Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Marine Technology

Daniel Wu

Investigation of the Effects of Mass Flow Meters on the Singaporean Bunker Industry

Master's thesis in Marine Technology
Supervisor: Bjørn Egil Asbjørnslett
February 2019

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Kunnskap for en bedre verden

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MASTER'S THESIS IN MARINE TECHNOLOGY
Autumn 2018
for stud. techn. Daniel Si-Lu Wu

Investigation of the Effects of Mass Flow Meters on the Singaporean Bunker Industry

Background
Marine fuel, called bunkers, are the largest cost element in most commercial voyages. To battle malpractices and improve transparency in the world's biggest bunkering port, Singapore Maritime and Port Authorities (MPA) introduced mandatory use of mass flow meters (MFMs) onboard all licensed bunkering barges. The enforcement took effect on January 1, 2017 and Singapore was the first port in the world to mandate use of such a fuel measuring device.

The aim of this study is to investigate whether any effects from MFMs can be proven and should therefore be of interest to various stakeholders within the maritime industry. To the author's knowledge, there has not yet been any studies investigating the potential effects of mass flow meters in Singapore.

Objective
The overall objective of this thesis is to investigate whether the introduction of mass flow meters in Singapore has had any measurable effects on the bunker industry in Singapore. For this purpose, fuel quality testing data and fuel price data shall be analyzed.

Scope of Work
The candidate shall/is recommended to address the following main points:

1. Provide adequate background information to understand why Singapore port authorities made the use of mass flow meters (MFMs) mandatory.

2. Rationalize what aspects of bunker fuel delivery could be affected by MFMs, and how that may materialize in the available data sources.

3. Explore the data and formulate testable hypotheses around potential effects of MFMs.

4. Select and describe the statistical methods used for hypothesis testing.

5. Compile and discuss the results from the analysis to conclude on whether MFMs have any effect on the Singaporean bunker industry.

General

In the thesis the candidate shall present his personal contribution to the resolution of problems within the scope of the thesis work. Theories and conclusions should be based on mathematical derivations and/or logic reasoning identifying the various steps in the deduction.

The candidate should utilise the existing possibilities for obtaining relevant literature.

The thesis should be organised in a rational manner to give a clear exposition of results, assessments, and conclusions. The text should be brief and to the point, with a clear language. Telegraphic language should be avoided.

The thesis shall contain the following elements: A text defining the scope, preface, list of contents, summary, main body of thesis, conclusions with recommendations for further work, list of symbols and acronyms, references and (optional) appendices. All figures, tables and equations shall be numbered.

The supervisor may require that the candidate, in an early stage of the work, presents a written plan for the completion of the work. The original contribution of the candidate and material taken from other sources shall be clearly defined. Work from other sources shall be properly referenced using an acknowledged referencing system.

Supervisor: Professor Bjørn Egil Asbjørnslett

Co-supervisor in DNV GL: Thomas Mestl

Deadline: February 18, 2019

Prof. Bjørn Egil Asbjørnslett

Preface

This thesis marks the final part of my Master of Science degree with specialization in Marine Systems Design at the Department of Marine Technology (IMT). The work has been carried out at the Norwegian University of Science and Technology (NTNU) and DNV GL Høvik during the autumn semester of 2018, January and February 2019. The master thesis was written under the supervision of Prof. Bjørn Egil Asbjørnslett and Dr. Scient. Thomas Mestl from DNV GL. Dr. Mestl had the idea for the project.

Oslo, February 15, 2019

Daniel Wu

Daniel Wu

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I would like to thank and express my sincere gratitude to the following persons and actors for their contribution to my thesis:

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My co-supervisor, Dr. Thomas Mestl, for many enlightening discussions and his help in R programming which has significantly raised the quality of the project.
A great thanks to Bunker Index, for providing me with bunker price data.

D.W.

Summary

This thesis investigates whether mass flow meters (MFMs) have any effects on the Singaporean marine fuel (bunker) industry. Fuel quality testing data and bunker price data are analyzed for changes caused by potential effects of MFMs. A literature review is presented to assess the research within the bunker industry. It was discovered that no former research had been done on the effects of MFMs in Singapore or other ports.

The traditional bunker operations and their shortcomings are described. With knowledge about the weaknesses of traditional bunker procedures, we propose some potential effects of the MFMs. Hypotheses are formulated to test if there are any changes captured in the data, and whether these can be related to MFMs. It is presented how statistical hypothesis testing can be applied to the fuel quality data. Several types of statistical tests are assessed for feasibility.

The formulated hypotheses can be summarized into five points. The hypotheses state that mass flow meters have lead to a: (1) bunker price increase in Singapore, (2) decrease in price difference between Singapore and Hong Kong, (3) change in distribution of decimal digits in the stated bunker density parameter, (4) change in mean delta density, shortlifting benchmark and occurrence of shortlifting; (5) change in variance of the delta density parameter and shortlifting benchmark.

Price analysis showed that changes in bunker price and price difference between Hong Kong and Singapore were present. The analysis found little reason to attribute the price changes to a potential MFM effect, thus hypothesis (1) and (2) were rejected. The distributions of decimal digits in the stated bunker density parameter before and after the use of MFMs were found to be relatively unchanged. The hypothesis (3) was therefore rejected. The fuel quality testing data was divided into groups based on density levels to test the hypotheses in (4) and (5). This was done to mitigate dependencies from another effect that is not related to MFMs. The data was grouped into 30 bins according to fuel density, and hypothesis testing was conducted on each bin. It was concluded that no clear sign of change was evident, based on an assessment of the collective results of the tests. Thus, the hypotheses included in (4) and (5) were rejected.

The study concludes that the introduction of MFMs have not caused any significant measurable effect on the price or fuel quality testing data. Finally, other means of identifying effects of MFMs are proposed. These are: (1) to investigate duration of bunker operations, (2) to conduct an opinion survey among ship operators to assess Singapore as a bunkering port, and (3) to study whether there has been a fall in demand for bunker quantity surveys.

Sammendrag

Denne oppgaven undersøker om massestrømmålere har en effekt på bunkersindustrien i Singapore. Drivstoffkvalitetsdata og prisdata blir analysert for å finne endringer som følge av eventuelle effekter av massestrømmålere. Et literaturstudie presenteres for å undersøke relevant forskning innen bunkersindustrien. Det ble oppdaget at ingen tidligere forskning har blitt gjort på effekten av massestrømmålere i Singapore eller andre havner.

Det blir gitt en beskrivelse av tradisjonelle bunkringsoperasjoner og tlhørende ulemper. Med kunnskap om ulempene ved disse prosedyrene, blir det foreslått noen potensielle effekter fra massestrømmålere. Hypoteser er formulert for å teste om det finnes endringer i dataen som kan relateres til massestrømmålere. Anvendelse av statistisk hypotesetesting på drivstoffkvalitetsdata blir beskrevet. Flere forskjellige statistike tester er undersøkt for egnethet.

De formulerte hypotesene kan oppsumeres i fem punkter. Hypotesene påstår at massestrømmålerne har ført til: (1) økning i bunkerprisnivå i Singapore, (2) minskning av prisforskjell mellom Singapore og Hong Kong, (3) endring i fordeling av desimaltall i rapportert drivstoffstetthet, (4) endring i gjennomsnittlig deltadensity, shortlifting benchmark og forekomst av shortlifting, (5) endring i varians av deltadensity parameteren og shorlifting benchmark.

Prisanalyser viste at endringer i bunkringsprisen og prisdifferansen mellom Hong Kong og Singapore fant sted. Disse analysene fant derimot lite grunn til å tilegne prisedringene til en massestrømmålereffekt. Derfor ble hypotese (1) og (2) avvist. Fordelingen av desimaltall i rapportert drivstoffstetthet var uendret, og hypotese (3) ble dermed avvist. For å teste hypotesene i (4) og (5), ble drivstoffkvalitetsdataen fordelt inn i grupper basert på tetthetsnivå. Dette ble gjort for å redusere avhengighet av en annen effekt som ikke var relatert til massestrømmålere. Dataen ble delt inn i 30 grupper basert på drivstofftetthet, og hypotesetesting ble gjort for hver gruppe. Etter en samlelet evaluering av de forskjellige resultatene fra testene, ble det konkludert at ingen endringer var tydelige. Dette førte til at hypotesene i (4) og (5) ble avvist.

Studiet konkluderer med at introduksjonen av massestrømmålere ikke har påført noen signifikante målbare effekter på pris eller drivstoffkvalitetsdata. Avslutingsvis blir andre måter å måle massestrømmålereffekter foreslått. Disse er som følger: (1) å undersøke varighet av bunkringsoperasjoner, (2) utføre en menighetsmåling blant skipsoperatører for å evaluere Singapore som en bunkringshavn og (3) å studere etterspørselen for bunkerskvanitetsinspeksjoner.

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Acronyms

AIS Automatic Identification System

DD Delta density

ISO International Organization for Standardization

MFM Mass flow meters

MPA Maritime and Port Authority of Singapore

pre-MFM The period period before MFMs were implemented, before January 1, 2016.

post-MFM The period after MFMs were implemented, after December 31, 2016.

SL Shortlift

Chapter 1

Introduction

1.1 Background

Marine fuel, called bunkers[1], are the largest cost element in most commercial shipping voyages. The transfer of bunkers from a bunker barge to a receiving ship can be regarded as an operation where a commodity of high value exchanges hands during a short amount of time. Traditionally, largely manual methods are being used for verifying the transfer of fuel from barge to ship, e.g. sounding of the bunker tanks. Such methods give room for error and potential fraud. Maersk, the world's largest container shipping company with a $7 billion annual spend of fuel, reported that there is an average discrepancy of 1,5 % between the readings taken by Maersk vessels and those provided by suppliers or barge operators (Henry (2014)). Disputes over delivered/received fuel quantity are rarely resolved as post-delivery investigation on quantity shortages are often costly and inconclusive.

To battle malpractices and improve transparency in the world's biggest bunkering port, Singapore Maritime and Port Authorities (MPA) introduced mandatory use of mass flow meters (MFMs) onboard all licensed bunkering barges. The enforcement took effect on January 1, 2017 and Singapore is the first port in the world to require such a device. The use of MFMs for bunkering operations has the potential of setting a new benchmark for bunkering practices worldwide. It can be expected that many other ports are willing to introduce mass flow meters, if their ability to improve transparency and reduce malpractice can be proven. The research objective of this thesis is to investigate whether

[1] The term "bunkers" originates from the time of coal-powered steamships. The storages of coal were called "coal bunkers".

any effect from MFMs can be identified and it should therefore be of interest to various stakeholders within the maritime industry. To the author's knowledge, there has not yet been any studies investigating the potential consequences of mass flow meters in Singapore.

1.2 Literature Review

The papers reviewed give a impression of of the relevant available literature for the topic of this thesis. Papers related to bunkers are presented, each paper focuses on different topics within bunkering as a research topic. Some papers related to statistical methods were also review in order to get an idea of how methods within statistics could be applied for our problem.

Anfindsen et al. (2012) constructed a benchmark to assess bunker fuel suppliers and derived a comparison method of fuel suppliers with the benchmark. The benchmark method is based on using "best practice" as reference. The authors emphasized that the process of appointing "best practice" require a degree of subjectivity. The advantages of the approach is that it is relatively independent of sample size and distribution of the data, in addition to being computationally efficient.

A literature review on bunkering and bunkering decisions was done by Sevgili and Zorba (2017). The study examined bunkering decision criteria and research methods about bunkering in literature. A total of 54 articles were identified by searching for the terms "bunkering", "refueling" and "marine fuel", 36 articles were deemed relevant. The examined articles were divided into five sections: illegal bunkering, alternative marine fuels, environmental, bunker management and bunker services. The study then lists and counts the criterion for bunkering decisions found through the literature review. Most stated bunkering criterion in literature were determined as "bunker price and price competition", "quality of bunker" and "geographical advantage of refueling area".

Chang and Chen (2006) developed a knowledge-based simulation model to evaluate the overall system performance of the Port of Kaohsiung (POK), where the sole bunker supplier is the Chinese petroleum company (CPC). The system consist of the allocation decisions to assign the six CPC owned bunker barges to refuel inbound vessels. The motivation behind the study was that the barge allocation assignment is a key operation for the POK in terms of efficiency and to remain competitive against other ports. Taiwan also launched a vision for the POK to serve as a regional marine transportation center in the Asian Pacific, thus the number of ships calling to port with bunkering requests were expected to increase. Bunkering delays disrupt the schedules of outbound vessels, which inflict demurrage charges against the ship owners or operators, which in turn lead to lost business for the POK. The current procedure of assigning bunker barges to requests were manual and relied heavily on experience of the CPC senior engineers. The simulation model presented by the paper uses both expert system and discrete event simulation techniques. The expert system was developed replace the role of a human expert in the existing system. The results of the expert system, in the form of a bunkering work schedule, provide input for the simulation model. The model was verified by comparing computer-generated results with historical working schedules. The comparison showed that the deviation between the records and the simulation results were small, which indicated that the simulation model was highly reliable. The study concludes that the simulation model allow system mangers to easily test revised programs, or strategic plans to improve overall managerial efficiency of the bunkering services in the POK.

Lam et al. (2011) developed a framework for assessing the competitiveness of bunkering ports. Based on industry opinion surveys and interviews, ten significant attributes were identified and ranked. The results showed that the five most important consideration attributes were, in order of decreasing importance: (1) bunker quality, (2) market transparency (corruption free), (3) bunker price competitiveness, (4) reliability and punctuality of suppliers, (5) bunkering facilities. Assessment of Singapore and Shanghai as bunkering ports was done based on the identified attributes. Singapore was found to be a better performer as a bunkering port than Shanghai. This is mainly due to its strategic location which attracts large cargo volume, and the liberal market structure which provides attractive pricing and efficient practices. The Singapore Maritime and Port Authority (MPA) upholds a stringent quality control system, but keeps the regulation to a subtle level so that the bunker market remains market driven. Weak attributes for Singapore were the reliability and punctuality of bunker suppliers, in addition to the availability of low sulphur fuel. The weakest aspect for Shanghai was the uncompetitive bunker price. It is described that foreign ship operators only bunker in Shanghai in emergency situations, or for newly launched vessels from Chinese shipyards. In emergency situations, operators only fill enough bunkers to sail to the next port where where full tank will be filled for long hauls.

Aarsnes (2018) investigated the feasibility of assessing bunkering operations with the use of AIS data. A framework for identifying bunkering operations was constructed, this was embedded into an algorithm that appoints the most probable bunker customer (receiving ship) for a given bunker barge. By cross validating a range of bunkerings proposed by the algorithm with with a list of officially approved bunker barges and fuel quality testing data of bunker operations, a range of high likelihood bunkerings were established. The time parameters for these bunkerings were analyzed statistically. A method for creating a bunkering quality index based on the the time distribution of waiting time and post bunkering time for a given operation was proposed. It was suggested that further work would be to incorporate other aspects of a bunker operation into the quality index, such as fuel quality data.

Beber and Scacco (2012) derived and applied a method to detect manipulation of electoral return sheets through a digit-based test. The paper showed that, given a wide range of distributional assumptions, the last digits of electoral results can be expected to occur with equal frequency. The paper emphasized that due to psychological biases, humans have difficulties in reproducing random patterns. The authors focused on four findings that the experimental literature suggested: "Humans (1) do not select digits with equal frequency, (2) avoid repetition, (3) prefer serial sequences, and (4) select pairs of distant numerals relatively infrequently". By searching for patterns caused by these biases, for these four biases in data from electoral return sheets, the authors showed that their approach was sensitive to known electoral frauds while it produced a null result in a nonfraudulent environment.

Vollset (1993) compared thirteen methods for computing binomial confidence intervals, based on each method's coverage properties, widths and errors relative to exact limits. The use of the standard textbook method is discouraged.

Nahm (2012) discussed the basic concepts and practical use of nonparametric statistical tests. The authors try to provide actual cases of nonparametric statistcal techniques to enhance the reader's understanding of nonparametric tests. The paper emphasize that nonparametric tests are a correct choice when parametric tests cannot be used due to violation of the assumption of normality. However, nonparametric tests have less statistical power.

Concluding the literature review, it is evident that no other studies have researched the topic of effects from mass flow meters. Reviewing different papers on statistical methods showed that the statistical methods can easily be applied to many disciplines. However, there are many pitfalls, and the user must be conscious on the assumptions of the methods being used.

1.3 Objectives

The overall objective of this thesis is to investigate whether the introduction of mass flow meters in Singapore has had any measurable effects on the bunker industry in Singapore. For this purpose, fuel quality testing data and fuel price data shall be analyzed.

To address the overall objective, the following main tasks are identified:

1. Provide adequate background information to understand why Singapore port authorities made the use of mass flow meters (MFMs) mandatory.
2. Rationalize what aspects of bunker fuel delivery could be affected by MFMs, and how that may materialize in the available data sources.
3. Explore the data and formulate testable hypotheses around potential effects of MFMs.
4. Select and describe the statistical methods used for hypothesis testing.
5. Compile and discuss the results from the analysis to conclude on whether MFMs have any effect on the Singaporean bunker industry.

1.4 Scope and Limitations

The main limitation of this thesis is related to the availability of relevant data. The fuel quality testing data used in this study only represent a fraction of all bunkerings. To which extent this data can be a general representation for all bunkerings in Singapore is not assessed.

1.5 Outline

The rest of the thesis is organized as such:

Chapter 2 provide background infromation about bunker operations and mass flow meters. In the end, a rationalization about potential effects of mass flow meters is done.

Chapter 3 introduces and explores the available data sources. Relevant parameters of the data are plotted, and initial remarks based on visual assessments are made. Testable hypotheses around potential effects of MFMs are also formulated.

Chapter 4 describes how statistical methods can be applied to the available data. Assessment of the assumptions and limitations of the selected methods are also done.

Chapter 5 describes the change analysis on the different hypotheses using the selected methods.

Chapter 6 discusses and concludes the work done in this thesis in the light of the objectives. Recommendations for further work is also given.

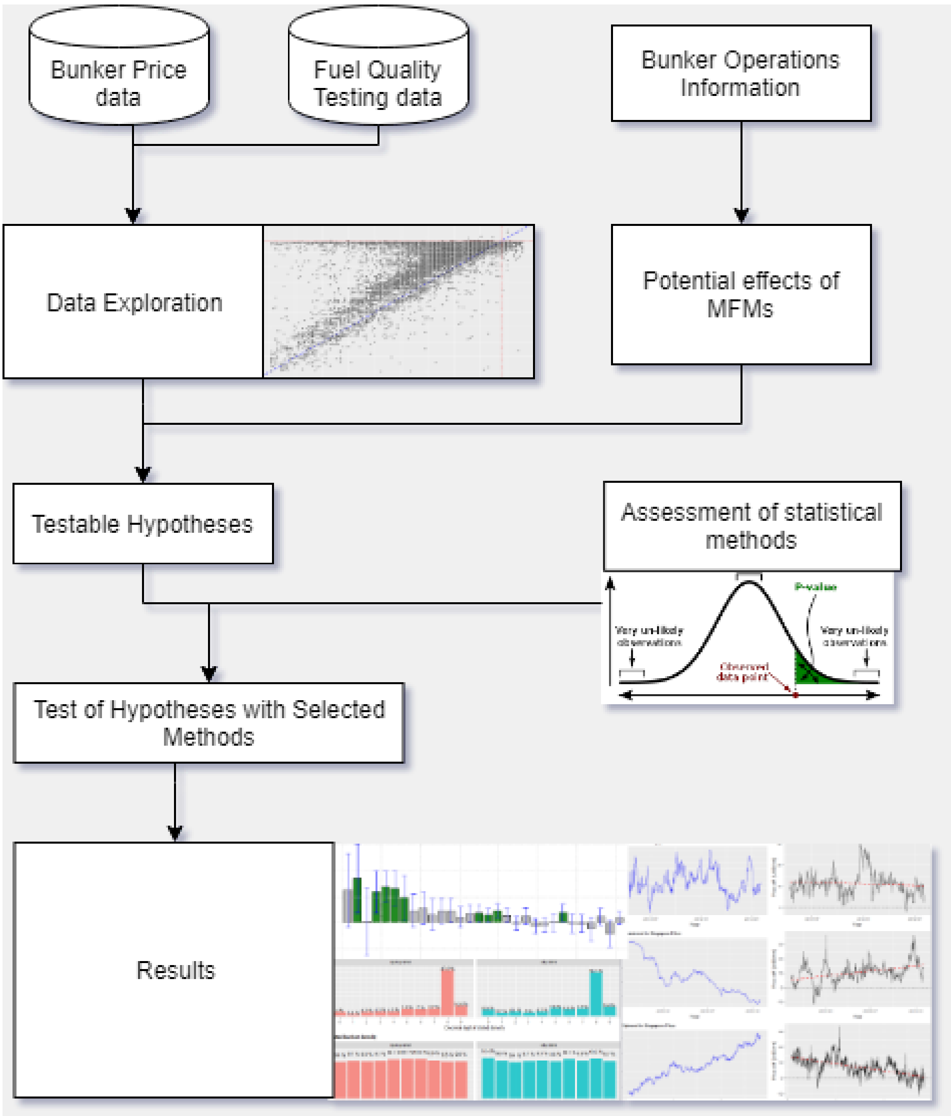

Figure 1.1: Overview of project stages

Chapter 2

Bunker Operations and Potential Effects of Mass Flow Meters

The aim of this chapter is to provide background information about bunker operations and mass flow meters. In the end we rationalize about what could be potential effects of mass flow meters.

2.1 Heavy Fuel Oil as a Marine Fuel

Marine fuels are generally divided into two different classes: heavy fuel oil and distillates. Distillates are commonly known as marine gas oil (MGO). The first group, the heavy fuel oils, is a generic term describing fuels that possess a particularly high density and viscosity that are used to generate motion and/or heat (Marquard & Bahls (2015)). Heavy fuel oil (HFO) is at the time the most common marine fuel. The MARPOL Marine Convention of 1973 defines HFO either by a density of above 900 kg/m^3 at 15 °C or a kinematic viscosity of higher than 180 mm^2/s at 50 °C.

Heavy fuel oil is incurred as the residual fuel during the distillation of crude oil, and its qualities is therefore dependent on the qualities of the crude oil being refined and the refining process. Various specifications and quality levels of HFO can be achieved by blending with lighter fuels such as marine gasoil or marine diesel oil. These blends are also referred to as intermediate fuel oil (IFO) or marine diesel oil. Most commonly used class of such blends are IFO 180 and IFO 380, named after their viscosities of 180 mm^2/s and 380 mm^2/s.

Density of heavy fuel oils are dependent on how much lighter fuel the refineries are willing to extract. If prices for distillates are high, additional refining can be justified, and the residual fuel possess a high density. If prices for distillates are low, less distillation is done, and the residual fuel possess a lower density. In addition, it also depends on the properties of crude oil batch that is imported to the refinery.

Since 1987, International Maritime Organization (IMO) has specified requirements for petroleum-based fuels used in diesel engines and boilers in the shipping industry with the ISO 8217 standard. The standard defines the different classes of marine fuels with specifications for quality parameters, e.g. viscosity, ignitability, acid content, sulfur content and density.

2.2 Bunker Operation

The bunker operation is a process where a vessel is supplied with fuel for operation of its machinery system. An order of bunker specifying grade and amount will typically be placed by the operator of a ship or a bunker broker that is engaged by the ship operator. The quantity of bunkers to be bought is given in mass, in the unit of metric tons. Buyer and supplier will agree upon operational details such as location and time for the bunkering. The stages in a bunker operation was roughly summarized by Wu and Aarsnes (2017):

- Bunker barge moves alongside the ship
- Bunker barge hose connects with fuel tank hose
- Measuring of bunker quantities at both vessels
- Commencement of bunkering
- Completion of bunkering
- Paperwork and related procedures that confirm agreement of transacted bunker quantity
- Disconnection of barge hose and fuel tank hose
- Bunker barge leaves the ship

Paperwork and related procedures has the purpose of documenting the bunker quality received on board and its compliance with the stated requirements. IMO requirements oblige vessels to document bunkerings through bunker delivery notes (BDN). Wärtsila (2017) describes bunker delivery notes as follows:

The standard document required by Annex VI of MARPOL which contains information on fuel oil delivery: name of receiving vessel, port, date, data of a supplier, quantity and characteristics of fuel oil. Every BDN is to be accompanied by a representative sample of the fuel oil delivered. Fuel oil suppliers are to provide the bunker delivery note. The note is to be retained on the vessel, for inspection purposes, for a period of three years after the fuel has been delivered.

Traditional Bunker Delivery Verification

Traditionally (prior to introduction of mass flow meters), the delivered mass is calculated by multiplying the bunker density (as stated by the supplier) with the deliveredvolume (Gregory et al. (2008). Delivered volume was estimated by manual measurement methods, mainly tank sounding. In this procedure, the level of fuel in the bunker barge tank(s) is recorded, prior to the transfer of fuel to receiving ships. In addition, temperature information, draught and trim of the ship should be registered (Wankhede (2018)). The tank sounding procedure is repeated at the end of the bunker transfer. Ship specific calibration tables are needed to map the recorded dip levels into corresponding volumes. The difference in volume between the beginning and end of the bunkering operation yields the transferred volume. The tank calibrations tables are seldom derived through tank calibration of measurement and filling, but rather calculated data (Gregory et al. (2008)). The delivered mass is obtained through calculations based on the density of the fuel, as stated by the supplier.

