093	9160310	9645085	9260483	9063902	9368649	9268370
9458248	9427081	9004401	9645047	9314727	9280201	9464118	9413456
9361134	9378242	9213911	9640516	9268344	9280213	9452763	9352341
9184031	9350771	9369291	9640554	9268344	9575321	9464106	8614273
8977273	9350783	9369306	9486324	9314727	9575319	9404637	8755663
9034743	9301603	9428669	9638771	9342932	9575307	9891191	9428671
9338242	9301598	9428657	9638812	9273662	9736690	8410847	8677299
9533373	9498963	8751215	9638800	1012610	9745720	7916997	9302308
9187057	9547776	9610597	9351153	9637973	9575345	9393785	9345714
7310507	9547764	9593921	9352339	9621558	9633549	9372212	9368247
9240005	9498975	9125413	9277319	9612909	9575292	9362140	9374090
9212773	9235842	9540352	9327322	9637961	9736688	9404364	9331452
8914128	9752498	9540364	9317808	9342657	9575333	9403827	9353046
9147863	9766140	9560936	9277345	9352705	9771999	9203710	9409754
9147863	9820776	9285366	9277321	9369617	9174359	9008067	9116101
9147875	8105404	9447287	9277333	9354636	9174361	9008110	9368259
9218193	8808604	9447304	9186405	9377042	9181900	9746827	9346550
9218208	9126223	9120205	9188506	9269350	1012983	9187928	9331799
9042295	9126247	9447299	9186388	9453418	9134971	9187916	9368261
9208605	9126235	9412701	9175157	9621560	9399404	9377183	9368209
9412361	5220605	9160487	9229087	9612923	9399387	9410519	9317016
7418452	9586447	9160475	9255579	9208497	9399399	8516990	9094157
9001150	8767666	9043055	9038531	8916504	9407419	9481908	9268241
9142320	9341108	8822583	9286437	8912912	9684122	8216722	9268253
9819052	9318955	9120217	9829693	9213894	9684108	9016155	9247625
9395367	9374387	9163403	9566784	9286815	9684110	9410507	9247637
9268291	9363508	9135822	9566796	9555204	9711248	9008093	9247613
7528611	9492634	8918318	9010929	9152844	9729582	8500599	9247601
9276224	9488499	9640578	9396309	9766073	9729594	7917018	8890396
8508670	9495612	8951346	9381380	9417531	9718923	9078098	9220445
9234393	9486295	8949367	9495832	9417957	9753844	8507470	9142875
9838199	9386146	8942931	9577991	9417529	9753818	9148570	9735139
9838204	9462859	8869945	9578000	9382190	9310331	9008079	9735141
9119907	9611101	9804227	9578036	9418016	9753820	8752609	9749130
9829069	9349978	8945086	9578012	8869543	9538115	9199854	9749154
9846237	9349992	9485186	9353022	9506112	9826706	8717647	9252503

9199311	9428152	9543316	9405796	9506136	9207261	9539858	9211535
9199323	9452452	9522738	9405772	9457103	9433339	9474292	8520886
9272814	9468750	9506409	9448891	9457115	9433341	9372846	9868730
9569528	9349980	9492933	9438286	9506124	9433365	8624292	9868742
9569530	8927979	9543328	9141663	9506148	9433389	8624278	9868766
9454216	9437634	9454125	9083902	9457153	9433377	8720230	9220536
9454228	9367358	9784893	9000247	8753031	9433353	9403815	9087544
9166948	8986389	9109304	9000235	9280146	9630444	7915307	9123324
9566679	8972261	9279123	9053919	9382140	8720993	9249685	9159579
9555436	8986365	8804555	9420344	9387176	7118698	9173202	8308006
9436252	8972259	8920995	9201774	9387188	9299173	9752589	8955720
9436264	9386158	8819275	9141106	9381615	7802964	9045699	8914776
9436276	9386160	8804543	7330064	9382138	9297204	8213732	9001136
9436240	9486300	8819304	9360714	9185970	9300489	8213718	9818797
9436238	9216470	8819299	9360726	9269025	9633484	9368572	9147887
9436226	8873489	8804567	9420332	9175171	9719525	9368601	9362827
9137234	8933564	8920983	9203368	9175183	9719513	9368596	9362815
9341160	8873324	8804529	9501954	9175248	9707194	9368613	9439216
9341172	8850906	8804579	9468566	9175169	9401300	9368584	9414187
9698367	7306702	8804531	9650377	9175212	9386378	8117847	9414199

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