In other words, many factors influence the bunker quantity delivered. It is a complex procedure to determine the correct quantity, making these manual measuring methods prone to error and potential fraud.

2.3 Non-transparent Parameters and Malpractices

There are pitfalls for errors and malpractice when marine fuel is transported from refinery to bunker barge and then to a receiving ships. These pitfalls can contribute to a difference between quantity claimed to have been delivered and the quantity received by

Figure 2.1: Sounding tape used for manual sounding of tanks. Image downloaded from https://www.alibaba.com/ in January 2019.

the ship. There are documented methods of deliberate short supplying of the amount of bunker. Examples of malpractices have been mentioned by Aarsnes (2018) and Anfindsen et al. (2012). The practices can be grouped based on the parameter that is manipulated. The most relevant parameters for this study are volume and density, but other parameters can be energy content.

Volume

Marine Insight (2016) states that deliberate methods for inaccurate measurement of delivered volume can be to use a modified gauging pin, infuse air into the bunker prior to delivery or to tilt the bunker barge to interfere with tank readings.

Another practice described Marine Insight (2016) is cappuccino bunkers, which is the result of compressed air blown through the delivery hose. The frothed bunker will naturally have a higher volume when sounded, and give the impression that more fuel is delivered than in reality.

Inflated and deflated tank volumes can also be achieved by pouring respectively diesel oil and paint thinner into the sounding pipe prior to gauging. The thinner washes off the oil level marking on the sounding tape, making it indicate a lower level of oil.

Density

As the bunker is delivered in volume but paid in weight, the fuel density is an essential property in the bunkering operation. By reporting a higher density, the monetary value of the delivered fuel will be less than the monetary amount paid for the delivered fuel. The reported bunker density is documented in a bunker delivery note.

As petroleum products have a high rate of thermal expansion, temperature must be taken into account during a bunker transfer. Tampering with temperature can therefore create a difference between quantity on paper and quantity delivered. A barge could under-declare the temperature at time of opening gauge and over-declare during closing gauge. This malpractice will result in that during tank dipping before and after pumping, the fuel density will be lower (with over-declared temperature) prior to pumping and higher after pumping (with under-declared temperature). Thus, the volume difference will be made greater on paper then what it in reality was.

DNV Research & Innovation (2012) analysed over 50 000 samples of fuel oil tested by DNVPS in 2011 indicated with an average over-reporting of 0.6 kg/m3. With a global average bunkering of 965 Metric Tonnes (MT) per lift, over-reporting can equal an average loss of about 0,6 MT per 1000 MT lifted according to DNV Research & Innovation (2012).

2.4 Mass Flow Meters

The Maritime and Port Authority of Singapore (MPA) enforced the use of mass flow meters (MFMs) for higher viscosity grades (heavy fuel oils) of bunker fuel with effect from 1st of January 2017:

> *With effect from 1 January 2017, it is mandatory to use MPA-approved MFM system for all Marine Fuel Oil (MFO) bunker delivery in the Port of Singapore. The delivered quantity of MFO stated in the Bunker Delivery Note shall be based on the bunker tanker's MFM system as witnessed by the cargo officer, the chief engineer and bunker surveyor (if engaged).*
>
> *Maritime and Port Authority of Singapore (2016)*

As a consequence, malpractices in volume and density reporting should in theory become inefficient. This initiative is an attempt to improve transparency in bunker operations and the reputation of Singapore as a preferred bunker port. A mass flow meter enables direct measurement of delivered mass. The need to measure and correct for pressure, temperature and density fluctuations during bunker transfer are eliminated. The MPA has recently announced that use of MFMs for marine gas oils will be mandated with effect from 1st of July 2019.

2.4.1 Principle of the Mass Flow Meter

Mass flow meters, also called Coriolis meters, consists of a vibrating flowtube through which the fuel passes, and a transmitter. The meter operates based on the Coriolis effect. Henry (2014) describe that along a section of the flowtube, two electromagnetic drivers forces two parallel pipes to vibrate. The frequency of vibration are monitored and measured by two sensors. Fuel flow though the vibrating tubes will cause a twisting of the pipework, this can be detected through a phase shift between the two sensor signals. The transmitter, the other part of the meter, collects the sensor signals, carries out the mass flow calculations, and feeds the electromagnetic drivers with appropriate frequency, phase and amplitude characteristics to maintain flowtube vibration.

Baboo (2015) states that the mass flow of a U-shaped coriolis flow meter can be given as:

$$Q_m = \frac{K_u - I_u \omega^2}{2Kd^2} \cdot \tau. \tag{2.1}$$

Where K_u is the temperature dependent stiffness of the flow tube, K a shape dependent factor, d the diameter of the tube, τ the time lag, ω the vibration frequency and I_u is the inertia of the tube.

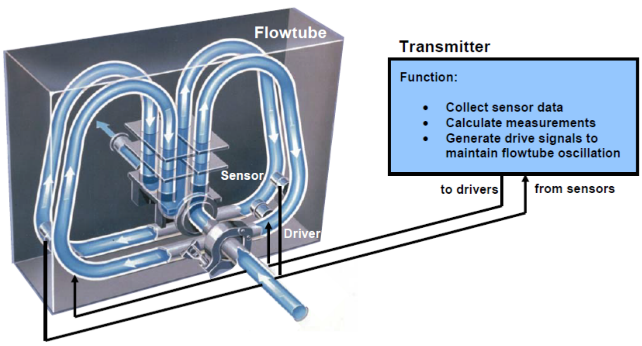

Figure 2.2: The mass flow meter, consisting of a mechanical flow tube and an electronic transmitter (Henry (2014)).

2.4.2 Mass Flow Meter Implementation in Singapore During 2016

Mass flow meters were gradually implemented on the Singaporean bunker barge fleet. Ship & Bunker (2016) reported that by May 2016, about one third of the Singaporean bunker barge fleet were equipped with Singapore Maritime Port Authority approved mass flow meters. The same figure was reported by Shippingwatch (2016) to be about 45 percent by August 2016.

> *I am pleased to share that we now have 73 bunker tankers approved for mass flow meter delivery for marine fuel oil and we are seeing close to 1 million metric tonnes of bunkers being delivered via MPA-approved mass flow meters every month.*

It is therefore important to bear in mind that any potential effect from MFMs, would gradually take effect throughout 2016.

2.5 Rationalization about Potential Effects caused by MFMs

The previous section has elaborated how mass flow meters can reduce uncertainty about delivered bunker quantity. To find any potential effects caused by MFM to the bunkering process, we need to rationalize on which aspects (parameters) of the bunkering process may be affected.

Price

One of the goals of the MFM implementation was to improve transparency of bunkering operations and hinder malpracticing suppliers. Price can potentially be affected by flow meters as malpracticing suppliers could lose revenue obtained through shortlifting. Before MFMs were implemented, these suppliers could set an artificially low price in order to attract customers. Which would result in buyers paying less per tonne on paper, but ending up with a short delivery. If MFM successfully rule out the possibility of such practice, it is therefore reasonable to believe that these suppliers will have to raise their bunker prices to a realistic level in order to cover expenses. Flow meters can therefore have a potential effect of pushing bunker price levels higher in Singapore.

Bunker Density

MFMs' ability to measure mass directly implies that stated density is not needed[1] to determine the mass of delivered fuel. The price of the transferred bunker fuel is therefore

[1] Even though the stated density is not needed for determining mass, it is still used to tune the fuel separators on board that filter the fuel for impurities.

no longer dependent on fuel density as stated by the supplier. As a result, overstating density is no longer a way for suppliers to obtain financial gain.

Without the mentioned incentive for overstating bunker density, one may speculate whether the reporting behaviour might change. Several changes may be imaginable:

(1) The suppliers become more accurate when stating the density, that is the stated density is closer to the real fuel density. This change can imply two effects: (a) the mean difference between the stated and true density shift towards zero and (b) a decrease in the variance of density difference.

(2) On the other hand, a supplier may become indifferent to the accuracy of their stated density, which may result in an increase in variance of density difference. The reasoning behind that is that the difference between two independent random variables is again a random variable with a variance equal to the sum of each of the random variables.

(3) If the stated density is derived from measurements, then one should expect a uniform distribution of the decimal digit in the stated density. Any deviation from uniformity, could be an indication of human manipulation. As MFMs makes the stated density obsolete one could expect a shift towards uniform distribution among the decimal digits. As human manipulation should not have any purpose in making financial gain.

Expected Speed of Changes

As MFM are gradually introduced by port authorities during 2016 one could expect that any effects of MFM should materialize already by the beginning of 2017. Potential effects related to bunker price should manifest quickly, as suppliers will lose money immediately if not. Effects related to reporting of bunker density may change slower as it has no immediate consequences and it needs a change in human reporting behaviour.

Chapter 3

Data Sources and Observations

This chapter introduces and explores the available data sources. Relevant parameters of the data are plotted, and initial remarks based on visual assessments are made. Testable hypotheses around potential effects of MFMs are also formulated.

Approach

3.1 Bunker Price Data

Upon request, Bunker Index[1] has kindly provided daily bunker price indices for this study. The price indices that were analyzed in this study are Hong Kong IFO 380, Singapore IFO 380 and Worldwide IFO 380. These are plotted in figure 3.1. The data ranges from 2010 till November 2018 in time, with the unit of USD per metric ton. The indices are based on prices gathered from Bunker Index's network of sources consisting of bunker suppliers, traders and brokers. The published price index of a given day represents the median of the prices received through the network on a given day (not weighted).

[1] www.bunkerindex.com

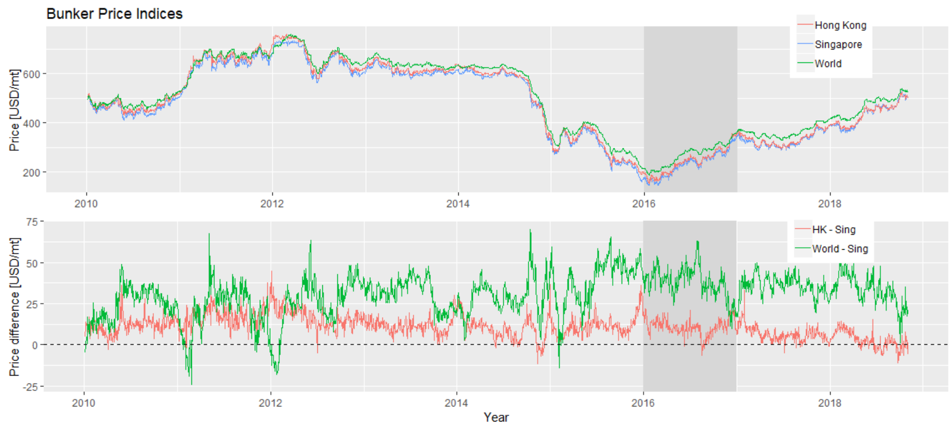

Figure 3.1: IFO 380 grade price indices (upper graph) and index price gaps between HK vs. Singapore and worldwide vs. Singapore (lower graph). MFM implementation period (2016) is marked by the grey area.

Observations

In the index plot (upper graph) of 3.1 we notice a falling trend from mid 2014 ($ 600) till end 2015 ($ 200), and a rising trend from 2016 till November 2018 ($ 200). In the price gap plot, there is a rising trend and falling trend in approximately the same periods, respectively. A falling price gap between Hong Kong and Singapore from 2016 and forward, supports the argument that MFM has pushed price levels higher in Singapore. However, it may also be argued that decreasing/increasing price levels can cause to increasing/decreasing trends in price difference.

3.2 Fuel Quality Testing Data

The second data source obtained for this study is fuel quality testing data from Veritas Petroleum Service (VPS). VPS is a bunker testing agency that conducts testing of fuel quality for their customers. VPS' customers are mainly ship operators and owners. Such tests enables the customer to monitor the accuracy of fuel quality specifications stated by the supplier. A representative fuel sample is collected by the customer during a bunkering operation and then sent to VPS. VPS then tests the sample for various parameters. The test results can then be compared against the specifications stated by the bunker supplier.

The data set contains around 45 000 samples from Singapore and around 6 000 samples from Hong Kong in the period of 2013 - 2018. There are 20 parameters related to density, energy content and various measures of contamination. As emphasized in section 2.5, our rationale is that MFM will affect the reporting of stated density among suppliers. As a result, the study has been focused on density related parameters, while the parameters related to energy content and contamination are disregarded. The density related parameters are listed in table 3.1. The report SL benchmark and report max SL benchmark are functions proposed by Anfindsen et al. (2012).

Table 3.1: Density related parameters in the fuel quality testing data set.

Parameter	**Description**
Density (Tested density)	Density of bunker sample as tested by VPS.
Stated Density	Density stated by a supplier.
Delta Density	Density - Stated Density = Delta Density.
Report SL Benchmark & Report Max SL Benchmark	Two benchmark scores on how likely a deliverance can be regarded as a shortlift.

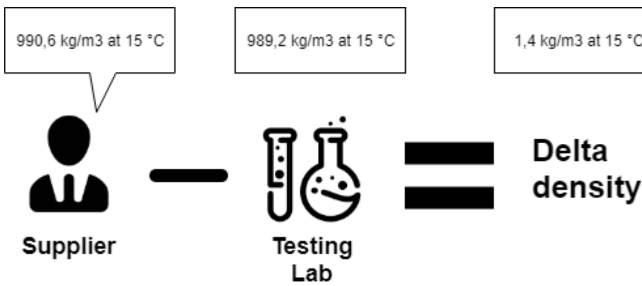

Figure 3.2: Stated density, density and delta density parameters illustrated.

3.2.1 Limitations and Data Preparation

A limitation of the fuel quality data is that the data samples with density value lower than 979,998 kg/m^3 or higher than 993,002 kg/m^3 are given as "< 979,998" or "> 993,002". There are altogether 786 of such samples, which constitute 1,7 % of the total 45 393 samples. These samples will have to be disregarded when calculating the mean and standard deviation, but can be included when calculating median. As seen in figure 3.3, "> 993,002" samples are more common than the counterpart.

A second limitation of the data set is also related to the resolution in density value. The density value for all density parameters has three decimal digits, but every entry has "86" as the last two decimal digits. This is most likely caused by the storage routines in the database, so the accuracy of the density parameter is one decimal digit.

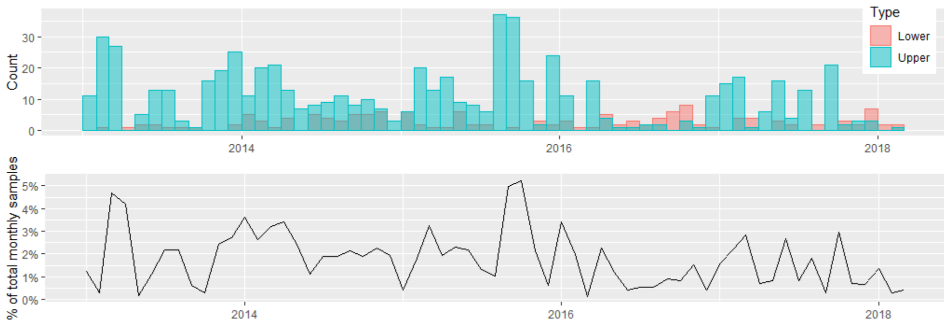

Figure 3.3: Upper graph shows count of data samples with "> 993,002" and "< 979,998" as density entry by month. Lower graph shows their percentage fraction per month.

3.2.2 Characteristics of Fuel Quality Testing Data

ISO 8217 standard - Maximum Density Limit

As mentioned in section 2.1, the ISO 8217 standard sets specifications that bunker fuel has to fulfill. The specification most relevant for our investigation is the max density limit, which for fuel grade IFO 380 is 991 kg/m3.

3.2.3 Tested Fuel Density

Daily, weekly and monthly medians were plotted in figure 3.4 to get an impression of the tested bunker density variations over time. Median as measure was chosen over mean as it is believed to give a better representation of the central tendency of the data. Medianas a measure, uses the ranked order of each data point as information, in contrast to mean which relies more on the value of each data point. By changing the density values for the border values (below 979,998 kg/m^3 and greater than 993,002 kg/m^3) to 979 kg/m^3 and 993 kg/m^3, when calculating the median, the limited resolution does not affect the median. That is, if the true density of these values would have been known, the median would have been the same. Anfindsen et al. (2012) emphasized that the mean value of ten bunkerings could easily be offset by one extreme value, while the median is less sensitive to such outliers.

Weekly median is considered to be the most appropriate resolution, as it provides sufficient detail without loosing clarity due to noise. The weekly median will thus be used for further plotting.

The weekly median together with the 1st and 3rd quartiles are shown in figure3.5. Two

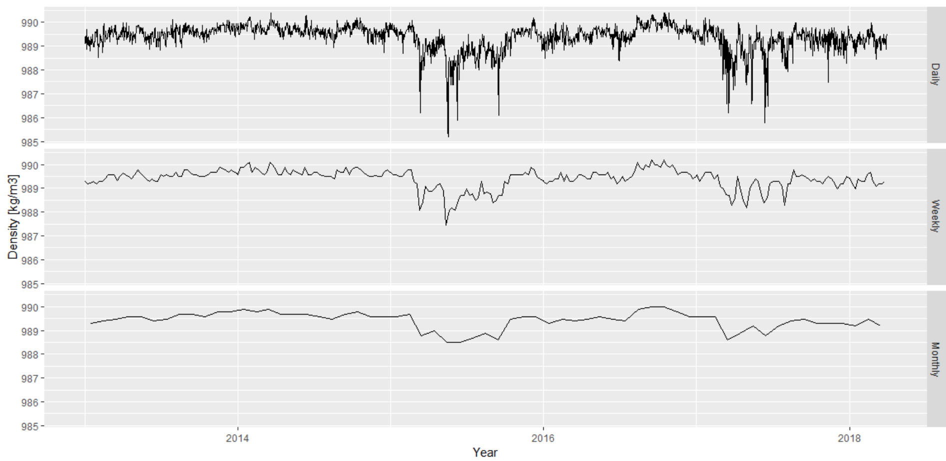

Figure 3.4: Daily, weekly and monthly sample median of bunker density in Singapore

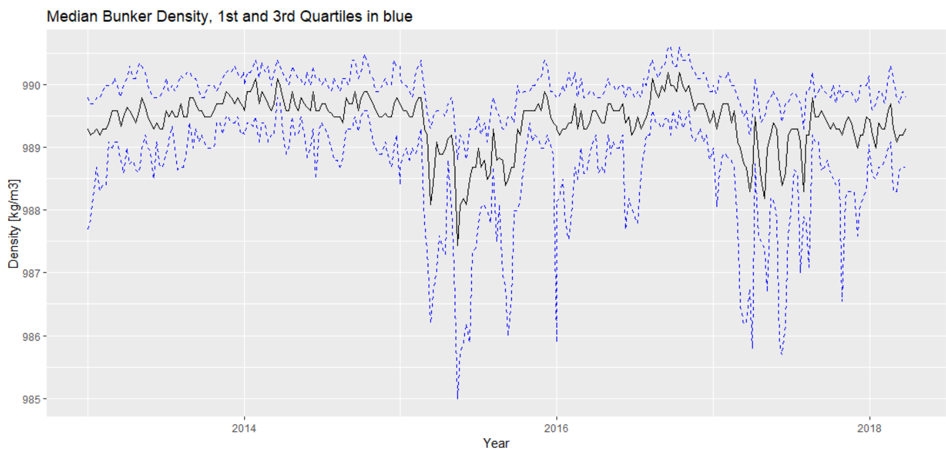

Figure 3.5: Weekly median bunker density, with 1st and 3rd weekly quartile. The quartiles provides a representation of the variations in variance of the data.

remarks were noted. Firstly, it becomes apparent that the process is not stationary[2] as variance and median changes over time. Secondly, the density distribution is significantly asymmetric with respect to the median. This is evident from figure 3.5, where the lower quartiles (blue lines) are further apart from the median than the upper quartiles. This attribute can be regarded as a result of the ISO 8217 standard which sets the maximum density to 991 kg/m3, which yields a smaller distribution for the data above the median.

[2]In mathematics and statistics, a stationary process is a stochastic process whose unconditional joint probability distribution does not change when shifted in time. Consequently, parameters such as mean and variance also do not change over time.

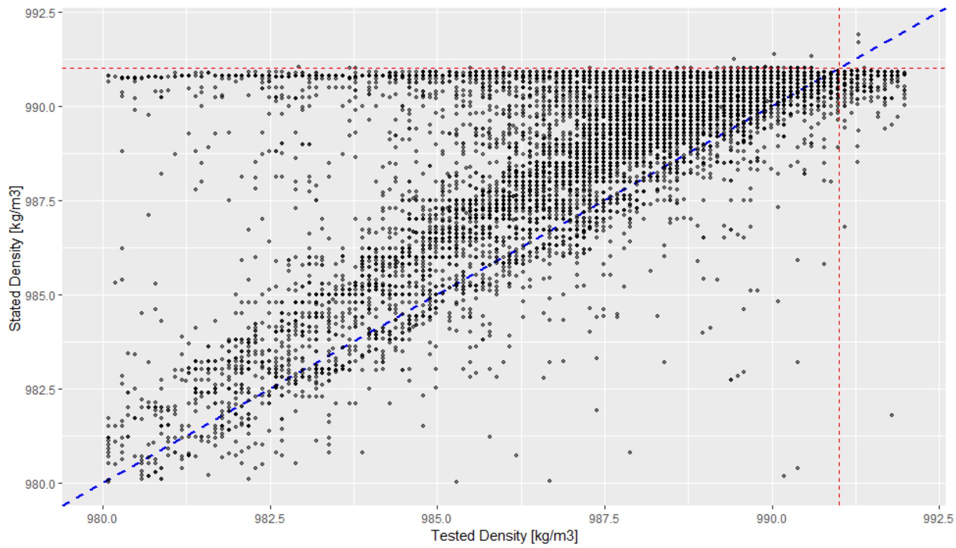

Figure 3.6: Stated vs tested density for 2013-2018. Perfect reporting line in blue and red lines represent 991 kg/m3 (ISO 8217's maximum density limit). Noteworthy are a) a tendency that data samples are above the perfect reporting line (blue dashed line) and b) the grouping of samples at or below the red horizontal line. Observe that almost no samples are stated as over 991 kg/m^3.

The median of tested density gives a picture of the general density level of the fuel sold in Singapore. This parameter is not likely to be affected by the introduction of mass flow meters, as it depends on the degree of distillation at the refineries are and the properties of imported crude oil.

3.2.4 Stated Fuel Density

The stated density is the density written in the bunker delivery note by the supplier (Gregory et al. (2008)). Anfindsen et al. (2012) visualized fuel quality testing sample data through scatter plots of tested versus stated bunker density. Figure 3.6 is a corresponding plot, which shows tested density versus stated density for all data (2013-2018).

Each dot in the scatter plot represent at least one bunker sample. A "perfect reporting" line represent the line where stated density equals the tested density. This line is illustrated by the blue dashed line. The red horizontal and vertical dashed lines represent the upper density limit as given by the ISO 8217 standard.

Regarding reporting behaviour of Singaporean suppliers, two behaviours can be identified from the scatter plot in figure 3.6. Firstly, it is apparent that the samples are not symmetrical about the "perfect reporting" line for a given value of tested density. If the intention of all suppliers were to state density as accurately as possible, it would be reasonable to believe that the distribution would center around the "perfect reporting line". However, the mean is skewed towards higher values in our case.

It is challenging for the supplier to know the exact density of the fuel that is being supplied. Therefore, it can be suspected that the shifted mean is caused suppliers are inclined to put on a "safety margin" to ensure that they are not selling at a lower density.

Secondly, there is a clear tendency of samples grouped along the lower side of the red horizontal line. In other words, these samples represent suppliers that state the density as right below the ISO 8217 limit of 991 kg/m3. Some of these samples can be considered as malpracticing suppliers who deliberately overstate the density to achieve financial gain.

3.2.5 Delta Density - A Measure of Overstated Density

The third relevant parameter in the quality testing data set is delta density. This is simply the difference between the stated density and tested density, d_{stated} - d_{tested} = delta density. This parameter therefore directly represents the amount of overstated density (or understated density in cases of a negative delta density). A delta density of 0 means that the supplier stated the same density as what was tested in the laboratory. The maximum delta density for a given sample is achieved when supplier states 991 kg/m3 as density. Recalling the scatter plot in figure 3.6, delta density can be repre-

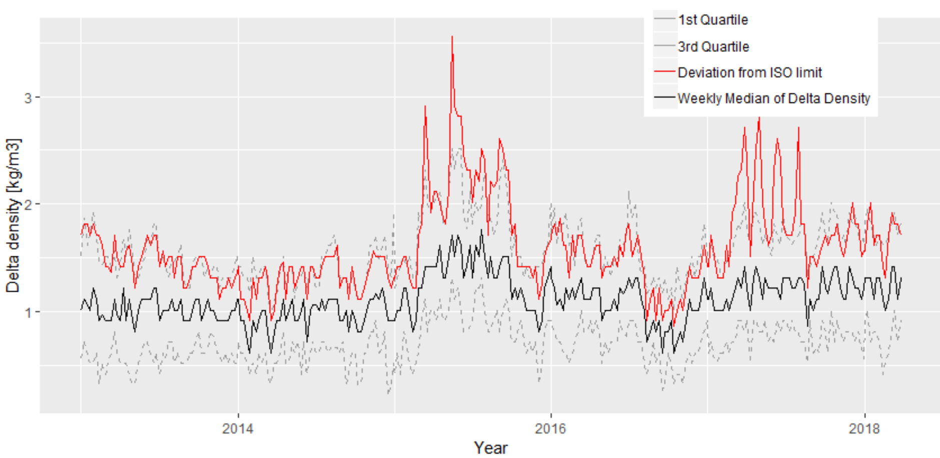

Figure 3.7: Deviation from ISO limit, weekly Median of Delta Density with 1st and 3rd quartiles. Observe that delta density increases when the deviation from ISO limit increases (corresponding to decreasing fuel density).

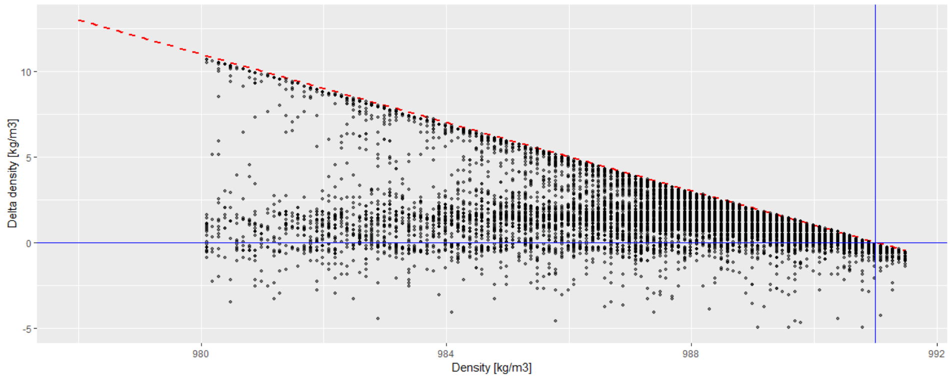

Figure 3.8: Delta density versus density. Obvious tendency of delta density being a function of density. Mean and variance of delta density decreases as density approaches 991 kg/m^3 from below.

sented as the distance between eact point and the "perfect reporting" line.

The weekly median of delta density is plotted in figure 3.7, along with weekly quartiles. Median deviation from the ISO limit, or the difference between the ISO limit and the weekly median of delta density, is also plotted (991 - median delta density).

A clear covariance between the two measures is obvious in the plot. Since delta density raises with deviation from ISO limit, one can say that the suppliers overstate more when the fuel density (tested density) gets low. The domain of delta density gets higher as lower density will allow for greater difference between actual density and stated density.

The relationship between delta density and density is also evident in 3.8. The mean and variance of delta density can be seen as a function of density.

3.2.6 Short Lift Benchmark and Max Short Lift benchmark

Benchmarking scores have been developed by VPS and DNV GL as described in Anfindsen et al. (2012). The benchmarking scores that are relevant for density are the shortlift and max shortlift benchmark. These two benchmark scores uses delta density as function input. The benchmarking system allocates a score between 0 and 1 as to whether a sample can be regarded as a shortlift and gives indication of amount of shortlift. The benchmarking method is based on the concept of membership functions from fuzzy logic, the theory behind the benchmarking method will not be further described. The benchmark scores can be useful in that it acts as an indicator on how much a sample can be regarded to be a shortlift (SL).

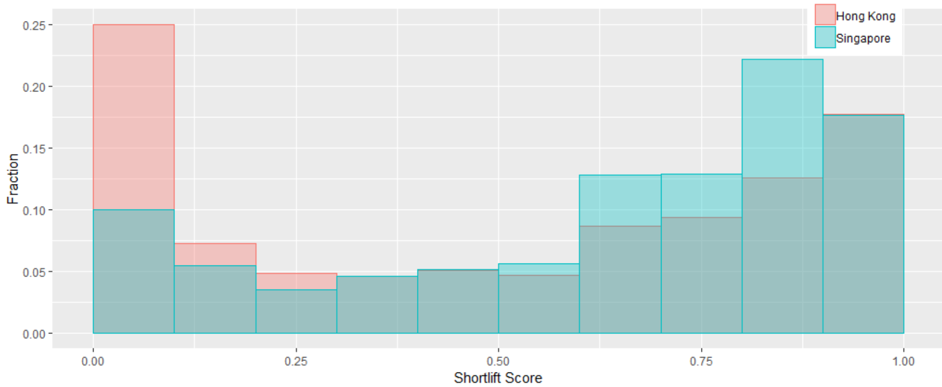

Figure 3.9: Short Lift Benchmark Histogram for 2013-2018, Singapore and Hong Kong. Singapore has a higher fraction of shortlifting samples, i.e. overstating density is more widespread in Singapore.

Observing the benchmark histogram in figure 3.9, it is noted that Singapore's benchmarks are generally higher than its neighbouring port. Meaning that the scoring method indicates that a larger portion of Singapore's bunkerings are considered to be shortlifting, relative to Hong Kong.

Weekly mean of the two shortlift benchmarks for Singaproe samples are plotted in figure 3.10. It can be seen that weekly mean and standard deviation have not been significantly changed.

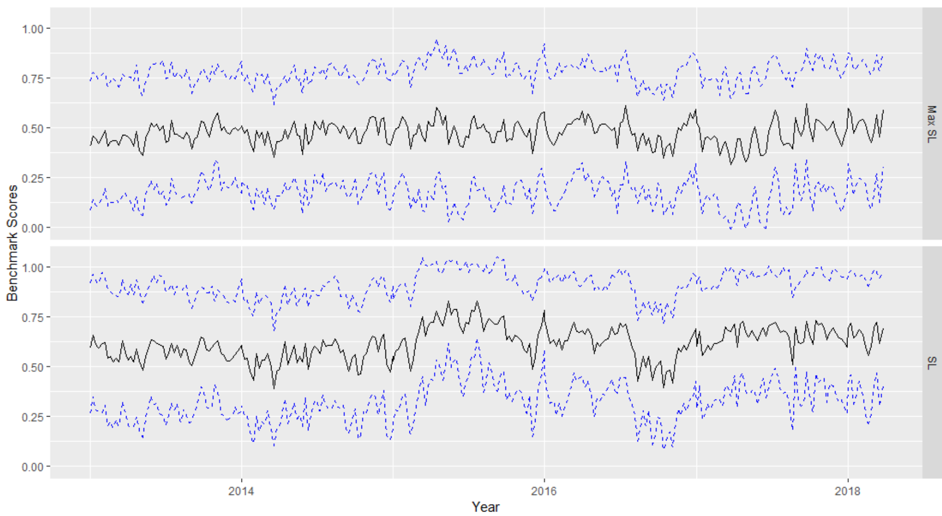

Figure 3.10: Weekly mean of shortlift (SL) benchmarks and standard deviation (dashed lines). Max SL benchmark (top) and SL (bottom).

3.3 Summary and Formulation of Hypotheses

With the insights gained from data exploration, the expected effects as rationalized in section 2.5 can be formulated into hypotheses that are appropriate to test based on the available data. The testable hypotheses can be formulated as follows:

1. MFMs will lead to price increase in Singapore.
2. MFMs will lead to a decrease in price difference between Singapore and Hong Kong.
3. MFMs will lead to change in distribution of decimal digits in the stated bunker density parameter.
4. MFMs will lead to a change in mean delta density, shortlifting benchmark and occurrence of shortlifting benchmark.
5. MFMs will lead to a change in variance of the delta density parameter.

Price

The expected effect of MFMs on bunker prices was rationalized to be a price increase. Based on this rationalization, a hypothesis could be that MFMs have caused a rise in Singaporean bunker prices. To test this hypothesis, we would check whether prices after MFM introduction are higher than prior to MFM introduction. Obviously, the prices have risen since January 1, 2017 as evident in figure 3.1. However, the drivers behind the bunker price include macroeconomic factors such as geopolitical issues, crude oil price (Hellenic Shippipng News (2015)) and so forth. As a consequence, the results of the proposed hypothesis test does not provide a conclusive answer on whether the price rise can be attributed to mass flow meters.

Focusing on the price gap between Hong Kong and Singapore, a decrease in price difference is evident from figure 3.1. On the other hand, it is noted that trends in general price levels have occurred in the same periods as trends in price difference.

Analyzing the bunker price difference between Hong Kong and Singapore can be a way to identify any potential MFM effect. As the geographical positions of Singapore and Hong Kong lie close, some price driving factors that affect both ports can be expected to cancel out when studying the price difference. Thus any development in the price difference might be attributed to a potential MFM effect. On the other hand, a potential price effect from MFM can be disturbed by the differences in factors affecting the ports. That is differences such as different political situation or different bunker supplier market environment which drive the price differently in the two ports.

With this reasoning as backdrop, the hypothesis is that mass flow meters will cause Singaporean bunker prices to rise, which will result in a decrease in the price difference between Hong Kong and Singapore.

Tested Bunker Density

It was decided to inspect density levels with the resolution of weekly medians. It is noted that the variance and mean are not constant, thus we assume that the density does not behave as a stationary process. The distribution is not symmetric around the median. We see this as a result of the ISO 8217 density limit. It is rationalized that mass flow meters are not likely affect bunker density. Therefore no hypotheses regarding a potential effect on tested bunker density is formulated.

Stated Density

Figure 3.6 revealed that stating density right below 991 kg/m^3 at 15 °C, with no regard to real density, is a widespread practice. This is most likely because, prior to introduction MFM, a higher stated density would result a higher delivered mass when calculating density · volume = mass.

As mentioned in the literature review, Beber and Scacco (2012) showed that analysis of digit distribution can be used to investigate electoral frauds. A similar approach can be be utilized on the fuel quality testing data by investigating the distribution of last digits (decimals) in the stated density parameter. The hypothesis becomes "MFM affects the distribution of decimal digits in the stated bunker density".

Delta Density

In figure 3.8 it was observed that delta density increased with decreasing density, which imply a negative correlation between delta density and density. This can translate into that suppliers tend to state a higher density when density decreases.

It was rationalized that suppliers would start to state density more accurately. This is expected because the transferred mass is directly read off from the MFM, meaning that there is no longer any financial gain in overstating density. Thus, two hypotheses regarding delta density can be formulated as "mass flow meters cause a decrease in the delta density levels" and "mass flow meters reduces the variance in delta density".

Chapter 4

Change Detection and Methodology

The aim of this chapter is to describe and select appropriate statistical methods, based on insights gained from data exploration in the previous chapter, that can be used for hypothesis testing around potential effects of mass flow meters. Assessment of the assumptions and limitations of the selected methods are also done.

4.1 Investigate Potential Effects with Statistical Hypothesis Testing

As mentioned when rationalization and formulating hypotheses, it is expected by the author that any potential effects of MFM mayl cause various changes in the data. In this study, the term "change" is considered as a difference in a certain characteristic.

Hopefully, such potential changes can be quantified through statistical hypothesis testing. To identify changes due to the MFM, the data should be grouped into before and after the introduction of MFM. Recalling section 2.4.2, it was emphasized that MFMs were implemented gradually throughout 2016. Therefore, we may assume hat any potential change has happened during 2016. We label the period earlier than January 1, 2016 for the pre-MFM period and the period later than December 31, 2016 for the post-MFM period. Due to the time range of the fuel quality testing data (January 2013 - March 2018), the pre-MFM period include January 1, 2013 - December 31, 2015, while

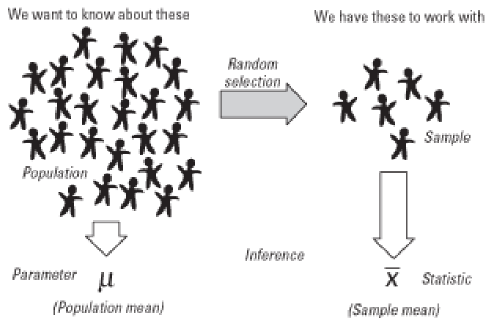

Figure 4.1: Relationship between population and sample, in addition to population parameter and sample statistic (CliffsNotes (2015)).

the post-MFM period include January 1, 2013 - March 31, 2018.

Figure 4.1 illustrates the different statistical terms involved in hypotheses testing. To illustrate how to formulate a hypothesis test, delta density can be used as an example. Consider the question of whether delta density levels have changed after the introduction of mass flow meters. Table 4.1 shows how each term is interpreted in the context of testing a potential change in delta density.

It is important to be aware of the limitations of statistical tests; they do not explain the reasons as to why any difference exist. They can only indicate whether the differences are due to the random fluctuations of sampling or due to other reasons. Therefore such

Table 4.1: Relationship between hypothesis testing terms in general and corresponding values in the context of testing delta density values.

General context	**Comparing pre-MFM and post-MFM delta density**
Population A & B	Delta density values of all bunkerings in the pre-MFM and post-MFM period.
Population parameter A & B	Mean of delta density values of all bunkerings in the pre-MFM and post-MFM period.
Sample A & B	Delta density values of the bunkerings in the fuel quality data set (pre- and post-MFM).
Sample statistic A & B	Mean of delta density values of the bunkerings in sample A and sample B.
Null hypothesis, H_0 Alternative hypothesis, H_1	$\mu_{\text{delta density, pre-MFM}} = \mu_{\text{delta density, post-MFM}}$ $\mu_{\text{delta density, pre-MFM}} \neq \mu_{\text{delta density, post-MFM}}$

tests do not tell us as to which are the other reasons causing the potential differences.

In our context, it should be acknowledged that the we do not know all the factors affecting the phenomena generating delta density values. Thus, this study is not conducted in a controlled environment at all. An example of studying a phenomena in a controlled environment would be an experiment conducted in a laboratory, where all the major factors are known. As a result, we cannot be completely certain that any detected change can be a result of MFM implementation as it may be caused by other factors that we do not have knowledge of. Even in the case of not identifying any changes, we may not be certain that MFMs have not caused any changes. It could be that any effects from MFMs are blurred by other more dominant effects.

4.2 Comparing results in Singapore with results in Hong Kong

A way to gain additional information on whether a change can be attributed to MFMs is to conduct the similar hypothesis test on Hong Kong data, and compare the results. For a port, there can either be a change or no change. Comparison of two ports with two outcomes yields four different scenarios. The different scenarios and their implications can be summarized in a scenario matrix as shown in figure 4.2. For instance, if a change has been identified as statistically significant for both Singapore and Hong Kong (scenario A), the scenario would weaken that there is a causality between MFMs and the identified change. This is due to that Hong Kong have not mandated the use of mass flow meters. So the scenario suggests that the changes in the two ports are caused by an effect affecting both ports.

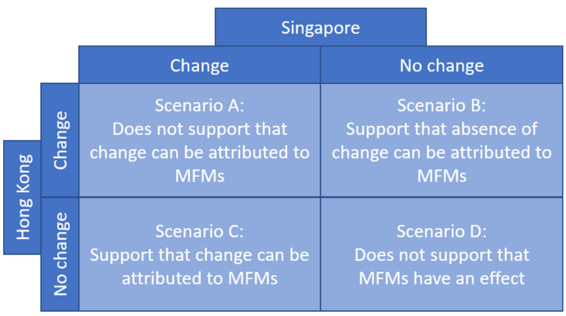

Figure 4.2: Scenario matrix describing proposed causality between MFM and identified change when comparing to Hong Kong.

Another interesting outcome is scenario B: no change in Singapore but a change in Hong Kong. This may support that MFMs have an effect in Singapore. This implication relies on the assumption that there is an effect that affects both ports, but the change is countered by MFMs in Singapore while the change is evident in Hong Kong. However, the implication that scenario B indicate that MFMs are countering another effect can be regarded as a more doubtful implication than the implication of scenario A.

To further understand the feasibility of using hypothesis testing to make conclusions regarding potential effects of mass flow meters, we study statistical hypothesis testing in general and a handful of test methods in the rest of this chapter.

4.3 Statistical Hypothesis Testing

A statistical hypothesis is a proposition, or conjecture, about the population. The aim of testing statistical hypotheses is to determine whether a conjecture about a feature of a population is supported by the information obtained from the sample data. Hypothesis testing is a type of statistical interference where the plausibility of the hypothesis is evaluated based on experimental data (information obtained by sampling from the population (Bhattacharyya and Johnson (1977))). Typically, The conjecture should involve a statement, or assertion, about the value of a population parameter. As an assertion may be true or false, two complementary hypothesis can be formulated.

The hypotheses are formulated as the null hypothesis and alternative hypothesis. These are denoted as H_0 and H_1, respectively. The hypothesis suggesting the negation of the assertion is labelled the null hypothesis, and the assertion itself is formulated as the alternative hypothesis, H_1. To be able to reject the null hypothesis, the concept of p-value is used. P-value is the probability of obtaining the sample data result or more extreme (unlikely) under the circumstances of the null hypothesis. The concept of p-value and its relationship to the sample data result is illustrated in figure 4.3. The null hypothesis can be rejected if the sample data result is a unlikely realization of the null hypothesis. The required level of unlikelihood to reject H_0 is called the significance level, denoted α, of the statistical hypothesis test. The significance level is conventionally set to $\alpha = 0,05$, but depends on the field of study. In the case of hypothesis testing with $\alpha = 0,05$, the H_0 can be rejected if the p-value $\leq \alpha$. Rejecting the null hypothesis corresponds to accepting that the sample data gives reasonable evidence to support the alternative hypothesis.

In testing the null against the alternative hypothesis, the attitude is to uphold H_0 as true unless the data strongly speak against it. This attitude implies that the error of falsely

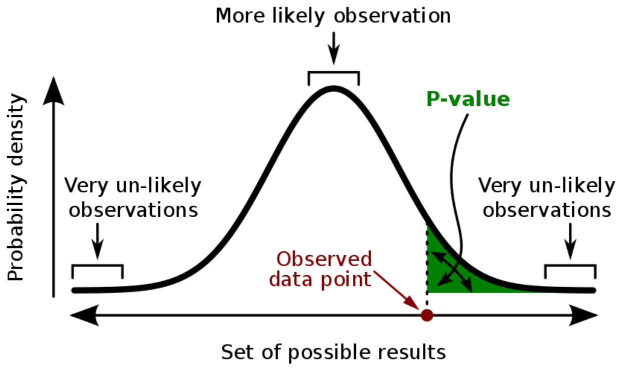

Figure 4.3: Illustration of a p-value computation. The vertical coordinate is the probability density of each outcome (x-axis), computed under the null hypothesis. The p-value of the observed data point (red) is the green area under the curve (Wikipedia contributors (2019b)).

rejecting H_0 is considered more serious than failing to reject H_0 when H_1 is true.

Confidence intervals, an alternative to p-values

Both p-values and confidence intervals can be used to determine whether the observed results are statistically significant. The p-value and confidence interval will always agree on whether to reject the null hypothesis. The confidence level of a confidence interval is related to the significance level in that the confidence level is equivalent to $1-\alpha$.

Estimation by confidence intervals is to produce an interval of values that has a certain probability to contain the true value of the population parameter. The null hypothesis assumes a certain value for the population parameter. If the computed confidence interval does not include the population parameter, the null hypothesis can be rejected.

Let θ be an unknown population parameter and L and U be functions of the random sample $X_1, ..., X_n$, such that

$$P[L < \theta < U] = 1 - \alpha. \tag{4.1}$$

Then (L,U) is called a $100 \cdot (1-\alpha)\%$ confidence interval, and (1-α) is the confidence level associated with the interval.T In finding the expressions for L and U, mind that the normal table shows that a random variable will lie within 1,96 standard deviations from its mean with a 95% probability. For the mean of the sample observations, $\overline{X}$, this can be expressed as

$$P\left[\mu - 1,96\frac{\sigma}{\sqrt{n}} < \overline{X} < \mu + 1,96\frac{\sigma}{\sqrt{n}}\right] = 0,95. \tag{4.2}$$

By rearranging the expression, the probability statement can be alternatively expressed as:

$$P\left[\overline{X} - 1,96\frac{\sigma}{\sqrt{n}} < \mu < \overline{X} + 1,96\frac{\sigma}{\sqrt{n}}\right] = 0,95. \tag{4.3}$$

Now the confidence interval can be identified as:

$$L = \overline{X} - 1,96\frac{\sigma}{\sqrt{n}} \quad \text{and} \quad U = \overline{X} + 1,96\frac{\sigma}{\sqrt{n}}. \tag{4.4}$$

4.4 Testing the Mean of a Population with T-tests

A t-test, or student's t-test, is a statistical hypothesis test and is commonly used to determine whether the mean of a population has a value specified in a null hypothesis (Snedecor and Cochran (1989)). It is also common to use t-tests to determine if the means of two populations are equal. The t-test assumes that the sample statistic follow a normal distribution.

One-Sample T-test and Two-Sample T-test

Given a random sample $X_1, ..., X_n$ (of size n) from a normal population $N(\mu,\sigma)$ and the sample mean and sample standard deviation are expressed:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad \text{and} \quad s = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n-1}} \tag{4.5}$$

then the distribution of the t-statistic,

$$t = \frac{\overline{X} - \mu}{s/\sqrt{n}}, \tag{4.6}$$

is called the Student's t distribution with n-1 degrees of freedom. For two-sample T-tests, the definition can be given as (Snedecor and Cochran (1989)):

$$
\begin{aligned}
H_0: &\quad \mu_1 = \mu_2 \\
H_1: &\quad \mu_1 \neq \mu_2 \\
\text{Test Statistic}: &\quad T = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{s_1^2/n_1 + s_2^2/n_2}} \\
\text{Significance Level}: &\quad \alpha \\
\text{Critical Region}: &\quad \text{Reject the null hypothesis if } |T| > t_{1-\alpha/2,\nu}, \text{where } t_{1-\alpha/2,\nu} \text{ is the} \\
&\quad \text{critical value of the t distribution with } \nu \text{ degrees of freedom.} \\
\text{Degrees of Freedom}: &\quad \nu = \frac{(s_1^2/n_1 + s_2^2/n_2)^2}{(s_1^2/N_1)^2/(N_1-1) + (s_2^2/N_2)^2/(N_2-1)}.
\end{aligned}
$$

Sample Size and Normality

If we are sampling from a population with unknown distribution, the sampling distribution of the sample mean, $\overline{X}$, will still be approximately normal, provided that the sample size is large enough. This result is an immediate consequence of the Central Limit Theorem (Walpole et al. (2012)). The normal approximation of $\overline{X}$ will generally be good if the sample size $n \geq 30$, given that the population is not terribly skewed.

4.5 Wilcoxon Rank-Sum Test - A Nonparametric Statistical Test

The most common statistical tests are often parametric. Many parametric tests, such as the t-test, assume that the sample population is normally distributed. Normality implies normally distributed samples and stationary variance (not changing over time). When this assumption is not satisfied, parametric tests can be misleading (Nahm (2012)). In such circumstances, nonparametric tests are available alternatives. A nonparametric statistic does not require modeling a population in terms of a specific parametric form of density curves, such as normal distributions. The great disadvantage of nonparametric tests are that they have less statistical power than parametric tests.

The Wilcoxon Rank-Sum test is a nonparametric (also called distribution-free) test, which tests the null hypothesis that it is equally likely that a randomly selected value from one population should be less than or greater than a randomly selected value from a second

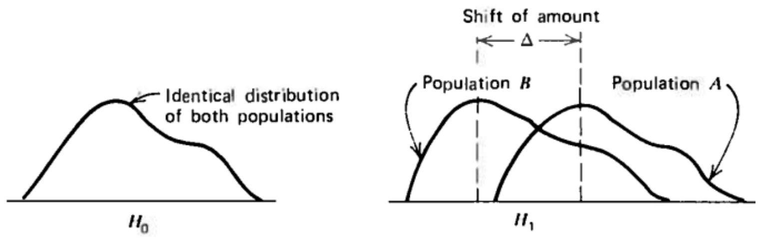

Figure 4.4: Representation of H_0 and H_1 in the Wilcoxon Rank-Sum Test (Bhattacharyya and Johnson (1977)).

population (Bhattacharyya and Johnson (1977)). That is to say, the distributions of the two populations are equal while the alternative hypothesis states that the populations' distributions are not equal. An example of Wilcoxon Rank-Sum hypotheses is shown in figure 4.4, here the alternative hypothesis is that the distribution of population A is shifted to the right of population B's distribution. Note that the hypotheses does not make any assumptions regarding the distribution shapes of the populations.

The basic concept underlying the rank-sum test can be explained as such: Suppose two sets of observations, A and B, are plotted on a line diagram as in 4.5. The observations are plotted in ascending value from left to right. In the case of the null hypotheses, that the two samples are picked from the same population, the two sets of points should be well mixed. This is illustrated by example a in figure 4.5. An alternative outcome is that the larger observations are mostly associated with observations from set B. As illustrated in example b in figure 4.5. Given the latter outcome, it is reasonably to infer that one of the populations is possibly shifted to the right of the other. It is clear that the test is based on the rank of the observations of the two samples, and it does not account for how big the differences are between the values. The disregard of this information weakens its statistical power.

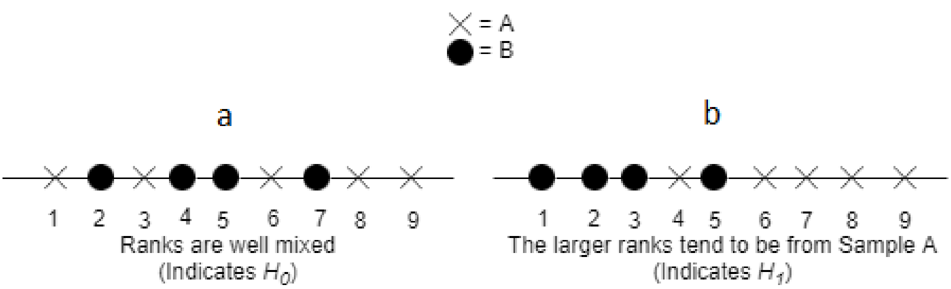

Figure 4.5: Two examples (a and b) of combined plot of the two samples and the combined sample ranks (Bhattacharyya and Johnson (1977)).

The rank sum for one of the sets are taken as the test statistic. For figure 4.5b, the rank sums are:

$$W_A = 4 + 6 + 7 + 8 + 9 = 37$$
$$W_B = 1 + 2 + 3 + 5 = 11$$

To establish a rejection region with a specified level of significance, the distribution of the rank-sum statistic under the null hypothesis must be considered. The following example is adapter from Bhattacharyya and Johnson (1977) and is given to give an introduction to the concept behind the Wilcoxon Rank-Sum Test. Say we would like to compare two geological formations with respect to richness of mineral content. The mineral contents of 4 specimens of ore collected from formation A and 5 specimens of ore collected from formation B are measured by chemical analysis. The observations are ranked with respect to mineral content according to 4.5b. We wish to determine if the data provide strong evidence that formation A has higher values than formation B. We decide to conduct the test with a significance level, α, close to 0,05. The sum of ranks of the smaller sample (which is the test statistic) is $W_B = 11$. Depending on the alternative hypothesis, there are three alternatives in using the Wilcoxon table. As of this example, the H_1 is that the population corresponding to the smaller sample (A) is shifted to the left of the other population (B). Then the rejection region is set on the form $W_B \leq c$, and take c as the largest x^* value for which $P \leq \alpha$. The Wilcoxon table

SMALLER SAMPLE SIZE = 4

LARGER SAMPLE SIZE

4			5			6			7		
x	P	x^*	x	P	x^*	x	P	x^*	x	P	x^*
22	.171	14	25	.143	15	28	.129	16	31	.115	17
23	.100	13	26	.095	14	29	.086	15	32	.082	16
24	.057	12	27	.056	13	30	.057	14	33	.055	15
25	.029	11	28	.032	12	31	.033	13	34	.036	14
26	.014	10	29	.016	11	32	.019	12	35	.021	13
27	0	9	30	.008	10	33	.010	11	36	.012	12
			31	0	9				37	.006	11

8			9			10		
x	P	x^*	x	P	x^*	x	P	x^*
34	.107	18	36	.130	20	39	.120	21
35	.077	17	37	.099	19	40	.094	20
36	.055	16	38	.074	18	41	.071	19
37	.036	15	39	.053	17	42	.053	18
38	.024	14	40	.038	16	43	.038	17
39	.014	13	41	.025	15	44	.027	16
40	.008	12	42	.017	14	45	.018	15
			43	.010	13	46	.012	14
						47	.007	13

Figure 4.6: Wilcoxon Table for Distribution under the Null Hypothesis (Bhattacharyya and Johnson (1977)).

is given in figure 4.6. Given a smaller sample is of size 4, and a larger sample size of 5 the correct table can be found. As the $P[W_B \leq 13] = 0,056$, the rejection region with $\alpha = 0,056$ is established as $W_B \leq 13$. Since the observed value of W_B falls within this region, the null hypothesis is rejected with a significance of $\alpha = 0,056$. In fact, the null hypothesis can be rejected with a significance of $\alpha = 0,016$ given the result of $W_B = 11$.

4.6 Normality Testing with the Shapiro-Wilk Test

Many statistical procedures are parametric tests which depend on normally distributed data for being valid. Normality and other assumptions of statistical tests should be seriously considered. Conclusions of such tests may be far from reality if assumptions are not held. Among normality tests, the Shapiro-Wilk test was highly recommended by Ghasemi and Zahediasl (2012).

The Shapiro-Wilk test tests the null hypothesis that a random sample $X_1, ..., X_n$ is drawn from a normally distributed population. Thus, the null hypothesis is rejected if the p-value is less than the chosen alpha level. Which means that the test indicate that there is evidence that the data tested are not sampled from a normal distribution. The test-statistic is given as

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n} \left(x_i - \overline{x}\right)^2}, \tag{4.7}$$

where $x_{(i)}$ is the ith order statistic, i.e. the ith-smallest number in the sample; and a_i are constants generated from the covariances, variances and means of the sample from a normally distributed sample.

4.7 Two Proportions Z-test

In statistics, a proportion refers to the fraction of the total population that possess a certain attribute. A two sample proportion test will test the equality of two proportions against the alternative that they are not equal. The null and alternative hypotheses are given as: $H_0 : p_1 = p_2$ and $H_1 : p_1 \neq p_2$. The test statistic for testing the null hypothesis (which is equivalent to the difference in two population proportions) is:

$$Z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}}. \tag{4.8}$$

Where $\hat{p} = \frac{X_1+X_2}{n_1+n_2}$, that is the proportion of the two samples combined that possess the certain attribute. $\hat{p}_1$ and $\hat{p}_2$ are the sample proportions for population 1 and 2. This test statistic follows the Z-distribution (Bhattacharyya and Johnson (1977)).

4.8 Testing for Homogeneity of Variance

Many statistical procedures, such as the Student's t-test assume that the variance of the two tested populations are equal and unchanged. In statistics it is conventional to use the F-test to check whether two populations have equal variance (Conover et al. (1981)). But F-test has normality as an assumption. In cases where the data is not normal, the nonparameteric Fligner-Killeen test should be used to check homogeneity of variance. The null hypothesis is that the variances of the two populations are not equal.

4.9 Distribution of Decimal Digits

Beber and Scacco (2012) derived implications and ran simulations that supported their claim that the last digits of fair electoral results are likely to be distributed uniformly. Lab experiments also indicated that human individuals tend to favor small numbers, even when subjects have incentives to properly randomize.

Analogously for bunker density, the decimal digit of the true density of the fuel is assumed by us to follow a random process. This assumption lies on the belief that suppliers or refineries are not deliberately trying to achieve a certain decimal digit for the density value.

We see the supplier's decision on which decimal digit he or she is going to use in the stated density as a process. This process of of generating decimal digits can be seen a function of the density decimal digit as perceived by the supplier and different biases (both conscious and unconscious) that the supplier may possess. This can be illustrated by

$$\text{stated decimal digit} = f\left(x, y_1, \ldots, y_n\right), \tag{4.9}$$

where x is the density decimal digit as perceived by the supplier, and $y_1, \ldots, y_n$ are all the biases that the supplier possess when deciding on which decimal digit to state on the bunker delivery note.

As the aim of this study is to investigate potential changes caused by MFM, whether the distribution of decimal digits is uniform will not be the main focus. The main area of interest is to see whether there are any significant changes in the distribution of decimal digits.

Chapter 5

Change Detection Analysis

This chapter applies the methods described in chapter 4 to test the hypotheses that were formulated in chapter 3. The hypotheses were:

1. MFMs will lead to price increase in Singapore.
2. MFMs will lead to a decrease in price difference between Singapore and Hong Kong.
3. MFMs will lead to change in distribution of decimal digits in the stated bunker density parameter.
4. MFMs will lead to a change in mean delta density, shortlifting benchmark and occurrence of shortlifting benchmark.
5. MFMs will lead to a change in variance of the delta density parameter.

5.1 Bunker Price

ShippingWatch (The Shipping Watch (2017)), an online media delivering news about the maritime industry, reported that sentiment among bunker companies were that mass flow meters has driven up the price for bunker oil in Singapore:

> *The prices for bunker oil in Singapore, the world's largest port for sales of marine fuel, have risen by an average USD 5-10 per ton in 2017.*

> *The explanation for the price increase is directly related to the new requirements from authorities concerning the use of mass flow meters, which aim to ensure, along with control systems and other measures, that the vessels take delivery of the correct fuel volumes paid for by the carriers.*
>
> *This is the sentiment among bunker companies in Singapore speaking to ShippingWatch.*

Lower graph of figure 5.1 shows the price gap, or price difference, between Hong Kong and Singapore (Hong Kong - Singapore = price gap) for IFO 380 fuel grade in the period after MFM implementation. The difference in price can be seen as a proxy for whether Singapore prices are rising faster (decreasing price gap) or slower (increasing price gap) than Hong Kong. By simply fitting a linear regression to the price gap data, a long term trend towards 0 is seen. The news article from Shippipngwatch states that the sentiment is that MFM has lead to a price increase in Singapore. Given that the sentiment is correct, prices in Singapore should rise more than prices in Hong Kong, as MFM is not mandated in Hong Kong. As a result, there should be a decrease in price gap. The fitted linear model shows that there has been a decrease in price gap since January 2017, which supports the sentiment in the article above.

On the other hand, it is apparent from figure 5.1 that prices in both ports have risen from \$300 in 2017 to over \$500 in the end of 2018. Recalling figure 3.1, the world index has also risen in the same period. As prices in both ports have risen, MFM might not be the mechanism behind the rise as they are not implemented in Hong Kong.

As commented in section 3.1, changes in price gap could be related to price movements.

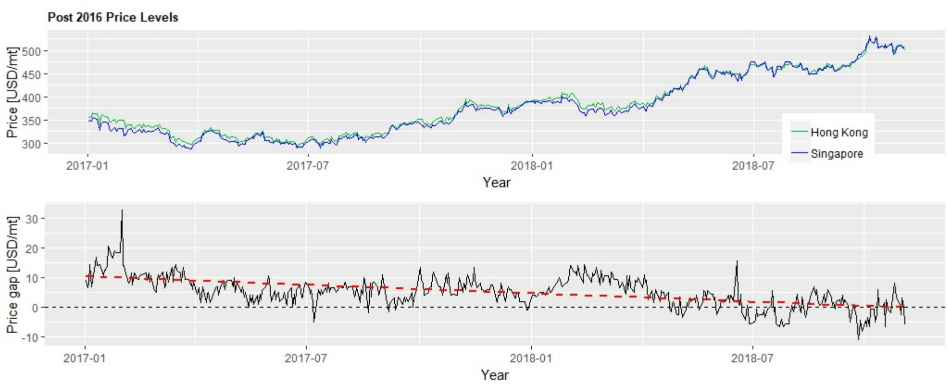

Figure 5.1: Top: Price of IFO 380 after MFM implementation 1st of Januar 2017 (post-MFM). Bottom: Price gap between Hong Kong and Singapore (Price_{HK} - Price_{S} = price gap) and a fitted linear regression model of the price data.

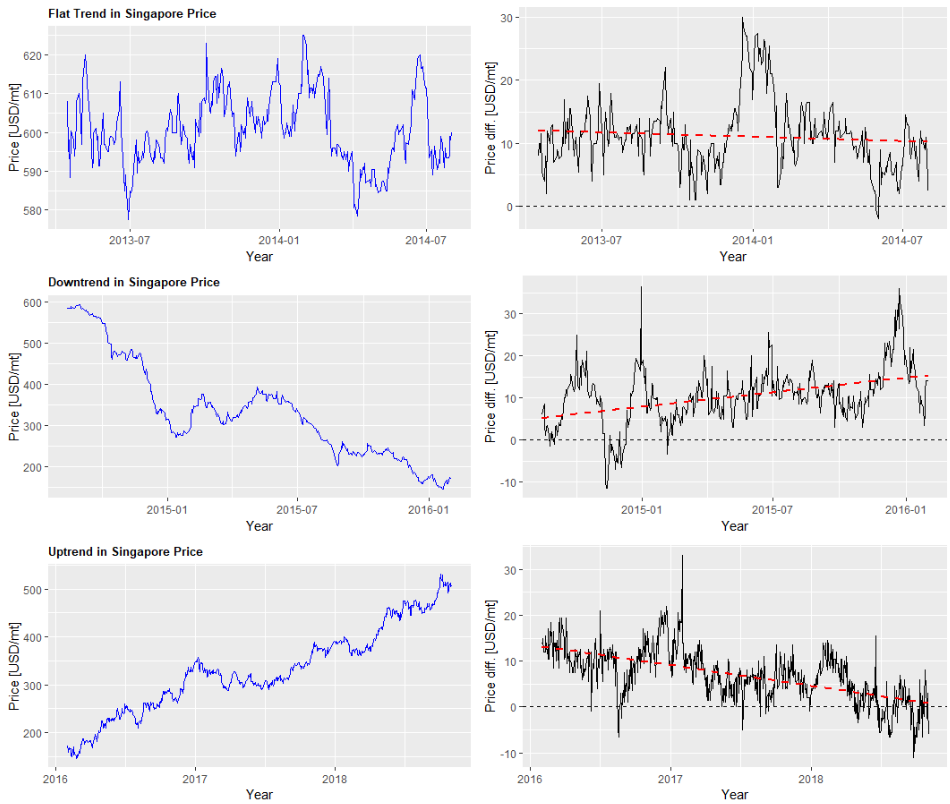

Figure 5.2: Price (left) and corresponding price gap (right) for HK - Singapore in three periods of different price trends. Linear regression for price gap in red. Graphs suggest negative correlation between price and price gap.

To investigate this further, we analyzed three periods where the fuel price had a flat, significant downward and significant upward trend. The selected periods were: April 2013 - August 2014 (flat), August 2014 - February 2016 (decreasing) and February 2016 - November 2018 (increasing). Figure 5.2 gives reason to believe that another mechanism than MFM introduction may cause the trends in the price gap. The first row shows a time period of flat trend in price, the second row shows a time period of downward trend in price and the third row shows a time period of uptrend in price. In the right column the price gap is plotted with a fitted linear model. The first row shows a insignificant slope linear model, the second row shows a significant slope upward slope and the last rows shows a significant downward slope. Thus, it is clear that during a time period of price downtrend, the price gap showed a uptrend and in a time period of price uptrend, the price gap showed a downtrend. At the same time, a period of flat trend in price, there was a flat trend price as well. These findings suggest a negative correlation between the price and price gap.

These findings may indicate that the rise in Singaporean bunker price should not be solely attributed to MFM, as it may be an effect of a uptrend in price. In addition, prices are rising in Hong Kong and the world index have also risen in the period after MFM introduction. Which can suggest that there are some macroeconomic factors that are causing the prices to rise. Thus, by analyzing the price data, the statement that MFM has lead to a rise in bunker prices can not be clearly supported by the price data. The reducing price gap may be entirely attributed to the rising fuel prices.

5.2 Distribution of Decimal Digits in Stated Bunker Density

The distribution of first decimal digits (only one decimal given in the data) in the stated bunker density parameter before and after MFM introduction is shown in figure 5.4. Eight is clearly the most frequently stated decimal digit. As rationalized in 4.9, the decimal digit of the true density can be expected to be a random process. This assumption is clearly supported by the distribution of decimal digits of tested density, as shown in in lower graph of figure 5.4. Therefore, the expectation was that the distribution would have been uniform if the suppliers were attempting to state the true bunker density unbiased. Figure 5.4 exhibits a strong indication that the decimal digits of tested bunker density have a uniform distribution.

It is hard to point out why the eight-digit is over represented (45 % - 47 %), but perhaps it is related to that eight is a lucky number in Asian cultures[1]. The similar procedure was done with fuel quality testing data in Rotterdam, and results showed that the most stated digit was the digit "9", with the fraction of about 25 %. Suggesting that suppliers in Singapore interfere with the true bunker density to a higher degree. In terms of equation 4.9, when comparing Singapore and Rotterdam, the biases, $y_1, ..., y_n$, are more dominant than the true bunker density, x, when the Singaporean suppliers determine decimal digit of the stated density.

But the most important insight for the investigation is that there are no significant change in the distribution when comparing the distribution before and after MFM implementation. Excluding the 8-digit from the inspection, it is noteworthy that the digits 5-9 are generally more frequent than 1-4. It could be affiliated with that suppliers are inclined to state higher digits which yields a higher energy content.

[1] The opening ceremony of the 2008 Olympics in Bejing began on 8/8/08 at 8 minutes and 8 seconds past 8 pm local time (Wikipedia contributors (2019a)).

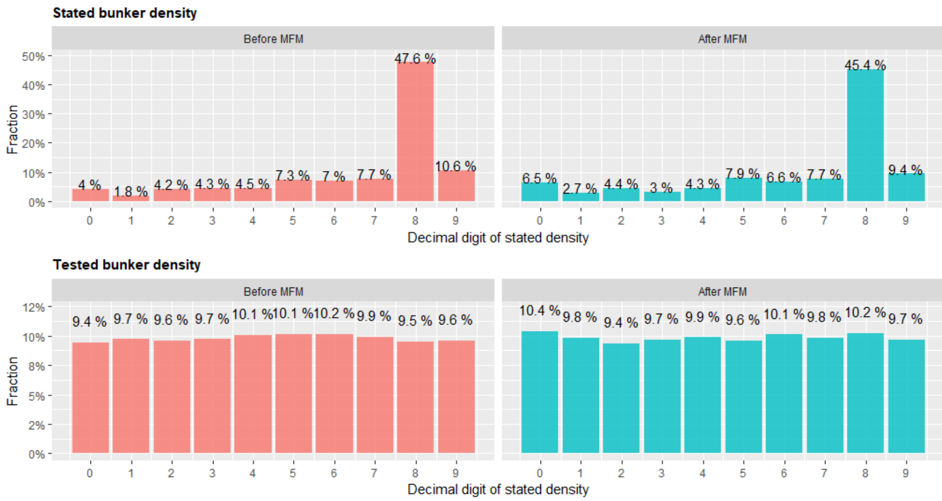

Figure 5.3: Distribution of decimal digits in stated density (upper) and tested density (lower), before and after MFM introduction.

It was mentioned in section 4.9 that the decimal digit of the stated density is related to human behaviour. The post-MFM digit distribution can be further investigated to see whether a potential MFM effect is gradually materialising. This was investigated by comparing the digit distribution of January 2017, August 2017 and March 2018. The distributions are shown in figure 5.3. No significant difference can be observed. It was rationalized in section 2.5 that reporting of density might be a parameter where a potential MFM effect would gradually take effect, rather than seeing an instant effect or change. However, the results from the digit distribution analysis strongly indicate that the process that generates decimal digits of the stated density parameter has remained unchanged, as (1) there have been no change between the pre-MFM and post-MFM

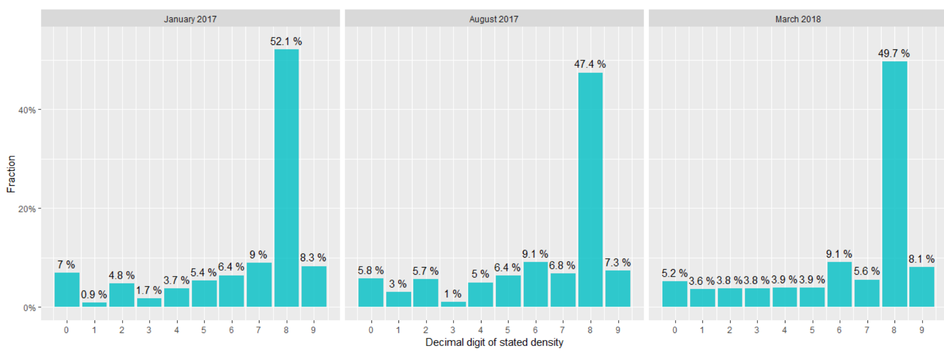

Figure 5.4: Distribution of decimal digits in stated density in three months of post-MFM period. Show no signs of a gradual effect in the post-MFM period.

digit distribution and (2) that no gradual change is observable in the post-MFM period either.

5.3 Delta Density

5.3.1 Comparing Mean Delta Density, pre-MFM vs. post-MFM

Recalling figure 3.7, which shows development of delta density (weekly median), no significant change after 2016 is observable at first glance. One could expect that the delta density would decrease from 1st of January 2017. To investigate a potential change the data was divided in two periods, a pre-MFM period (1st of January 2016 and earlier) and a post-MFM period (1st of Janaury 2017 and later). The delta density distribution and the mean delta density of the two periods are shown in figure 5.5. It is evident that the red distribution, which represents the pre-MFM samples, are skewed to the left of the post-MFM samples. This indicates that the delta density has increased after MFM was implemented, in contrast of what could be expected. To further investigate whether this change in delta density is statistically significant, the difference between mean delta density of the pre-MFM samples and post-MFM samples, $mean(dd_{pre-MFM}) < mean(dd_{postMFM})$, are tested according to the t-test procedure as described in section 4.4.

To test whether the difference is significant, a two-sample t-test with confidence level of 95 %, as described in section 4.4, is conducted. The results are that the p-value for the difference in mean is below 5 %, in fact below 0,1 %, which indicates that the delta density values of post-MFM samples are significantly higher than the pre-MFM samples. Thus, this result contradicts the expectation of MFM lowering delta density. However, it may be caused by other effects than MFM. To examine this thought, the same test is performed for delta density data in Hong Kong. The test yielded the same results. That

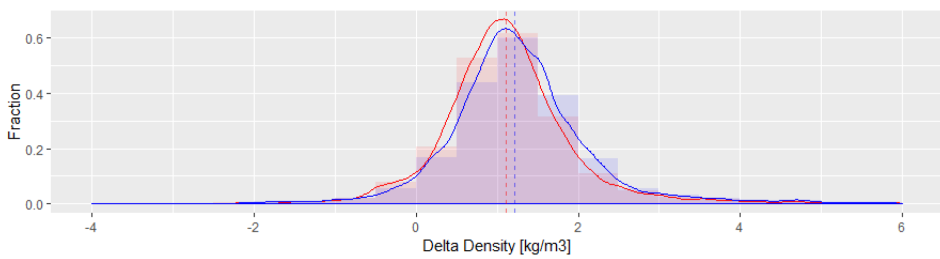

Figure 5.5: Delta density distribution of pre-MFM (red) vs. post-MFM (blue) samples with their respective means (vertical dashed lines).

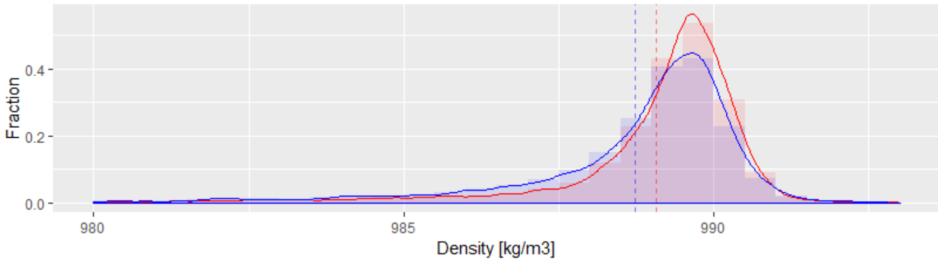

Figure 5.6: Density distribution of pre-MFM (red) vs. post-MFM (blue) samples with their respective means (vertical dashed lines).

is, mean delta density values ofthe pre-MFM period are significantly higher than corresponding values from the pre-MFM period, $mean(dd_{pre-MFM}) < mean(dd_{postMFM})$. As MFMs are not mandated in Hong Kong, a potential relationship between the significant increase in delta density and introduction of MFMs is less plausible. As mentioned in section 4.1, any potential MFM effect may be masked by a greater effect. As Hong Kong and Singapore had the same test result, it is plausible that another greater effect is present.

Recalling figure 3.8, it is apparent that density affects the distribution of delta density. Based on the distribution of the scatter plot, one see that variance and mean of delta density increases with decreasing density. As discussed in section 3.2.5 and evident in figure 3.7, lower density yields higher delta density.

Figure 5.6 shows the density distribution of the two periods. It can be observed that density was generally lower in the post-MFM period than the pre-MFM period. With the rationale of lower density lead to higher delta density, the increase in delta density can be explained by a decrease in density from pre-MFM to post-MFM. As density levels is most likely unaffected by MFM (reasoned for in section 3.2.3), this approach to compare delta density should be considered too blunt as density is affecting the levels of delta density which blur out any potential MFM effect. In order to do a more accurate comparison where the samples from the two periods are compared on more equal terms, the density dependency should be accounted for.

5.3.2 Mitigating the Effect of Density Dependency

A better comparison would be to compare bunker samples of similar tested density. This can be achieved by grouping the bunker samples into bins based on their density. Then, the post-MFM and pre-MFM samples in each bin are separately tested for any significant difference in mean. In order to have a sufficient sample size in each bin, a

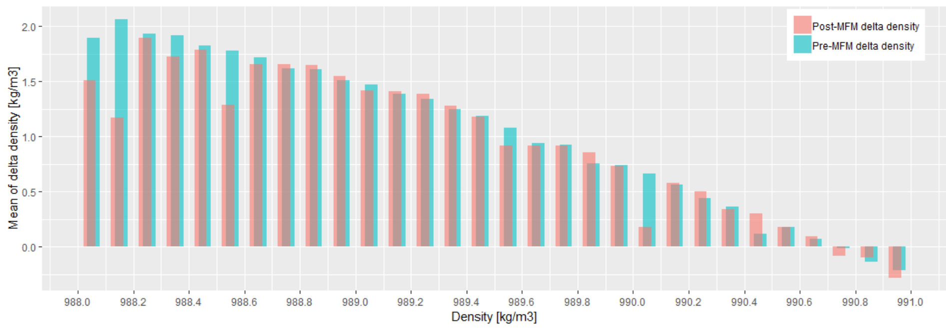

Figure 5.7: Means of delta density in density bins of width 0,1 kg/m^3, post-MFM (red) and pre-MFM (teal) MFM implementation. It is observed that the post-MFM samples possessed lower delta density than the pre-MFM samples for lighter fuel densities.

density range of 988 kg/m^3 to 991 kg/m^3 was selected. With a bin width of 0,1 kg/m3, the density range gives 30 bins. In figure 5.7 the mean delta density values for each bin is plotted. The difference in mean delta density between the pre-MFM and the post-MFM periods for each bin can now be tested for statistical significance.

5.3.3 Property Assessment of Binned Samples

Before proceeding with conducting tests in each bin, the properties of the samples should be assessed. This is done to assure that the data complies with the assumptions of each test. A flowchart in appendix A.1 illustrates the procedure of property assessment to select a appropriate test for difference in mean. As we are going to compare the Singapore results with Hong Kong, the sample properties of the Hong Kong data are also assessed.

Sample Size

The sample sizes of each bin are plotted in figure 5.8. We see that the pre-MFM samples are generally much more than the post-MFM samples. The sample size of each bin in Singapore exceed 100, with exception of some bins close to 991 kg/m^3. Anyhow, it was controlled that these bins contain over 30 observations. For Hong Kong, the observations are much fewer. We see that many bins have below 30 observations, but the bins in the range of 988,7-990,4 kg/m^3 exceed 30 observations.

As stressed in section 4.4, the guiding rule is that if the sample size $n \geq 30$, the sampling distribution of the sample mean will be approximately normal as a result of the central

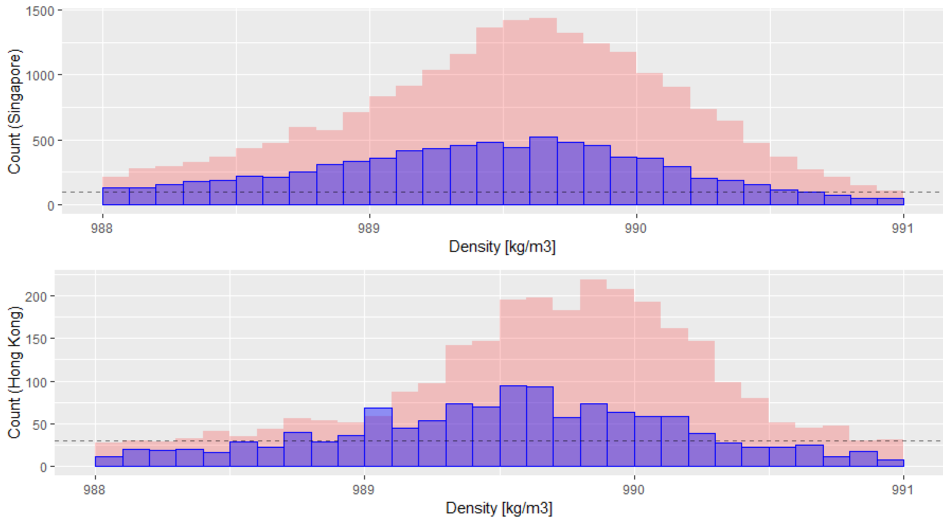

Figure 5.8: Count of samples in each density bin in Singapore (top) and Hong Kong (bottom). Colored by period, pre-MFM (red) and post-MFM (blue). Dashed horizontal lines represent 100 samples (top) and 30 samples (bottom).

limit theorem. Now we know that the t-test can be conducted on the Singapore data and the Hong Kong bins in the range of 989-990,4 kg/m^3. If the samples in the remaining Hong Kong bins are normally distributed, t-tests can be conducted. If this is not the case, the non-parameteric Wilcoxon rank sum test should be used.

Normality

To test the normality of the Hong Kong data, the Shapiro-Wilk as described in section 4.6 will be applied. The null hypothesis of the test is that the data is not normally distributed. The test is done with significance level of $\alpha = 0,005$ the results are plotted in in figure 5.9. Only one bin can be regarded as normally distributed. We should therefore use the Wilcoxon Rank Sum test for the bins which do not comply with sample size $n \leq 30$, that is the bins <988,8 kg/m^3 and >990,4 kg/m^3.

5.3.4 Binwise Testing for Difference in Mean Delta Density

T-tests (section 4.4) were performed on each of the 30 bins, comparing post-MFM and pre-MFM mean density difference, i.e. $Mean(dd_{post-MFM})-$ $Mean(dd_{pre-MFM})$ = mean differenec. The results of the 30 t-tests are plotted in figure 5.10 (top). The null and alternative hypotheses for these tests can be given as:

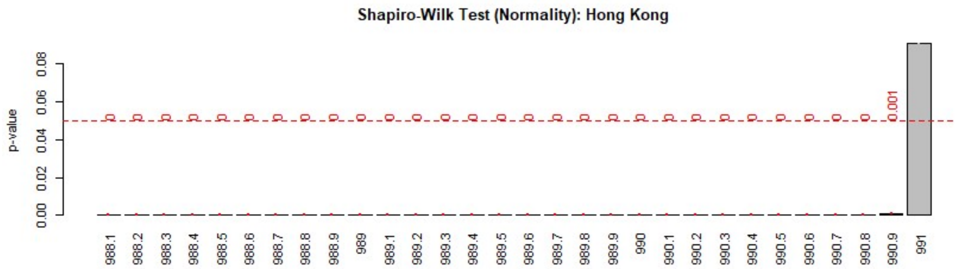

Figure 5.9: Normality test conducted on post-MFM data in Hong Kong. H_0 is that the data is not normally distributed. When p-value < 0,05, the H_0 is rejected. H_0 is rejected for every bin, with exception of 991.

(i) H_0: $\mu_{\text{dd, pre-MFM}} = \mu_{\text{dd, post-MFM}}$ (ii) H_1: $\mu_{\text{dd, pre-MFM}} \neq \mu_{\text{dd, post-MFM}}$

The blue whiskers represent the 95 % confidence intervals (section 4.3) of the differences in mean delta density in each bin. The color of each bar indicates the statistical significance of the difference. Red/green (negative/positive) represent a statistical difference, non-significant results are colored grey. Note that negative values correspond to situations where delta density has decreased after the introduction of MFM, i.e. $dd_{pre-MFM} > dd_{post-MFM}$.

According to the test, only two bins show significant differences. Three remarks regarding the results are made. (1) The uncertainties of these two bins are considered high as the whiskers are close to zero. Especially for the green bin. (2) Considering the results for all bins, the majority of differences are close to zero. (3) In addition, the differences seem to fluctuate randomly around zero. Based on these three remarks, no obvious pattern is evident in the Singapore data. That is, a significant change in density shortlifting behaviour cannot be observed.

For comparison, the same t-test procedure was conducted on data for Hong Kong. The results are plotted in figure 5.10 (bottom). The majority of the results show that $dd_{pre-MFM} < dd_{post-MFM}$. Indicating that delta density is greater for the post-MFM samples than pre-MFM samples. There are nine bins where the difference is statistically significant. However, as emphasized earlier some bins have few observations, making the results less reliable. Compared to the results of Singapore, the results are generally positive (in the same direction).

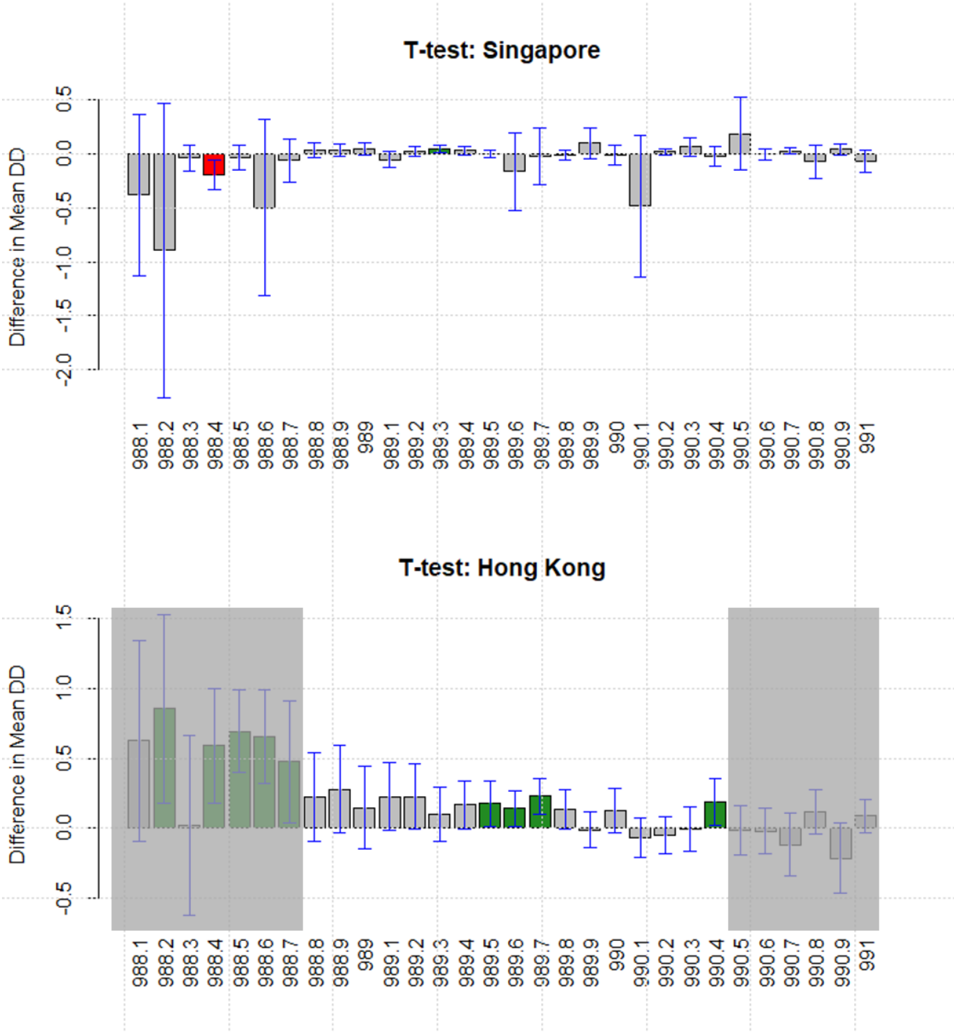

Figure 5.10: Significance difference of mean delta density between pre-MFM and post-MFM periods. Blue whiskers represent 95 % confidence interval for true difference in mean delta density (DD). Grey area is where the observations in the bins < 30, and thus less reliable results.

Wilcoxon Rank Sum Test

Due to the lack of normality and low number of observations in Hong Kong data, Wilcoxon rank sum tests are conducted. The results are shown in figure 5.11. For majority of the bins, the results show that $dd_{pre-MFM} < dd_{post-MFM}$, which is consistent with the t-test results (figure 5.10). It is evident that all the 95 % confidence intervals (blue whiskers in the figure), are close to zero. The two remarks makes the results unclear. However, as both the t-test and Wilcoxon rank sum test indicate a decrease in mean

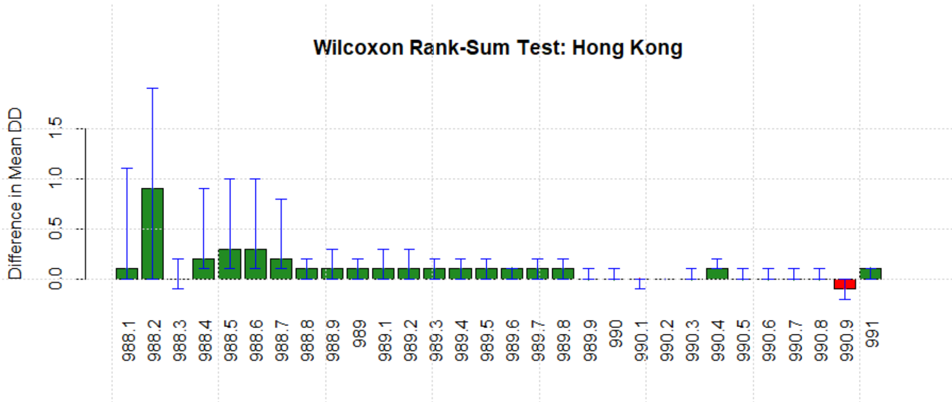

Figure 5.11: Significance of mean delta density differences between pre-MFM and post-MFM periods. Confidence intervals are represented by blue bars. All differnes have positive values, but the confidence intervals close to zero.

delta density, there is a slightly stronger indication of a significant increase in delta density in Hong Kong than Singapore.

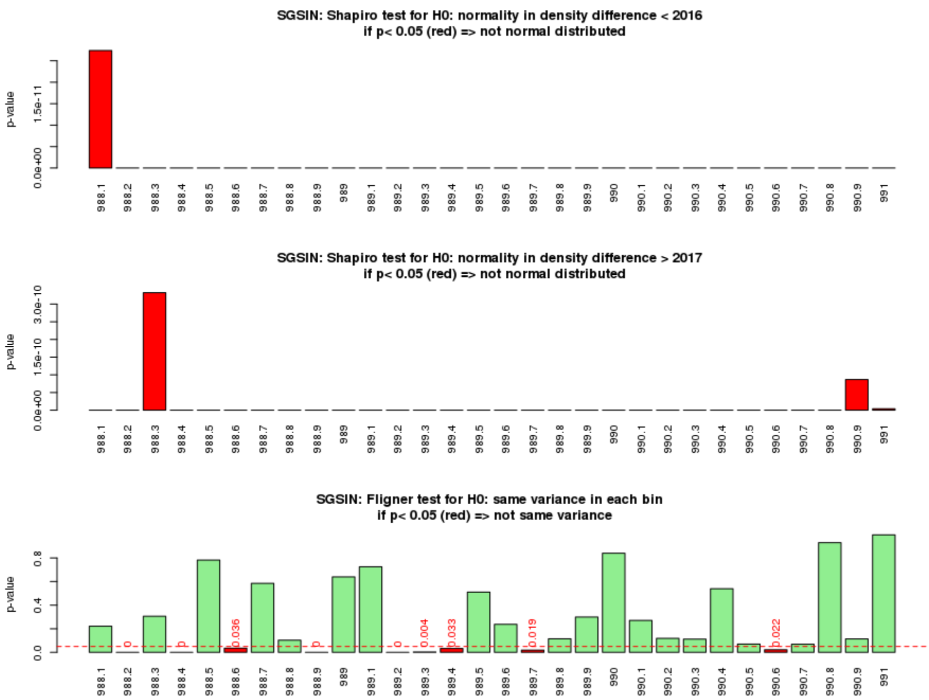

Figure 5.12: Normality tests for Singapore Delta Density Data (top and mid). Homogeneity of variance test between pre-MFM and post-MFM for Singapore data (bottom).

5.3.5 Testing for Change in Variance

As mentioned in section 4.8, the F-test and the Fligner-Killeen test can be used to check the homogeneity of variance, that is whether the two samples have equal variance. The F-test assumes that the samples to be tested are normally distributed. To check for normality on the Singapore data, the Shapiro-Wilk Test is done on the pre-MFM and post-MFM data. It is seen in figure 5.12 that the null hypotheses is rejected for both pre-MFM and post-MFM Singapore data. Therefore the Fligner-Killeen is used to check for homogeneity of variance between delta density in the two periods. The null and alternative hypotheses can then be formulated as:

(i) H_0: $\sigma^2_{\text{dd, pre-MFM}} = \sigma^2_{\text{dd, post-MFM}}$ (ii) H_1: $\sigma^2_{\text{dd, pre-MFM}} \neq \sigma^2_{\text{dd, post-MFM}}$

From the results in figure 5.12, we see that the H_0 is rejected in 9 bins out of 30. We do not see this as a clear change in variance for the delta density paramter in Singapore.

5.4 Shortlift Benchmark Scores and Max Shortlift Benchmark Scores

To investigate changes in occurrence of shortlift samples are assessed. A threshold of 0,1 for the benchmark score is selected, so if a sample scores above the threshold it is considered as a shortlift occurrence. By calculating the proportion of the samples that scores above 0,1, the two-proportions z-test can be applied on the data. As described in section 4.7, the question becomes whether the observed proportion of shortlift samples in each density bin are equal in the pre-MFM and post-MFM period. The null and alternative hypotheses can be given as:

(i) H_0: $p_{\text{SL, pre-MFM}} = p_{\text{SL, post-MFM}}$ (ii) H_1: $p_{\text{SL, pre-MFM}} \neq p_{\text{SL, post-MFM}}$

The results are shown in figure 5.13. As previously, a positive value represent that the post-MFM proportion is greater than the pre-MFM proportion, $p_{post-MFM} > p_{pre-MFM}$. Three bins are significantly different, where two of the red bins have a confidence interval quite close to zero. Thus, no clear change is observable.

The SL occurrence test investigates whether there has been a change in the amount or number of samples have been tested. This test would however not unveil a change in the amount of mean of shorlfting, i.e. has the overall score change. Timelines of

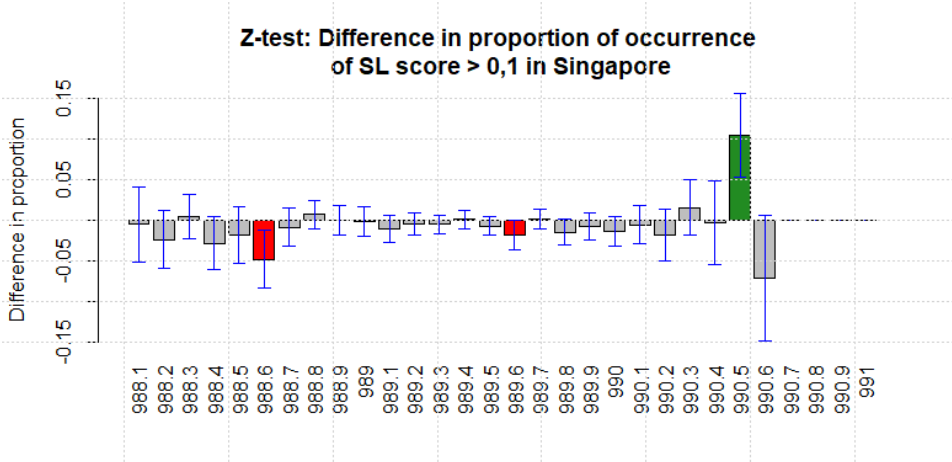

Figure 5.13: Significance of difference in fraction of occurence of SL score > 0,1 in Singapore. Green/Red represent a significant difference. Blue whiskers represent 95 % confidence interval.

mean shortlifting (SL) benchmark scores were commented in section 3.2.6. There were no significant changes based on the timeline plot in figure 3.9. A such change can be detected by testing whether the mean benchmark scores between the two periods are significantly different. This test is again done with the t-test, so the null and alternative hypotheses is given as:

(i) H_0: $\mu_{\text{SL, pre-MFM}} = \mu_{\text{SL, post-MFM}}$ (ii) H_1: $\mu_{\text{SL, pre-MFM}} \neq \mu_{\text{SL, post-MFM}}$

The results of this tests is shown in figure 5.14. Differences in seven bins are statistically significant, however, the confindence interval for the greeen bins are very close to zero.

Again, the difference in mean SL score should be tested for Hong Kong samples for comparison. The results are shown in figure 5.15. The results for Hong Kong are more consistent than for Singapore as all the bins have positive value. However, all the confidence intervals are quite close to zero.

The same procedure is done for Max SL benchmarks in both ports. The results are illustrated in appendix A.2 and appendix A.3. The results were similar to the SL benchmark and therefore we conclude that they do not indicate any significant change.

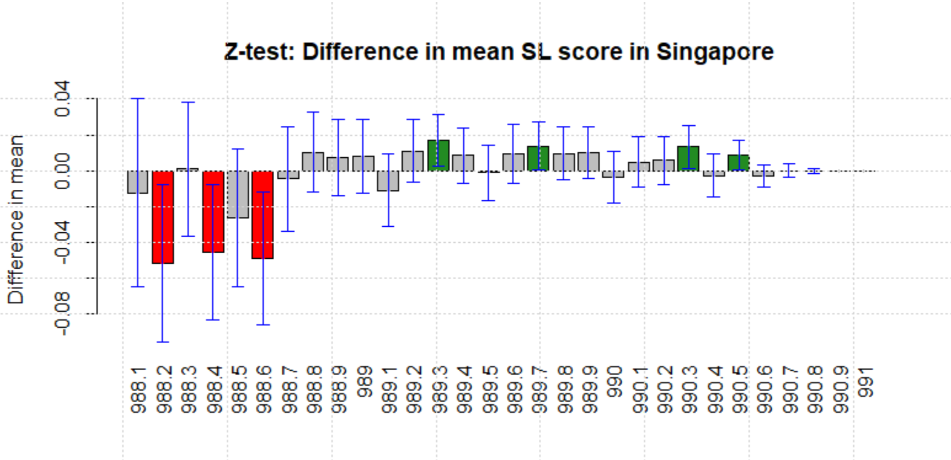

Figure 5.14: Significance of difference of mean SL score in Singapore. Green/Red represent a statistical significant difference at 5 % significance. Blue whiskers represent 95 % confidence interval.

5.5 Summary of Results

Price

The analysis could not support the claim of the sentiment reported by Shippingwatch (2016), that MFMs were responsible for the price increase, as the Hong Kong price and the world index have risen in the same period. In terms of price difference between Hong Kong and Singapore, it was acknowledged that the difference had signifantly decreased in the post-MFM period. However, it was remarked that trends in price difference might as well entirely be caused by trends in prices. Based on this finding, it was deemed that the decreasing price difference cannot be attributed to the introduction of

Table 5.1: Conclusions of all tests summarized.

Parameter	**Conclusion**
Price increase	Evident change, but not considered a MFM effect
Price difference decrease	Evident change, but not considered a MFM effect
Distribution of decimal digits	No significant change
SL Benchmarks	
Diff. in fraction of occurrence	No clear indication of change
Difference in mean	No clear indication of change
Delta density	
Difference in mean	No clear indication of change
Variance	No clear indication of change

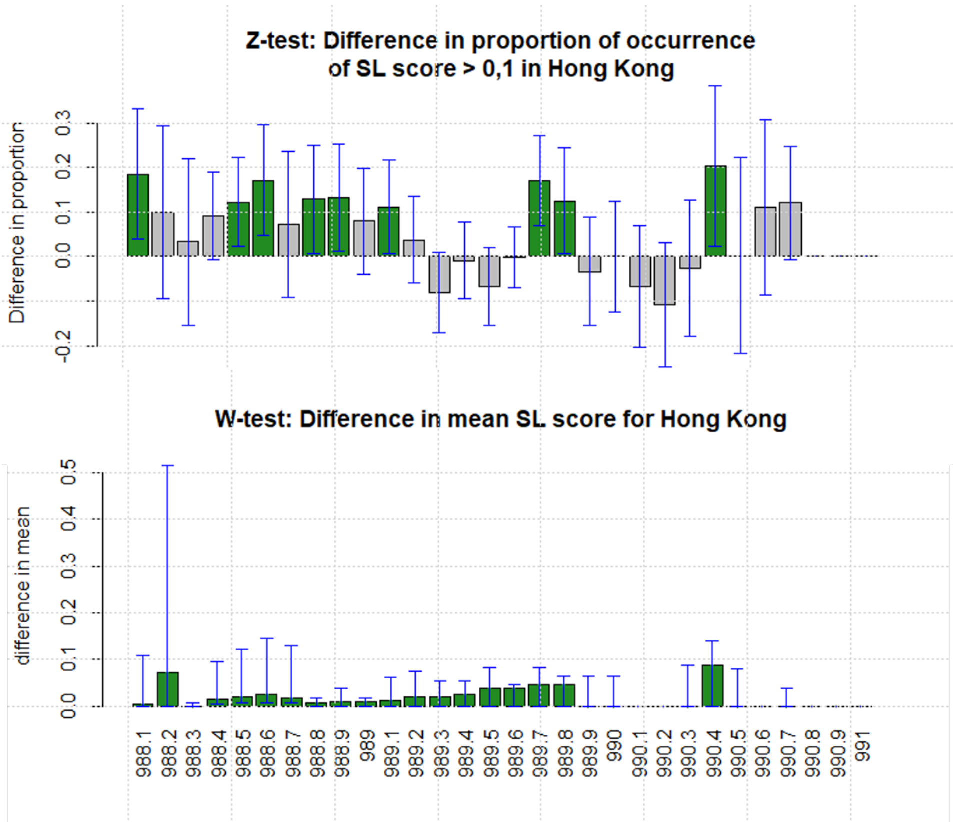

Figure 5.15: Significance of difference of proportion of occurrence of SL score > 0,1 (upper) and mean SL score in Hong Kong (lower). Green/Red represent a statistical significant difference at 5 % significance. Blue whiskers represent 95 % confidence interval.

mass flow meters.

Distribution of Decimal Digit

Distribution of the first decimal digit (only one decimal available in the data), as stated in the bunker delivery note compared between the pre-MFM and post-MFM period. The distributions of decimal digits seemed to be unchanged. A potential gradual change during the post-MFM period was also analyzed. The decimal digit distributions of January 2017, August 2017 and March 2018 showed that there was no significant change throughout the post-MFM period. These results indicate that mass flow meters have not changed the process of how suppliers' state decimal digits for bunker density.

Delta density and Shortlift Benchmark

The binned t-tests gave no clear indication that delta density levels in Singapore have decreased after the introduction of MFMs. In the case of delta density variance, the overall trend seem to be that variance of delta density have not changed, although a significant difference in variance in some bins were identified. Therefore, we conclude that there are no clear change for delta density levels in Singapore.

The results for Singapore were compared to Hong Kong data. Wilcoxon rank sum test for mean delta density slightly indicate a change. For delta density variance the pattern was similar to Singapore's pattern.

Recalling the scenario matrix in figure 4.2 for comparison of results between Singapore and Hong Kong, the case for change in mean delta density can be regarded as scenario B. This scenario support that absence of change in Singapore can be related to mass flow meters as there has been a change in Hong Kong. However, since the change in Hong Kong is not so distinct, we do not take this as a clear sign of an effect that can be attributed to mass flow meters.

Chapter 6

Discussion, Conclusion and Recommendations for Further Work

6.1 Discussion

6.1.1 Results of Change Analysis

The interpretation of results of the statistical tests of delta density and benchmarks levels will naturally contain some degree of subjectivity. However, to acknowledge the occurrence of a change, strong evidence should be present. Strong evidence could be in the form of clear and evident statistically significant differences across multiple bins, in the same direction. As seen in figure 5.10 and figure 5.14, the differences are fluctuating around zero. It cannot be imagined by the author how a potential MFM effect would cause a decrease in some bins while increase in other. Therefore, even with the presence of statistically significant differences in several, it is considered that a change has not occurred.

For Hong Kong, the test results show a stronger indication of change. Since all changes are in positive direction (see figure 5.11 and 5.15), which suggest that post-MFM delta density values are higher than the pre-MFM values. This indicates that delta density values in Hong Kong are higher in the post-MFM period, than pre-MFM. On the other hand, the lower limit of the confidence intervals are generally quite close to zero. This is related to that the Wilcoxon rank sum test had to be used due to the small sample sizes in each bin. Since they have less statistical power than the t-test, the confidence intervals are vaguer (interval is larger). Nevertheless, even if we had acknowledged the occurrence of a clear change in Hong Kong, one can not clearly conclude in accordance with the suggestion of scenario B (see figure 4.2). The scenario comments on the outcome where a change in a parameter has occurred in Hong Kong, but not in Singapore. But the proposition is disregarded as the result in Hong Kong are not considered strong enough.

6.1.2 Data

The tests done on decimal digit distributions, delta density and fuel shortlifting benchmarks have been based on fuel quality testing data provided by Veritas Petroleum Service. In terms of figure 4.1, which illustrated the relationship between population and sample, this study try to gain insight on all bunkerings in Singapore based on the fuel quality testing data. For the conclusions from our analysis to be representative for all bunkerings, the fuel quality testing data should representative for the all bunkerings in Singapore. In other words, the sample (fuel quality data) has to be randomly selected from the population (all bunkerings in Singapore for the same period). If the sample is not randomly selected, it is likely to be biased in some way (Bhattacharyya and Johnson (1977)).

It is challenging to assess the randomness in the selection. It can be argued that the majority of fuel samples sent to VPS for quality testing might be due to suspicion of the supplier. Then, the VPS data would be biased in that it mostly represent the suppliers that are "suspicious", and less the law-abiding suppliers. However, in the case of an occurred MFM effect, a change is expected to be more evident among the "suspicious" suppliers than other more righteous suppliers. In this way, a potential MFM effect can be detected even though if the selection was not random. A worse case would be if the selection was biased with representing the righteous suppliers, then a MFM change might not have been identified. A random selection process would also be more important if the goal was to quantify the degree of change. While our study has been more focused on whether a change has occurred or not.

6.1.3 Scope

The scope of the study has been limited by the data utilized. This implies that we cannot detect any change that is not captured in the data. When studying fuel quantity testing data, it became clear in the process of this project that the data set mainly reflect the stating behaviour of the suppliers. As the stated density is no longer used to calculate amount payable for a transaction. In the time before introduction of mass flow meters, the delta density value of a bunkering would be proportional to the amount of bunkers that would have been shortlifted. The shortlifted amount is in turn proportional to the money that is being paid excessively. But after the introduction of MFM, mass of transferred bunker is directly read off the display of the meter. Therefore, the fuel quality testing data does not give a indication of shortlifted amount in the same way as prior to MFM introduction.

6.2 Concluding Remarks

The objective of this study has been to investigate whether the introduction of mass flow meters in Singapore has had any measurable effects on the bunker industry in Singapore. Fuel quality testing data and fuel price data were analyzed. After exploration of the data, hypotheses to test potential effects were formulated as:

1. MFMs will lead to price increase in Singapore.
2. MFMs will lead to a decrease in price difference between Singapore and Hong Kong.
3. MFMs will lead to change in distribution of decimal digits in the stated bunker density parameter.
4. MFMs will lead to a change in mean delta density, shortlifting benchmark and occurrence of shortlifting benchmarks.
5. MFMs will lead to a change in variance of the delta density parameter and shortlifting benchmark.

Both hypotheses regarding price (1 and 2) were rejected. It was acknowledged that both a price increase in Singapore and decrease in price difference between Singapore and Hong Kong had occurred, but we did not find firm reason to attribute the price changes as results of mass flow meter introduction. The hypothesis regarding change in the distribution of decimal digit (3) was rejected. Plotting the distribution of decimal digits before and after introduction of MFMs showed that the two distributions were nearly the same. Hypotheses regarding change in mean of delta density and shortlifting benchmark (4) were also rejected, due to the absence of clear signs of change. Hypotheses regarding the variance of the same parameters (5) were also rejected, as no clear signs of change were present.

The study may therefore conclude that the introduction of mass flow meters has caused no measurable significant effect in the price and fuel quality testing data.

6.3 Recommendations for Further Work

As the findings of this study has been conclusive in not finding significant effects in the provided data, a natural continuance would be to investigate other aspects of bunkering operations using other data sets.

If mass flow meters are successful in reducing bunker operation disputes and the need for manual gauging methods, it might be expected that the average time for a bunker operation should decrease. With methods described by Aarsnes (2018), bunkering operations can be identified among AIS data, and the time of an operation can be obtained. Data for bunkering operation time can be gathered with this procedure, and then the data can be analyzed for any decrease in operation time.

Mass flow meters were introduced to improve Singapore's reputation as a leading bunker port. To assess whether the devices have indeed been successful in improving Singapore's reputation as a preferred bunker port, an opinion survey could be done among ship operators. This can be done in collaboration with Singapore Maritime and Port Authority (MPA) or academia in Singapore, such as National University of Singapore or Nanyang Technological University. The framework to assess the reputation can be inspired by the framework proposed by Lam et al. (2011) for assessment of the competitiveness of bunkering ports.

An expected effect of mass flow meters could be a reduction in the demand of bunker quantity surveys. A bunker quantity survey involves a surveyor taking measurements on board the bunker barge and on the receiving ship before and after a bunker transfer. Veritas Petroleum Services (VPS) had a bond issue listing on the Oslo Stock Exchange in 2015 (Veritas Petroleum Services B.V. (2015)), where MFMs are mentioned as a risk factor for their bunker survey businnes. Therefore, asking VPS or other fuel testing companies for change in demand of their bunker quantity survey services could give some insights on whether mass flow meters have improved transparency of bunker operations.

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Appendix A

Test Results

A.1 Flowchart for Statistical Testing

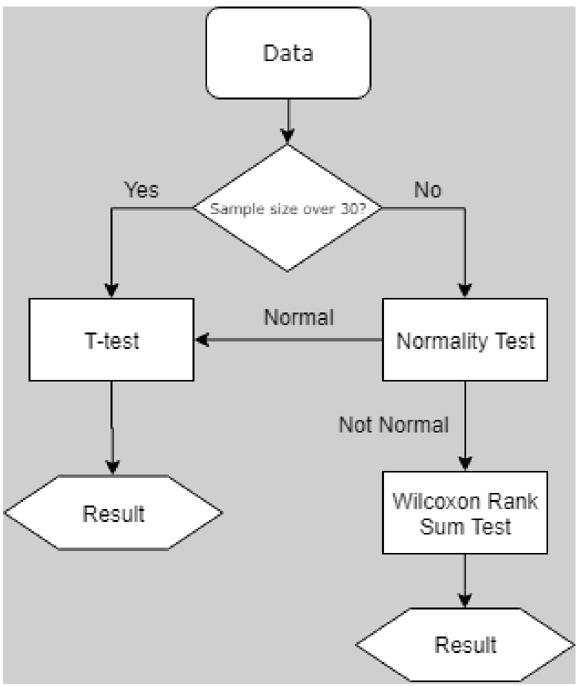

Figure A.1: Flow chart for procedure in testing difference in mean. This is applied in section 5.3.3

A.2 Singapore Max SL

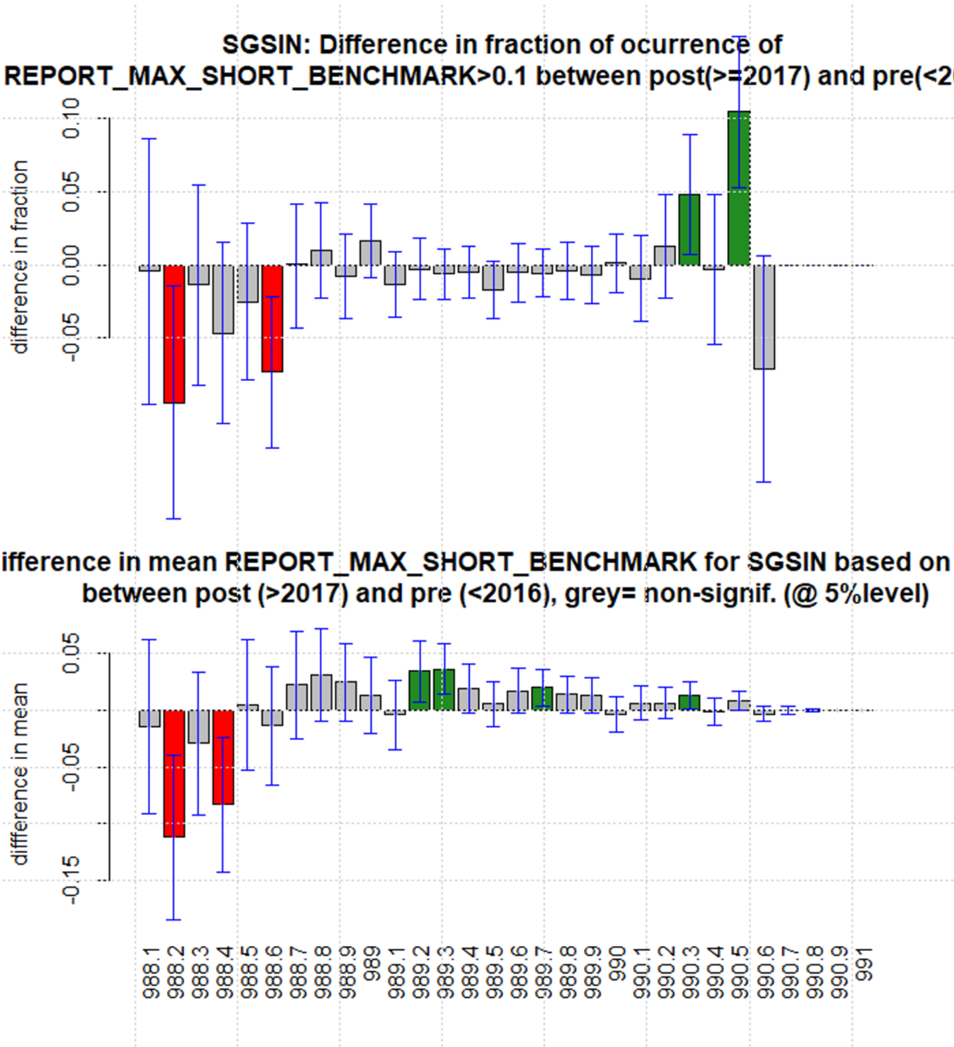

Figure A.2: Z-test on the difference in fraction of occurence of Max SL benchmark (Upper). T-test on the difference in mean SL benchmark (lower). Both graphs compares pre-MFM vs post-MFM data.

A.3 Hong Kong Max SL

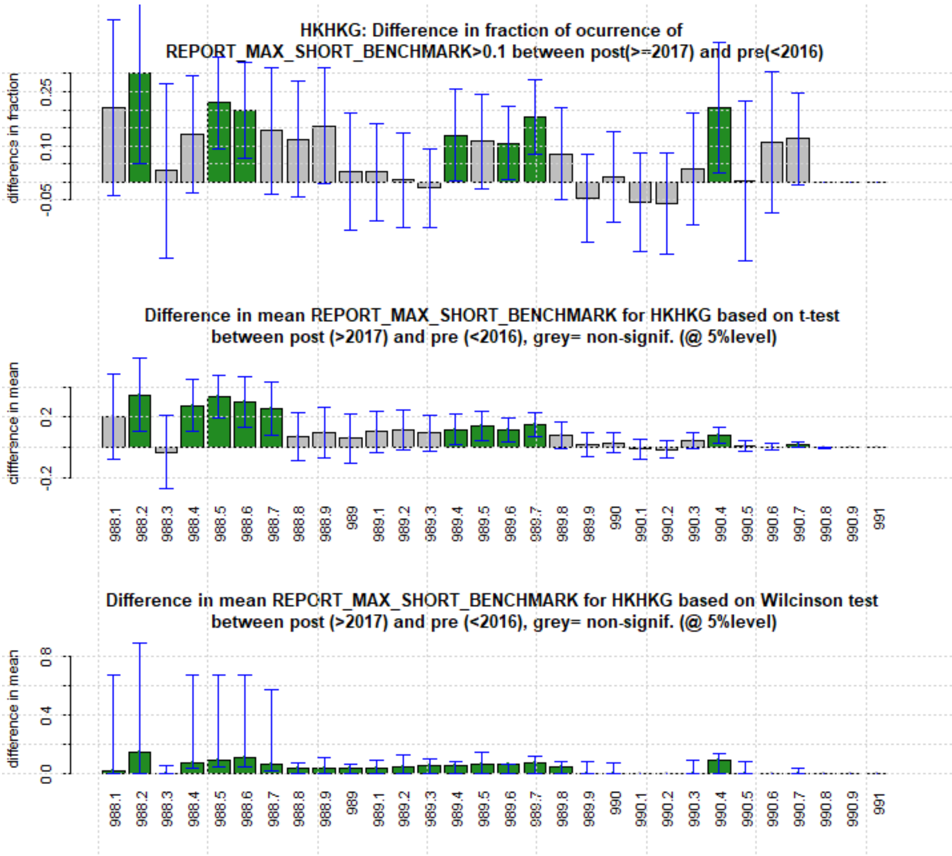

Figure A.3: Z-test on the difference in fraction of occurence of Max SL benchmark (Upper). T-test on the difference in mean SL benchmark(Mid). W-test on the difference in mean SL benchmark(Lower). Both graphs compares pre-MFM vs post-MFM data.

Appendix B

R-Script

B.1 Plotting

```

library("scales")
library("ggplot2")
library("dplyr")
library("lubridate")
library("tidyr")
library("plyr")
library("zoo")
show_col(hue_pal()(2))
#library(easyGgplot2)
library(reshape2)
library(plotly)
library("reshape2", lib.loc="~/R/win-library/3.4")
#install.packages("tidyverse")

#Mac
#setwd("~/Google Drive/Skole/Master/VPS data")
#PC
setwd("C:/Users/Daniel/Google Drive/Skole/Master/data")

# ================================================= VPS Fuel Data
    =================================================

Sing <- read.csv(file="HFO380_SGSIN.csv", header=TRUE, sep=",", stringsAsFactors = F
    )
HK   <- read.csv(file="HFO380_HKHKG.csv",  header=TRUE, sep=",", stringsAsFactors =
    F)
```

```r

Sing$Date <- as.Date(Sing$Date, format = "%Y-%m-%d")
HK$Date    <- as.Date(HK$Date,    format = "%Y-%m-%d")

#time ordering
Sing <- Sing[order(Sing$Date),]
HK    <- HK[order(HK$Date),]

#removal of na lines
index <- which(is.na(Sing$BK_SAMPLENO)); if(length(index)>0) Sing <- Sing[-index,]
index <- which(is.na(HK$BK_SAMPLENO));    if(length(index)>0) HK    <- HK[   -index,]

#Remove > and <
index <- which(substr(Sing$density,1,1) == "<" | substr(Sing$density,1,1) == ">" )
Sing <- Sing[-index,]
Sing$density <- as.numeric(Sing$density)


index <- which(substr(HK$density,1,1) == "<" | substr(HK$density,1,1) == ">" )
HK <- HK[-index,]
HK$density <- as.numeric(HK$density)


# ================================================= VPS data prep ================================================
#Sing$density_txt <- as.character(Sing$density_txt)
#index_bigger <-grep('>',Sing$density_txt)
#print(paste('fraction of > samples: (',length(index_bigger),'):',length(index_bigger)/nrow(Sing)))
#index_smaller <-grep('<',Sing$density_txt)
#print(paste('fraction of < samples: (',length(index_smaller),'):',length(index_smaller)/nrow(Sing)))
#index_blank <- which(is.na(Sing$REPORT_SHORT_LIFT_BENCHMARK))
#index_blank <- which(is.na(Sing$REPORT_MAX_SHORT_BENCHMARK))
# ================================================= Price data ================================================
ifo380_price<-read.csv("price_ifo380.csv", sep = ";")
ifo380_price$Date_hk <-    as.Date(ifo380_price$Date_hk,    format = "%d.%m.%Y")
ifo380_price$Date_sing <- as.Date(ifo380_price$Date_sing, format = "%d.%m.%Y")
ifo380_price$Date_w <-     as.Date(ifo380_price$Date_w    , format = "%d.%m.%Y")
ifo380_price$Date_mgosing <-     as.Date(ifo380_price$Date_mgosing    , format = "%d.%m.%Y")


# ================================================= End of data formatting and cleaning ========================================================

# ================================================= PROPORTION OF lowres DATa ================================================
index <- which(substr(Sing$density,1,1) == "<")
```

```
densitylimit <- data.frame(density = Sing$density[index] , Date = Sing$Date[index], Type = "Lower")
index <- which(substr(Sing$density,1,1) == ">")
y <- data.frame(density = Sing$density[index] , Date = Sing$Date[index], Type = "Upper")
densitylimit <- rbind(densitylimit, y)
densitylimit$Month <- as.Date(cut(densitylimit$Date, breaks = "month"))

#pre14<-c(31,30,31,30,31,31,30,31,30,31)
#mid <- rep(c(31,30,31,30,31,30,31,31,30,31,30,31),4)
#post17<-c(31,32)

index <- which(substr(Sing$density,1,1) != "<")
denslist <- data.frame(density = Sing$density[index] , Date = Sing$Date[index], Type = "Mid")
index <- which(substr(denslist$density,1,1) == ">"); if(length(index)>0) denslist <- denslist[-index,]

month_range <- unique(substr(denslist$Date,1,7)) # monthly
Dens_monthly <- data.frame(month = month_range)
Dens_monthly <- na.omit(Dens_monthly)

for (i in 1:nrow(Dens_monthly)) {
  index  = which(substr(denslist$Date,1,7)     == Dens_monthly$month[i])
  index2 = which(substr(densitylimit$Date,1,7) == Dens_monthly$month[i])
  Dens_monthly$Fraction[i] = length(index2)/length(index)
}

Dens_monthly$month <- as.Date(paste0(Dens_monthly$month, "-01", collapse = NULL))


p2 <- ggplot(Dens_monthly, aes(x=month, y=Fraction)) +
  geom_line() + scale_y_continuous(labels = scales::percent_format(accuracy = 1)) + labs(x= element_blank(), y="% of total monthly samples")


p <- ggplot(densitylimit, aes(x=Month, color = Type, fill = Type)) +
  geom_histogram(breaks = seq(as.Date("2013/1/1"), as.Date("2018/3/1"), by = "month"),
                 alpha = 0.5, position = "identity" ) + labs(x= element_blank(), y="Count") + theme(legend.position = c(0.95,0.79))

multiplot(p,p2)

# ============================================================================================================

# ================================================ Start of Price plots =========================================================
```

```
plot_price <- function(ifo380_price){

  hk_price     <- data.frame(date=ifo380_price$Date_hk,          price_hk=ifo380_price
     $Price_hk)
  sing_price   <- data.frame(date=ifo380_price$Date_sing,        price_s=ifo380_price$
     Price_sing)
  w_price      <- data.frame(date=ifo380_price$Date_w,           price_w=ifo380_price$
     Price_w)
  mgo_price    <- data.frame(date=ifo380_price$Date_mgosing,     price_mgo=ifo380_
     price$Price_mgosing)
  #removal of na lines
  index <- which(is.na(sing_price$price_s)); if(length(index)>0) sing_price <- sing_
     price[-index,]
  index <- which(is.na(hk_price$price_hk));   if(length(index)>0)   hk_price <-   hk
     _price[-index,]
  index <- which(is.na(w_price$price_w));    if(length(index)>0)     w_price <-    w_
     price[-index,]

  #time ordering
  hk_price     <- hk_price[order(hk_price$date),]
  sing_price   <- sing_price[order(sing_price$date),]
  w_price      <- w_price[order(w_price$date),]
  mgo_price       <- mgo_price[order(mgo_price$date),]

  price <- merge(hk_price, sing_price, by="date",all=F)
  price <- merge(price, w_price, by = "date", all = F)
  #price2 <- merge(hk_price, sing_price, by="date",all=T)
  price$hk_delta <- price$price_hk - price$price_s
  price$w_delta  <- price$price_w  - price$price_s



  index <- which(price$date>='2013-01-01' & price$date <='2014-12-31')
  preMFM   <- mean(price$deltaprice[index])


  index <- which(price$date>='2017-01-01')    # & Sing.deltadens$date<='2014-12-31')
  postMFM <- mean(price$deltaprice[index])






  # ============================================================ Definition of
     Multiplot
  multiplot <- function(..., plotlist=NULL, file, cols=1, layout=NULL) {
    require(grid)

    # Make a list from the ... arguments and plotlist
    plots <- c(list(...), plotlist)
```

```
  numPlots = length(plots)

  # If layout is NULL, then use 'cols' to determine layout
  if (is.null(layout)) {
    # Make the panel
    # ncol: Number of columns of plots
    # nrow: Number of rows needed, calculated from # of cols
    layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
                     ncol = cols, nrow = ceiling(numPlots/cols))
  }

  if (numPlots==1) {
    print(plots[[1]])

  } else {
    # Set up the page
    grid.newpage()
    pushViewport(viewport(layout = grid.layout(nrow(layout), ncol(layout))))

    # Make each plot, in the correct location
    for (i in 1:numPlots) {
      # Get the i,j matrix positions of the regions that contain this subplot
      matchidx <- as.data.frame(which(layout == i, arr.ind = TRUE))

      print(plots[[i]], vp = viewport(layout.pos.row = matchidx$row,
                                      layout.pos.col = matchidx$col))
    }
  }
} #========================== DEF OF MULTIPLOT END ==================

p2 <- ggplot(price, aes(x=date, y = hk_delta)) +
  geom_rect(aes(xmin = as.Date("2016-01-01", format = "%Y-%m-%d"), xmax = as.Date("2017-01-01", format = "%Y-%m-%d") , ymin = -Inf, ymax = Inf), fill = "grey", alpha = 0.02) +
  geom_line( aes(col = "HK - Sing")) + labs(x= "Year", y="Price difference [USD/mt]") +
  geom_line(aes(y=w_delta, col = "World - Sing")) +
      #geom_line( data=Rolling, aes(y=RMean ,x=Date, col = "Rolling Mean")) +
  geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2)

p2 <- p2 + scale_colour_manual(values = c("#f8766d", "#00ba38")) + theme(legend.position = c(0.87,0.9), legend.title = element_blank()) +
p2



# ================================================= Plotting price regime =================================================
```

```r
trendplot <- function(price){

i_const     <-    which(price$date>='2013-04-15' & price$date<='2014-08-01')
i_decrease  <-    which(price$date>='2014-08-15' & price$date<='2016-02-01')
i_increase  <-    which(price$date>='2016-02-01')

z<-lm(price$hk_delta[i_decrease] ~ price$date[i_decrease]);summary(z)
z<-lm(price$hk_delta[i_const] ~ price$date[i_const]);summary(z)
z<-lm(price$hk_delta[i_increase] ~ price$date[i_increase]);summary(z)

z<-lm(price$w_delta[i_decrease] ~ price$date[i_decrease]);summary(z)
z<-lm(price$w_delta[i_const] ~ price$date[i_const]);summary(z)
z<-lm(price$w_delta[i_increase] ~ price$date[i_increase]);summary(z)


p1 <- ggplot(price[i_const,], aes(x=date, y = price_s)) +
  geom_line(col = "blue") + labs(x= "Year", y="Price [USD/mt]")  + ggtitle("Flat Trend in Singapore Price") +
  theme(plot.title = element_text(size=10, face="bold"))


p2  <- ggplot(price[i_const,], aes(x=date, y = hk_delta)) +
  geom_line(col = "black") + labs(x= "Year", y="Price diff. [USD/mt]") +
  geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2) +
  geom_smooth(method="lm", se = F, linetype = 2, col = "red")
#scale_colour_manual(values = c("black"))
#+ theme(legend.position = c(0.87,0.9), legend.title = element_blank())

p3 <- ggplot(price[i_decrease,], aes(x=date, y = price_s)) +
  geom_line(col = "blue") + labs(x= "Year", y="Price [USD/mt]")  +ggtitle("Downtrend in Singapore Price") +
  theme(plot.title = element_text(size=10, face="bold"))

p4  <- ggplot(price[i_decrease,], aes(x=date, y = hk_delta)) +
  geom_line(col = "black") + labs(x= "Year", y="Price diff. [USD/mt]") +
  geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2) +
  geom_smooth(method="lm", se = F, linetype = 2, col = "red")
#scale_colour_manual(values = c("black"))
#+ theme(legend.position = c(0.87,0.9), legend.title = element_blank())

p5 <- ggplot(price[i_increase,], aes(x=date, y = price_s)) +
  geom_line(col = "blue") + labs(x= "Year", y="Price [USD/mt]") + ggtitle("Uptrend in Singapore Price") +
  theme(plot.title = element_text(size=10, face = "bold"))

p6  <- ggplot(price[i_increase,], aes(x=date, y = hk_delta)) +
  geom_line(col = "black") + labs(x= "Year", y="Price diff. [USD/mt]") +
  geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2) +
  geom_smooth(method="lm", se = F, linetype = 2, col = "red")
#scale_colour_manual(values = c("black"))
```

```
#+ theme(legend.position = c(0.87,0.9), legend.title = element_blank())

multiplot(p1, p3, p5, p2, p4, p6, cols=2)
}

# ====================== Plotting post mfm

i_postmfm  <- which(price$date>='2017-01-01')


p1 <- ggplot(price[i_postmfm,], aes(x=date, y = price_s)) + geom_line(aes(y=price_hk, col = "Hong Kong"))+
   geom_line(aes(col = "Singapore")) + labs(x= "Year", y="Price [USD/mt]") +ggtitle("Post 2016 Price Levels") +
   theme(plot.title = element_text(size=10, face="bold")) +
   scale_colour_manual(values = c("#00ba38", "blue")) + theme(legend.position = c(0.87,0.1), legend.title = element_blank())


p2  <- ggplot(price[i_postmfm,], aes(x=date, y = hk_delta)) +
   geom_line(col = "black") + labs(x= "Year", y="Price gap [USD/mt]") +
   geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2) +
   geom_smooth(method="lm", se = F, linetype = 2, col = "red")

multiplot(p1,p2,1)


p3 <- ggplot(price[i_postmfm,], aes(x=date, y = price_s)) + geom_line(aes(y=price_w, col = "World"))+
   geom_line(aes(col = "Singapore")) + labs(x= "Year", y="Price [USD/mt]") +ggtitle("Post 2016 Price Levels") +
   theme(plot.title = element_text(size=10, face="bold")) +
   scale_colour_manual(values = c("#00ba38", "blue")) + theme(legend.position = c(0.87,0.1), legend.title = element_blank())


p4  <- ggplot(price[i_postmfm,], aes(x=date, y = w_delta)) +
   geom_line(col = "black") + labs(x= "Year", y="Price gap [USD/mt]") +
   geom_abline(intercept = 0, slope = 0, col = "black", linetype = 2) +
   geom_smooth(method="lm", se = F, linetype = 2, col = "red")

multiplot(p3,p4,1)


# ====================== end of Plotting post mfm


#====== plotting trend
```

```
  p1 <- ggplot(price, aes(x=price$date, y=price$price_s)) +
    geom_rect(aes(xmin = as.Date("2016-01-01", format = "%Y-%m-%d"), xmax = as.Date(
     "2017-01-01", format = "%Y-%m-%d") , ymin = -Inf, ymax = Inf), fill = "grey",
     alpha = 0.02) +

    geom_line( aes(col = "Singapore")) +
    geom_line(aes(y=price_hk, col = "Hong Kong")) +
    geom_line(aes(y=price_w, col = "World")) +
    theme(axis.title.x=element_blank()) +
    ggtitle("Bunker Price Indices")
  #labs(title = "Bunker price in Hong Kong and Singapore and Price Difference")
  p1 <- p1 + scale_colour_manual(values = c("#f8766d", "#619cff", "#00ba38")) +
     theme(legend.position = c(0.87,0.9), legend.title = element_blank()) + labs(y="
     Price [USD/mt]")
  p1

    multiplot(p1, p2, cols=1) #



} #Price per metric ton of IFO380 singa blue and hk
# ================================================== End of Price plots
     ============================================================

# ================================================== Start of Density plots
     ==========================================================

#Density Data Formatting

index <- which(substr(Sing$density,1,1) == "<")
Sing$density[index] <- "979.998"
index <- which(substr(Sing$density,1,1) == ">")
Sing$density[index] <- "993.002"

Sing$density <- as.numeric(Sing$density)


#Plot Singapore Density
plot_density <- function(Sing, HK){

  #---------------------------------------------------- Monthly median density Singapore
     and HK -------------------------------------------------------------
  month_range <- unique(substr(Sing$Date,1,7)) # monthly
  Fuel_monthly <- data.frame(month = month_range)
  Fuel_monthly <- na.omit(Fuel_monthly)

  for (i in 1:nrow(Fuel_monthly)) {
    index = which(substr(Sing$Date,1,7) == Fuel_monthly$month[i])
    Fuel_monthly$median[i]      <- median(Sing$density[index], na.rm=T)
    Fuel_monthly$mean[i]        <-   mean(Sing$density[index], na.rm=T)
```

```
  Fuel_monthly$sd[i]           <-     sd(Sing$density[index], na.rm=T)
  Fuel_monthly$mad[i]          <-    mad(Sing$density[index], na.rm=T)

  Fuel_monthly$nrsamples[i]    <- length(index)
  error                        <- qnorm(0.975) * Fuel_monthly$sd[i]/sqrt(Fuel_monthly$nrsamples[i])
  Fuel_monthly$upper_conf[i]   <- Fuel_monthly$mean[i] + error
  Fuel_monthly$lower_conf[i]   <- Fuel_monthly$mean[i] - error
  Fuel_monthly$densdiff[i]     <- 991 - Fuel_monthly$median[i]

  #deltadens
  Fuel_monthly$mediandd[i]       <- median(Sing$deltaDensity[index], na.rm=T)
  #Diff between densitydeviation and difference between 991 and median density
  Fuel_monthly$cheating[i]         <- Fuel_monthly$densdiff[i] - Fuel_monthly$mediandd[i]
}

Fuel_monthly$month    <- paste(Fuel_monthly$month,"-15", sep="")
Fuel_monthly$month    <- as.Date(Fuel_monthly$month, format = "%Y-%m-%d")
# =============== HK =============

HK.month_range <- unique(substr(HK$Date,1,7)) # monthly
HK.Fuel_monthly <- data.frame(month = HK.month_range)
HK.Fuel_monthly <- na.omit(HK.Fuel_monthly)

for (i in 1:nrow(HK.Fuel_monthly)) {
  index = which(substr(HK$Date,1,7) == HK.Fuel_monthly$month[i])
  HK.Fuel_monthly$median[i] <- median(HK$density[index],na.rm=T)
}

HK.Fuel_monthly$month <- paste(HK.Fuel_monthly$month,"-15", sep="")
HK.Fuel_monthly$month <- as.Date(HK.Fuel_monthly$month, format = "%Y-%m-%d")


#----------------------------------------------- Daily Median Density, Singapore and HK ---------------------------------------------------------

date_range <- unique(Sing$Date) # daily
Fuel_daily <- data.frame(date=date_range)

for (i in 1:nrow(Fuel_daily)) {
  index = which(Sing$Date==Fuel_daily$date[i])
  Fuel_daily$median[i] <- median(Sing$density[index],na.rm=T)
}

# =============== HK =============

HK.date_range <- unique(HK$Date)
HK.Fuel_daily <- data.frame(date=HK.date_range)

```

```
# Hong Kong median daily density
for (i in 1:nrow(HK.Fuel_daily)) {
  index = which(HK$Date==HK.Fuel_daily$date[i])
  HK.Fuel_daily$median[i] <- median(HK$density[index],na.rm=T)
}

# ================================================== Weekly Median Density,
   Singapore and HK ==================================================

Sing$week <- paste(year(Sing$Date),week(Sing$Date),sep="-")

week_range       <- na.omit(unique(Sing$week))
Sing.Fuel_weekly <- data.frame(week=week_range,date=rep(NA,length(week_range)),
   stringsAsFactors = F)

Sing.Fuel_weekly$p <- NA
Sing.Fuel_weekly$n <- NA
for (i in 1:nrow(Sing.Fuel_weekly)){
  index                          <- which(Sing$week==Sing.Fuel_weekly$week[i])
  Sing.Fuel_weekly$median[i]     <- median(Sing$density[index], na.rm=T)
  Sing.Fuel_weekly$mean[i]       <- mean(Sing$density[index], na.rm=T)
  Sing.Fuel_weekly$sd[i]         <- sd(Sing$density[index], na.rm=T)
  Sing.Fuel_weekly$date[i]       <- Sing$Date[index[1]] # skal v re 1-tall
  Sing.Fuel_weekly$mad[i]        <- mad(Sing$density[index], na.rm=T)


  #Finne ensiding median deviation

  #m<-median(Sing$density[index],na.rm=T)
  m <- Sing.Fuel_weekly$median[i]
  p <- Sing$density[index]-m
  p <- p[p>0]
  Sing.Fuel_weekly$p[i] <- m + median(p,na.rm=T)
  n <- Sing$density[index] - m
  n <- n[n<0]
  Sing.Fuel_weekly$n[i] <- m + median(n,na.rm=T)

  #Differnece from ISO limit
  Sing.Fuel_weekly$densdiff[i]     <- 991 - Sing.Fuel_weekly$median[i]

  #deltadens
  Sing.Fuel_weekly$mediandd[i]       <- median(Sing$deltaDensity[index], na.rm=T)
  m_dd <- Sing.Fuel_weekly$mediandd[i]
  p_dd <- Sing$deltaDensity[index]-m_dd
  p_dd <- p_dd[p_dd>0]
  Sing.Fuel_weekly$p_dd[i] <- m_dd + median(p_dd,na.rm=T)
  n_dd <- Sing$deltaDensity[index] - m_dd
  n_dd <- n_dd[n_dd<0]
  Sing.Fuel_weekly$n_dd[i] <- m_dd + median(n_dd,na.rm=T)

```

```
    #Diff between densitydeviation and difference between 991 and median density
    Sing.Fuel_weekly$cheating[i]         <- Sing.Fuel_weekly$densdiff[i] - Sing.Fuel_
     weekly$mediandd[i]
    Sing.Fuel_weekly$overstrate[i]        <- Sing.Fuel_weekly$mediandd[i]/Sing.Fuel_
     weekly$densdiff[i] * 100

    # 95 % Confidence
    #Sing.Fuel_weekly$nrsamples[i] <- length(index)
    #error                          <- qnorm(0.975) * Sing.Fuel_weekly$sd[i]/sqrt(
     Sing.Fuel_weekly$nrsamples[i])
    #Sing.Fuel_weekly$upper_conf[i]<-  Sing.Fuel_weekly$mean[i] + error
    #Sing.Fuel_weekly$lower_conf[i]<-  Sing.Fuel_weekly$mean[i] - error #evt median
  }

  Sing.Fuel_weekly$dd_spread <- Sing.Fuel_weekly$p_dd - Sing.Fuel_weekly$n_dd
  Sing.Fuel_weekly$date <- as.Date(Sing.Fuel_weekly$date,origin = "1970-01-01",tz="
     UTC")





# =================================================== FACET PLOT FOR RESOLUTION
     ================
merge_density <- function(Fuel_daily, Sing.Fuel_weekly, Fuel_monthly){
  daily   <- data.frame(date=Fuel_daily$date,       Daily    = Fuel_daily$median)
  weekly  <- data.frame(date=Sing.Fuel_weekly$date, Weekly = Sing.Fuel_weekly$median
     )
  monthly <- data.frame(date=Fuel_monthly$month, Monthly = Fuel_monthly$median)

  dens <- merge(daily, weekly,       by = "date", all = T)
  dens <- merge(dens, monthly, by = "date", all = T)

  #convert to long datatable
  long_dens <- dens %>% gather(Resolution, Density, 2:4)
  #removing empty rows
  index <- which(is.na(long_dens$Density));    if(length(index)>0) long_dens    <-
     long_dens[  -index,]
  long_dens$Res_f <- factor(long_dens$Resolution, levels = c("Daily", "Weekly", "
     Monthly"))


  #Plotting faceted plot
  dens_plot <- ggplot(long_dens, aes(x=date, y = Density) ) + geom_line()
  dens_plot + facet_grid(rows = vars(Res_f) ) + labs(x= "Year", y = "Density [kg/m3]
```

```
")

}


}
#=========================================================== DENSITY PLOTS ========================================================================================

sing_price  <- data.frame(date=ifo380_price$Date_sing, price=ifo380_price$Price_sing)

#Plot Daily Density
ggplot(data=Fuel_daily, aes(x=date, y=median, group=1, colour = "red")) +
  geom_line() + geom_line(data=HK.Fuel_daily, aes(y=median, colour = "blue")) +
  ylab(label="Daily median density") + xlab("Date")

# Plot weekly density
week_dens <- ggplot(data=Sing.Fuel_weekly, aes ( x= date, y = median)) + geom_line() + ylab(label="Density [kg/m3]") + xlab("Year")
week_dens + geom_hline(yintercept=991, col = "red") + geom_line(aes(y=n), colour="blue", linetype=2) + geom_line(aes(y=p), colour="blue", linetype=2) + labs(title = "Median Bunker Density, 1st and 3rd Quartiles in blue")

#Plot Monthly Density
ggplot(data=Fuel_monthly, aes(x=month, y=median)) + geom_line() +
  ylab(label="Density") + xlab("Date") + labs(title = "Monthly sample median in Singapore")
# + geom_line(data=HK.Fuel_monthly, aes(y=median), colour = "blue")
# +  geom_ribbon(data=Fuel_monthly, aes(ymin=lower_conf, ymax=upper_conf), alpha=0.3)

#Plot density diff - dens and max dens
ggplot(data=Fuel_monthly, aes(x=month, y=densdiff)) + geom_line() +
  ylab(label="Density [kg/m3]") + xlab("Year") + geom_line(data=Fuel_monthly, aes(y=mediandd), col = "blue") + geom_line(data=Fuel_monthly, aes(y=cheating), col = "red" )


# SCATTER PLOT, stated vs tested
ggplot(data = Sing, aes(x=density, y=BDRdensity) ) + geom_abline(intercept = 0, slope = 1, col = "blue" , size = 1, linetype = 2) +
  geom_point(size = 1, alpha = 0.5)+ xlim(c(980,992)) + ylim(c(980,992)) +
  geom_hline(yintercept=991, col = "red", linetype = 2) + geom_vline(xintercept=991, col ="red", linetype = 2) +
  labs(x = "Tested Density [kg/m3]", y = "Stated Density [kg/m3] ")



# ==================================================== Plot delta density and
```

```
distribution for delta density data presentation ===================
p <- ggplot(data=Sing.Fuel_weekly, aes(x=date)) + geom_line(aes(y=mediandd, color ="Weekly Median of Delta Density"))
p <- p + geom_line(aes(y = p_dd, color = "3rd Quartile"), linetype = 2)
p <- p + geom_line(aes(y = n_dd, color = "1st Quartile"), linetype = 2)
p <- p + geom_line(aes(y = densdiff, color = "Deviation from ISO limit"))
# Modyfing colors and themes options
p <- p + scale_colour_manual(values = c("grey60", "grey60","red", "black")) + scale_linetype_manual(values = c(rep("dashed",4)))
p <- p + labs(y = "Delta density [kg/m3]",
              x = "Year")
p <- p + theme(legend.position = c(0.8,0.9), legend.title = element_blank())
p

p + geom_line(aes(y = dd_spread)) + geom_line(aes(y=densdiff, col ="blue"))

 scale_color_manual(values = c("red", "dodgerblue3", "red", "dodgerblue3")) +
  scale_linetype_manual(values = c(1, 1, 2, 2))




#plot cheating / utilisation
p <- ggplot(data=Sing.Fuel_weekly, aes(x=date)) + geom_line(aes(y=densdiff, color ="Difference from ISO limit"))


# adding the relative humidity data, transformed to match roughly the range of the temperature
p <- p + geom_line(aes(y= overstrate*(3.5/100), color = "Overstating Rate"), linetype=2)
p <- p + geom_line(aes(y= mediandd, color = "Median Delta Density"))

# now adding the secondary axis
p <- p + scale_y_continuous(sec.axis = sec_axis(~./3.5*100, name = "Overstating Rate [%]"))

# Modifying colours and themes options
p <- p + scale_colour_manual(values = c("blue", "black", "red"))
p <- p + labs(y = "Density [kg/m3]",
              x = "Year",
              colour = "Graphs"
              )
p <- p + theme(legend.position = c(0.8,0.9))
  p

  ylab(label="Density [kg/m3]") + xlab("Year") + geom_line(data=Sing.Fuel_weekly, aes(y=mediandd), col = "blue") +
  #geom_line(data=Sing.Fuel_weekly, aes(y=cheating), col = "red" ) +
  geom_line(data=Sing.Fuel_weekly, aes(y=overstrate), col = "red")
```

```
# ================================================= End of density plots ==========================================================

#geom_ribbon(data=predframe, aes(ymin=lwr, ymax=upr), alpha=0.3))    Standardvarians?

# ================================================= Histogram plots ==========================================================
plot_hist <- function(Sing){

  Sing.deltadens <- data.frame(date = Sing$Date, dd = Sing$deltaDensity)

  #removal of na lines
  index <- which(is.na(Sing.deltadens$dd)); if(length(index)>0) Sing.deltadens <- Sing.deltadens[-index,]

  #Time window 2013-2015
  index <- which(Sing.deltadens$date>='2013-01-01' & Sing.deltadens$date<='2014-12-31')
  h1 <- data.frame(date=Sing.deltadens$date[index], Period1 =  Sing.deltadens$dd[index])

  #Time window 2015-2016
  index <- which(Sing.deltadens$date>='2015-01-01' & Sing.deltadens$date<='2015-12-31')
  h2 <- data.frame(date=Sing.deltadens$date[index], Period2 =  Sing.deltadens$dd[index])

  #Time window 2016-2017
  index <- which(Sing.deltadens$date>='2016-01-01' & Sing.deltadens$date<='2016-12-31')
  h3 <- data.frame(date=Sing.deltadens$date[index], Period3 =  Sing.deltadens$dd[index])

  #Time window 2017-2019
  index <- which(Sing.deltadens$date>='2017-01-01' & Sing.deltadens$date<='2018-12-31')
  h4 <- data.frame(date=Sing.deltadens$date[index], Period4 =  Sing.deltadens$dd[index])


  #13-15
  ggplot(data=h1, aes(x=h1$dd)) +
    geom_histogram(breaks = seq(-3.5,4, by = 0.5),
                   col = "red",
```

```
                   fill= "blue",
                   alpha = .2,
                   aes(y=..count../sum(..count..))) +
  labs(title="Histogram for Delta Density", x="Delta Density", y="Fraction") +
  xlim(c(-4,4))

#15-16
ggplot(data=h2, aes(x=h2$dd)) +
  geom_histogram(breaks = seq(-3,10, by = 0.5),
                   col = "red",
                   fill= "blue",
                   alpha = .2,
                   aes(y=..count../sum(..count..))) +
  labs(title="Histogram for Delta Density", x="Delta Density", y="Fraction") +
  xlim(c(-3,11))


#16-17
ggplot(data=h3, aes(x=h3$dd)) +
  geom_histogram(breaks = seq(-3.5,8, by = 0.5),
                   col = "red",
                   fill= "blue",
                   alpha = .2,
                   aes(y=..count../sum(..count..))) +
  labs(title="Histogram for Delta Density", x="Delta Density", y="Fraction") +
  xlim(c(-4,8))



#17-18
ggplot(data=h4, aes(x=h4$dd)) +
  geom_histogram(breaks = seq(-3.5,8, by = 0.5),
                   col = "red",
                   fill= "blue",
                   alpha = .2,
                   aes(y=..count../sum(..count..))) +
  labs(title="Histogram for Delta Density", x="Delta Density", y="Fraction") +
  xlim(c(-4,8))

# ======= Faceted Histogram =======


dd <- merge(h1,h2, by = "date", all = T)
dd <- merge(dd, h3, by = "date", all = T )
dd <- merge(dd, h4, by = "date", all = T )

#Converting to long format
long_dd <- dd %>% gather(Period, deltadens, 2:5)

#removing empty rows
```

```
  index <- which(is.na(long_dd$deltadens)); if(length(index>0)) long_dd <- long_dd[-index,]

  #Plotting faceted plot
  dd_plot <- ggplot(data = long_dd, aes(x=long_dd$deltadens)) +  geom_histogram(breaks = seq(-2,4, by = 0.25),
                                                                    col = "red",
                                                                    fill = "blue",
                                                                    alpha = .2,
                                                                    #aes(y=..count../sum(..count..))
  )
  dd_plot + facet_grid(rows = vars(Period)) + labs(x="Delta Density [kg/m3]", y = "Count")



  dens_plot <- ggplot(long_dens, aes(x=date, y = Density) ) + geom_line()
  dens_plot + facet_grid(rows = vars(Res_f) ) + labs(x= "Year", y = "Density [kg/m3]")

  #Thomas plot
  hist(ddens.h1$dd,breaks=seq(min(ddens.h1$dd,na.rm=T),max(ddens.h1$dd,na.rm=T)+1,1),xlim=c(-5,5),freq=F)
}
# =============================== Shortlift benchmark ===============================================================================

plot_benchhist <- function(Sing, HK){

  sing_short <-  data.frame(Date = as.Date(Sing$Date) ,SL = Sing$REPORT_SHORT_LIFT_BENCHMARK, maxSL=Sing$REPORT_MAX_SHORT_BENCHMARK)
  hk_short   <-  data.frame(Date = HK$Date ,     SL = HK$REPORT_SHORT_LIFT_BENCHMARK, maxSL=HK$REPORT_MAX_SHORT_BENCHMARK)

  index <- which(is.na(sing_short$SL)); if(length(index)>0) sing_short <- sing_short[-index,]
  index <- which(is.na(hk_short$SL)); if(length(index)>0) hk_short <- hk_short[-index,]


  sing_short$week <- paste(year(sing_short$Date),week(sing_short$Date),sep="-")

  week_range          <- na.omit(unique(sing_short$week))
  sing.SL <- data.frame(week=week_range,date=as.Date(rep(NA,length(week_range))),stringsAsFactors = F)

```

```
sing.SL$p <- NA
sing.SL$n <- NA
for (i in 1:nrow(sing.SL)){
  index                      <- which(sing_short$week==sing.SL$week[i])
  sing.SL$median[i]     <- median(sing_short$SL[index], na.rm=T)
  sing.SL$mean[i]       <- mean(sing_short$SL[index], na.rm=T)
  sing.SL$sd[i]         <- sd(sing_short$SL[index], na.rm=T)
  sing.SL$date[i]       <- sing_short$Date[index[1]] # skal v re 1-tall
  sing.SL$p[i]          <- sing.SL$mean[i] + sing.SL$sd[i]
  sing.SL$n[i]          <- sing.SL$mean[i] - sing.SL$sd[i]

  #Finne ensiding median deviation

  #m<-median(Sing$density[index],na.rm=T)
  # <- sing.SL$mean[i]
  #p <- sing_short$SL[index]-m
  #p <- p[p>0]
  #sing.SL$p[i] <- m + mean(p,na.rm=T)
  #n <- sing_short$SL[index] - m
  #n <- n[n<0]
  #sing.SL$n[i] <- m + mean(n,na.rm=T)
}
sing.SL$BM <- "SL"
y <- data.frame(week=week_range,date=as.Date(rep(NA,length(week_range))), stringsAsFactors = F)

for (i in 1:nrow(y)){
  index                      <- which(sing_short$week==y$week[i])
  y$median[i]     <- median(sing_short$maxSL[index], na.rm=T)
  y$mean[i]       <- mean(sing_short$maxSL[index], na.rm=T)
  y$sd[i]         <- sd(sing_short$maxSL[index], na.rm=T)
  y$date[i]       <- sing_short$Date[index[1]] # skal v re 1-tall
  y$p[i]          <- y$mean[i] + y$sd[i]
  y$n[i]          <- y$mean[i] - y$sd[i]
 }
y$BM <- "Max SL"

sing.SL<-rbind(sing.SL,y)


ggplot(data=sing.SL, aes(x=date, y = mean)) + geom_line()+ ylab(label="Benchmark Scores") + xlab("Year") +
geom_line(aes(y=n), colour="blue", linetype=2) + geom_line(aes(y=p), colour="blue", linetype=2) + facet_grid(rows = vars(BM))
```

```

#==========================   HISTOGRAM  ============================

  sing_short <-  data.frame(Date = Sing$Date  ,sing = Sing$REPORT_SHORT_LIFT_BENCHMARK)
  hk_short   <-  data.frame(Date = HK$Date  ,    hk = HK$REPORT_SHORT_LIFT_BENCHMARK)

  sing_short$frac <- sing_short$sing/sum(sing_short$sing)
  hk_short$frac <- hk_short$hk/sum(hk_short$hk)



   shortlift <- sing_short


   shortlift$Port <- 'Singapore'
   names(shortlift)[2]<-'SLScore'
   x <- hk_short
   x$Port <- 'Hong Kong'
   names(x)[2]<-'SLScore'
   z <-rbind(shortlift,x)
   shortlift<-z

   #Alt 1

   ggplot(shortlift,aes(x=SLScore, stat(density))) +
     geom_histogram(data=subset(shortlift,port == 'Singapore'), breaks = seq(0,1,by = 0.1),fill = "green", alpha = 0.2, aes(col = "Singapore")) +
     geom_histogram(data=subset(shortlift,port == 'Hong Kong'), breaks = seq(0,1,by = 0.1), fill = "blue", alpha = 0.2, aes(col = "Hong Kong")) + theme_bw() +
     scale_colour_manual(values = c("blue", "green")) +
     theme(legend.position = c(0.8,0.9), legend.title = element_blank())

   #ALT 2

   ggplot(shortlift,aes(x=SLScore, fill=Port,color = Port)) +
     geom_histogram(aes(y=..density..*.1),
                    alpha=0.35, position="identity", breaks = seq(0,1,by = 0.1)) +
     theme(legend.position = c(0.9,0.95), legend.title = element_blank()) +
     labs( x="Shortlift Score", y="Fraction")
}
# ============================================================ SCATTER PLOTS ===============================================================================


  ggplot(data = Sing, aes(x=density, y=BDRdensity)) +
    geom_point(size=1, alpha = 0.5) + xlim(c(980,992)) + ylim(c(980,992))

  line <- data.frame(x= c(978, 991.5), y = c(13,-0.5))

```

```r
  ggplot(data = Sing, aes(x=density, y=deltaDensity)) + xlim(c(978,991.5)) + ylim(c(-5,13))  +
 geom_line(data = line, aes(x=x,y=y), col = "red" , size = 1, linetype = 2) + geom_point(size=1, alpha = 0.5) +
 geom_hline(yintercept=0, col = "blue", linetype = 1) + geom_vline(xintercept=991, linetype =1, col = "blue") + labs( x= "Density [kg/m3]" , y="Delta density [kg/m3]")

  Sing$reldens <- (991-Sing$BDRdensity)/(991-Sing$density)

   ggplot(data=Sing, aes(x=density, y= reldens)) + ylim(c(-4,4)) +
     geom_point(size=1, alpha = 0.5)

   ggplot(data = Sing, aes(x=Date, y=BDRdensity)) +
     geom_point(size=1, alpha = 0.5)


plot(Sing$density,(991-Sing$BDRdensity)/(992-Sing$density))

# ============================================================ Results/Data Analysis Chapter ==============================================================================


# ============================================================ DIGIT COUNT - https://en.wikipedia.org/wiki/Benford%27s_law

index <- which(Sing$Date <= '2015-12-31')
x<- Sing$BDRdensity[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

#data<-data.frame(  digit=as.numeric(x), date = Date, Period = rep("Before",length(x)))
#digitdata<-data.frame(  digit=seq(0,9), freq = rep(0,10), Period = rep("Before",10))

digitdata <- data.frame(digit=c(seq(0,9),seq(0,9)), freq = rep(0,20), Period = c(rep("Before MFM",10),rep("After MFM",10)))

for (i in 0:9){
  digitdata$freq[i+1] <- length(which(x == as.character(i)))/length(x)
}

index <- which(Sing$Date >= '2017-01-01')
x<- Sing$BDRdensity[index]
Date <- Sing$Date[index]
```

```
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

length(which(x == as.character(0)))
length(which(x == as.character(7)))
length(which(x == as.character(8)))

for (i in 0:9){
  digitdata$freq[i+11] <- length(which(x == as.character(i)))/length(x)
}

digitdata$Period_f <- factor(digitdata$Period, levels = c("Before MFM", "After MFM")
    )
digitdata$pct      <- as.numeric(format(round(digitdata$freq, 3), nsmall = 2))

pl <- ggplot(digitdata, aes(digit, freq, fill = Period_f)) +
  geom_bar(stat = "identity", alpha = 0.8) +
  scale_x_continuous(breaks=seq(0,9,1)) +
  #scale_y_continuous(labels = percent_format()) +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
  facet_grid(~Period_f) +
  labs( x="Decimal digit of stated density", y="Fraction") +
  geom_text(aes(y=freq,label = paste0(pct*100," %")), nudge_y = .019) +
  theme(legend.position = "none") + ggtitle("Stated bunker density") +
  theme(plot.title = element_text( size=11, face="bold"))


#====================================== TESTED BUNKER DENSITY
    ============================

index <- which(Sing$Date <= '2015-12-31')
x<- Sing$density[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

#data<-data.frame(  digit=as.numeric(x), date = Date, Period = rep("Before",length(x
    )))
#digitdata<-data.frame(  digit=seq(0,9), freq = rep(0,10), Period = rep("Before",10)
    )

digitdata <- data.frame(digit=c(seq(0,9),seq(0,9)), freq = rep(0,20), Period = c(rep
    ("Before MFM",10),rep("After MFM",10)))

for (i in 0:9){
  digitdata$freq[i+1] <- length(which(x == as.character(i)))/length(x)
```

```
}

index <- which(Sing$Date >= '2017-01-01')
x<- Sing$density[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

length(which(x == as.character(0)))
length(which(x == as.character(7)))
length(which(x == as.character(8)))

for (i in 0:9){
  digitdata$freq[i+11] <- length(which(x == as.character(i)))/length(x)
}

digitdata$Period_f <- factor(digitdata$Period, levels = c("Before MFM", "After MFM")
    )
digitdata$pct      <- as.numeric(format(round(digitdata$freq, 3), nsmall = 2))

p2 <- ggplot(digitdata, aes(digit, freq, fill = Period_f)) +
  geom_bar(stat = "identity", alpha = 0.8) +
  scale_x_continuous(breaks=seq(0,9,1)) +
  #scale_y_continuous(labels = percent_format()) +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
  facet_grid(~Period_f) +
  labs( x="Decimal digit of stated density", y="Fraction") +
  geom_text(aes(y=freq,label = paste0(pct*100," %")), nudge_y = .019) +
  theme(legend.position = "none") + ggtitle("Tested bunker density")+
  theme(plot.title = element_text( face="bold", size=11))



# =========== LAST AND FIRST MONTH POST MFM

postmfmdigit <- data.frame(digit=c(seq(0,9),seq(0,9),seq(0,9)), freq = rep(0,30),
    Period = c(rep("January 2017",10), rep("August 2017",10),rep("March 2018",10)))

index <- which(Sing$Date >= '2017-01-01'& Sing$Date <= '2017-01-31')
x<- Sing$BDRdensity[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

for (i in 0:9){
  postmfmdigit$freq[i+1] <- length(which(x == as.character(i)))/length(x)
```

```
}

#================================ 2017 Aug
index <- which(Sing$Date >= '2017-08-01'& Sing$Date <= '2017-08-31')
x<- Sing$BDRdensity[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

for (i in 0:9){
  postmfmdigit$freq[i+11] <- length(which(x == as.character(i)))/length(x)
}
#================= 2017 Aug end

#================================
index <- which(Sing$Date >= '2018-03-01')
x<- Sing$BDRdensity[index]
Date <- Sing$Date[index]
x<- as.character(x)
x<- substr(x,5,5)
i <- which(x=='')
x[i]<-'0'

for (i in 0:9){
  postmfmdigit$freq[i+21] <- length(which(x == as.character(i)))/length(x)
}
#==========

postmfmdigit$Period_f <- factor(postmfmdigit$Period, levels = c("January 2017", "
     August 2017", "March 2018"))
postmfmdigit$pct      <- as.numeric(format(round(postmfmdigit$freq, 3), nsmall = 3))


p2 <- ggplot(postmfmdigit, aes(digit, freq)) +
  geom_bar(stat = "identity", fill="#00bfc4", alpha = 0.8) +
  scale_x_continuous(breaks=seq(0,9,1)) +
  #scale_y_continuous(labels = percent_format()) +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
  facet_grid(~Period_f) +
  labs( x="Decimal digit of stated density", y="Fraction") +
  geom_text(aes(y=freq,label = paste0(pct*100," %")), nudge_y = .019)

# =========== =========== =========== =========== DIGIT END


# FRACTION OF POSITIVE DELTA DENSITY
index <- which(is.na(Sing$deltaDensity)); if(length(index)>0) Sing <- Sing[-index,]

```

```
index <- which(Sing$Date<'2016-01-01')
pre_sing  <- Sing[index,]

index <- which(Sing$Date>='2017-01-01')
post_sing <- Sing[index,]


#Set z-value
z        <- 1.96

#PRE MFM
n        <- nrow(pre_sing)
p_pre    <- length(  which(pre_sing$deltaDensity>0) ) / n
sd       <- z*sqrt( p_pre*(1-p_pre) / n   )
ci_pre   <- c(p_pre-sd,p_pre+sd)


#POST MFM
n        <- nrow(post_sing)
p_post   <- length( which(post_sing$deltaDensity>0) ) / n
sd       <- z*sqrt( p_post*(1-p_post) / n   )
ci_post   <- c(p_pre-sd,p_pre+sd)


#======================== PRICE COMPARE
    =====================================================


hk_price     <- data.frame(date=ifo380_price$Date_hk, price=ifo380_price$Price_hk)
sing_price   <- data.frame(date=ifo380_price$Date_sing, price=ifo380_price$Price_sing
    )

#removal of na lines
index <- which(is.na(sing_price$price)); if(length(index)>0) sing_price <- sing_
    price[-index,]
index <- which(is.na(hk_price$price));    if(length(index)>0)    hk_price <-    hk_
    price[-index,]

#time ordering
hk_price     <- hk_price[order(hk_price$date),]
sing_price   <- sing_price[order(sing_price$date),]

price <- merge(hk_price, sing_price, by="date",all=F)
#price2 <- merge(hk_price, sing_price, by="date",all=T)
price$deltaprice <- price$price.x - price$price.y

index  <- which(price$date >= "2014-06-15" & price$date < "2016-01-01")
index2 <- which(price$date >= "2016-01-01")

price1 <- price[index,]
```

```
price2 <- price[index2,]

#MULTIPLE LIN REG https://stackoverflow.com/questions/15633714/adding-a-regression-line-on-a-ggplot

p1 <- ggplot(price1,  aes(x=date, y = deltaprice)) +
  geom_line( aes(col = "Price difference")) + labs(x= "Year", y="Price difference [USD/mt]") +
  geom_abline(intercept = 0, slope = 0, col = "red") +
  scale_colour_manual(values = c("Black", "Red", "Blue")) + theme(legend.position = c(0.87,0.9), legend.title = element_blank())

ggplot(price1,aes(date,deltaprice))+stat_summary(fun.data=mean_cl_normal) +
  geom_smooth(method='lm') +
  geom_line()

p2 <- ggplot(price2,  aes(x=date, y = deltaprice)) +
  geom_line( aes(col = "Price difference")) + labs(x= "Year", y="Price difference [USD/mt]") +
  geom_abline(intercept = 0, slope = 0, col = "red") +
  scale_colour_manual(values = c("Black", "Red", "Blue")) + theme(legend.position = c(0.87,0.9), legend.title = element_blank())

ggplot(price2[ind,],aes(date,deltaprice))+stat_summary(fun.data=mean_cl_normal) +
  geom_smooth(method='lm') +
  geom_line() + labs(x="Time", y = "Price difference [USD/mt]")

#=========== Scatter Plot

pa <- ggplot(data = price1, aes(x=price.y, y=price.x) ) + geom_abline(intercept = 0, slope = 1, col = "blue" , size = 1, linetype = 2) +
  geom_point(size = 1, alpha = 0.5)+
  labs(x = "Singapore [USD]", y = "Hong Kong [USD]")

pb <- ggplot(data = pricelag1, aes(x=price.y, y=price.x) ) + geom_abline(intercept = 0, slope = 1, col = "blue" , size = 1, linetype = 2) +
  geom_point(size = 1, alpha = 0.5)+
  labs(x = "Singapore [USD]", y = "Hong Kong [USD]")

pc <- ggplot(data = price2, aes(x=price.y, y=price.x) ) + geom_abline(intercept = 0, slope = 1, col = "blue" , size = 1, linetype = 2) +
  geom_point(size = 1, alpha = 0.5)+
  labs(x = "Singapore [USD]", y = "Hong Kong [USD]")

pd <- ggplot(data = pricelag2, aes(x=price.y, y=price.x) ) + geom_abline(intercept = 0, slope = 1, col = "blue" , size = 1, linetype = 2) +
  geom_point(size = 1, alpha = 0.5)+
  labs(x = "Singapore [USD]", y = "Hong Kong [USD]")

multiplot(pa,pc,pb,pd, cols = 2)
```

```
#=========== Scatter Plot


# ============================================================ DELTA DENSITY Analysis ============================================================


n_pre    <- length(which(!is.na(Sing$deltaDensity[Sing$Date  < "2016-01-01"])))
n_post   <- length(which(!is.na(Sing$deltaDensity[Sing$Date >= "2017-01-01"])))
m_post   <- mean(Sing$deltaDensity[Sing$Date >= "2017-01-01"], na.rm = T)
m_pre    <- mean(Sing$deltaDensity[Sing$Date < "2016-01-01"], na.rm = T)
sd_pre   <- sd(Sing$deltaDensity[Sing$Date >= "2017-01-01"], na.rm = T)
sd_post  <- sd(Sing$deltaDensity[Sing$Date < "2016-01-01"], na.rm = T)

# m_pre-m_post

# 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post)

CI_pre <- c(     round(m_pre - 1.96*sqrt(sd_pre^2/n_pre),3)     ,   round(m_pre + 1.96*sqrt(sd_pre^2/n_pre),3)     )
CI_post <- c(     round(m_post - 1.96*sqrt(sd_post^2/n_post),3)     ,   round(m_post + 1.96*sqrt(sd_post^2/n_post),3)     )


conf_interval <- c(round(m_pre - 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3), round(m_pre + 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3))
conf_interval <- c(m, sort(conf_interval))

densdistr <- Sing[which(Sing$Date >= "2017-01-01"),]
densdistr$Period <- "Pre-MFM"
y          <- Sing[which(Sing$Date < "2016-01-01"),]
y$Period <- "Post-MFM"
densdistr <- rbind(densdistr,y)
densdistr <- densdistr[which(!is.na(densdistr$density)),]


#quartile function
quart <- function(x) {
  x <- sort(x)
  n <- length(x)
  m <- (n+1)/2
  if (floor(m) != m) {
    l <- m-1/2; u <- m+1/2
  } else {
    l <- m-1; u <- m+1
  }
  c(Q1=median(x[1:l]), Q3=median(x[u:n]))
}
median(Sing$density[which(Sing$Date >= "2017-01-01")])
qrt <- quart(Sing$density[which(Sing$Date >= "2017-01-01")])
```

```
ggplot(densdistr, aes(x=density, fill = Period)) +
  geom_histogram( breaks = seq(986,991,.1), alpha=0.75)


ggplot(plotframe, aes(densto, fill = Period)) +
  geom_bar(stat="identity", aes(y=mean), position = posn_d, alpha=.6) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Mean of delta density [kg/m3]") +
  scale_x_continuous(breaks = seq(988, 991, by = .2))
#alt 2
ggplot(plotframe, aes(densto, fill = Period)) +
  geom_bar(stat="identity", aes(y=mean), alpha=.5) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Mean of delta density [kg/m3]")



#===================================== Mean delta density, post mfm vs pre mfm
    =====================================

Fuel <- Sing

deltaDens  <- function(Fuel, densityRange =c(989.5,989.6)){
   i_post <- which(Fuel$Date >='2017-01-01' )
   i_pre  <- which(Fuel$Date < '2016-01-01' )
   d_post  <- Fuel$density[i_post]
   d_pre   <- Fuel$density[i_pre ]
   dd_post <- Fuel$deltaDensity[i_post]
   dd_pre  <- Fuel$deltaDensity[i_pre ]
   x <- data.frame(d=c(d_pre,d_post),dd=c(dd_pre,dd_post), ind=c(rep('pre',length(dd_
      pre)),rep('post',length(dd_post)) ))
   x <- x[order(x$d),]
   x <- x[which(!is.na(x$d)),]
   x <- x[which(!is.na(x$dd)),]
   y <- x[which(x$d> densityRange[1] & x$d<=densityRange[2]),]
   n_pre     <- length(y$dd[y$ind=='pre'])
   n_post    <- length(y$dd[y$ind=='post'])
   m_pre   <- mean(y$dd[y$ind=='pre'])
   m_post <- mean(y$dd[y$ind=='post'])
   sd_pre   <- sd(y$dd[y$ind=='pre'])
   sd_post <- sd(y$dd[y$ind=='post'])

   # m_pre-m_post
   # 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post)
   m <- m_post-m_pre
   #conf_interval <- c(round(m + 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3),round(m
      - 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3))
   conf_interval <- c(m_pre,m_post,sd_pre,sd_post,n_pre,n_post)
   return(conf_interval)
```

```
}

dRange =c(988,991)

Fuel <- Fuel[Fuel$density > dRange[1] & Fuel$density <= dRange[2] ,]
Fuel$density <- as.numeric(Fuel$density)
Fuel$deltaDensity <- as.numeric(Fuel$deltaDensity)
result <- NULL
bin <- seq(dRange[1],dRange[2],0.1)
for (i in 1:(length(bin)-1)) result <- rbind(result, c(bin[i], bin[i+1], deltaDens(
    Fuel, densityRange = c(bin[i], bin[i+1]))) )
result <- data.frame(result)
names(result) <- c('densFrom','densTo','m_pre','m_post','sd_pre','sd_post','n_pre','
    n_post')

plotframe <- data.frame(densto = result$densTo-.05, mean = result$m_post, Period = "
    Post-MFM delta density")
x         <- data.frame(densto = result$densTo-.05, mean = result$m_pre , Period =
    "Pre-MFM delta density")
plotframe <- rbind(plotframe,x)

posn_d <- position_dodge(0.03)

ggplot(plotframe, aes(densto, fill = Period)) +
  geom_bar(stat="identity", aes(y=mean), position = posn_d, alpha=.6) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Mean of delta density [kg/m3]") +
  scale_x_continuous(breaks = seq(988, 991, by = .2))

ggplot(plotframe, aes(densto, fill = Period)) +
  geom_bar(stat="identity", aes(y=mean), position = posn_d, alpha=.6) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Mean of delta density [kg/m3]") +
  scale_x_continuous(breaks = seq(988, 991, by = .2))

#alt 2 (brukes ikke)
ggplot(plotframe, aes(densto, fill = Period)) +
  geom_bar(stat="identity", aes(y=mean), alpha=.5) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Mean of delta density [kg/m3]")


# ======================================== Density histogram, pre-MFM vs post-MFM
    =========================================================

#Sing
densdistr <- Sing[which(Sing$Date >= "2017-01-01"),]
densdistr$Period <- "Post-MFM"
y         <- Sing[which(Sing$Date < "2016-01-01"),]
y$Period <- "Pre-MFM"
```

```

#HK
densdistr <- HK[which(HK$Date >= "2017-01-01"),]
densdistr$Period <- "Post-MFM"
y          <- HK[which(HK$Date < "2016-01-01"),]
y$Period <- "Pre-MFM"





densdistr <- rbind(densdistr,y)
densdistr <- densdistr[which(!is.na(densdistr$density)),]
densdistr <- densdistr[which(!is.na(densdistr$deltaDensity)),]
index <- which(is.na(densdistr$density)); if(length(index)>0) densdistr <- densdistr
    [-index,]
index <- which(is.na(densdistr$deltaDensity)); if(length(index)>0) densdistr <-
    densdistr[-index,]

i_pre  <- which(densdistr$Date < '2016-01-01')
i_post <- which(densdistr$Date >='2017-01-01' )

#t_test data
dd_pre  <- densdistr$deltaDensity[i_pre]
dd_post <- densdistr$deltaDensity[i_post]


m_pre  <- mean(densdistr$deltaDensity[i_pre])
m_post <- mean(densdistr$deltaDensity[i_post])

md_pre  <- mean(densdistr$density[i_pre])
md_post <- mean(densdistr$density[i_post])


mean(densdistr$deltaDensity)

#delta density distribution, post-MFM vs pre-MFM

ggplot(densdistr) +
  geom_histogram(data = densdistr[i_pre,],breaks = seq(-4,6,0.5), aes(x=deltaDensity
    , y = ..density..), alpha = .1, fill = "red") +
  geom_histogram(data = densdistr[i_post,],breaks = seq(-4,6,0.5), aes(x=
    deltaDensity, y = ..density..), alpha = .1, fill = "blue") +
  geom_density(data = densdistr[i_pre,],  col = "red",aes(x=deltaDensity, y = ..
    density..))+
  geom_density(data = densdistr[i_post,], col = "blue", aes( x=deltaDensity, y = ..
    density..)) +
  labs(x="Delta Density [kg/m3]", y="Fraction") +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  xlim(c(-4,6)) +geom_vline(xintercept=m_pre, col ="red", linetype=2, alpha= 0.5) +
```

```
     geom_vline(xintercept=m_post, col ="blue", linetype=2, alpha= 0.5)


#Density Distribution, post-MFM vs pre-MFM

ggplot(densdistr) +
  geom_histogram(data = densdistr[i_pre,],breaks = seq(980,992,0.5), aes(x=density,
     y = ..density..), alpha = .1, fill = "red") +
  geom_histogram(data = densdistr[i_post,],breaks = seq(980,992,0.5), aes(x=density,
      y = ..density..), alpha = .1, fill = "blue") +
  geom_density(data = densdistr[i_pre,],  col = "red",aes(x=density, y = ..density
     ..))+
  geom_density(data = densdistr[i_post,], col = "blue", aes( x=density, y = ..
     density..)) +
  labs(x="Density [kg/m3]", y="Fraction") +
  xlim(c(980,993)) +geom_vline(xintercept=md_pre, col ="red", linetype=2, alpha=
     0.5) + geom_vline(xintercept=md_post, col ="blue", linetype=2, alpha= 0.5)



ggplot(densdistr, aes(x=density, fill = Period)) +
  geom_histogram( breaks = seq(988,991,.1), alpha=0.75) +
  theme(legend.position = c(0.9,0.9), legend.title = element_blank()) +
  labs( x="Density [kg/m3]", y="Count") + geom_abline(intercept = 100, linetype = 2,
      slope = 0, col = "black") # +
  #geom_vline(xintercept = m_pre, col = "#F8766D" , linetype=2) + geom_vline(
     xintercept = m_post, col = "#00bfc4", linetype=2)



#=================Histogram binwise
ggplot(densdistr) +
  geom_histogram(data = densdistr[i_pre,],breaks = seq(988,991,0.1), aes(x=density,
     y = ..density..), alpha = .1, fill = "red" , col = "red") +
  geom_histogram(data = densdistr[i_post,],breaks = seq(988,991,0.1), aes(x=density,
      y = ..density..), alpha = .1, fill = "blue") +
  #geom_density(data = densdistr[i_pre,],  col = "red",aes(x=density, y = ..density
     ..))+
  #geom_density(data = densdistr[i_post,], col = "blue", aes( x=density, y = ..
     density..)) +
  labs(x="Density [kg/m3]", y="Fraction") +
  xlim(c(988,991))# +geom_vline(xintercept=md_pre, col ="red", linetype=2, alpha=
     0.5) + geom_vline(xintercept=md_post, col ="blue", linetype=2, alpha= 0.5)

HKhistogram<-ggplot(densdistr) +
  geom_histogram(data = densdistr[i_pre,],breaks = seq(988,991,0.1), aes(x=density),
      alpha = .2, fill = "red") +
  geom_histogram(data = densdistr[i_post,],breaks = seq(988,991,0.1), aes(x=density)
     , alpha = .4, fill = "blue", col="blue" ) +
  #geom_density(data = densdistr[i_pre,],  col = "red",aes(x=density, y = ..density
```

```
..))+
  #geom_density(data = densdistr[i_post,], col = "blue", aes( x=density, y = ..density..)) +
  labs(x="Density [kg/m3]", y="Count (Hong Kong)") +
  xlim(c(988,991)) +geom_hline(yintercept=30, linetype=2, alpha= 0.5) #+ geom_vline(xintercept=md_post, col ="blue", linetype=2, alpha= 0.5)

multiplot(Singhistogram, HKhistogram, cols=1)



```

B.2 Running Tests

```

 setwd("~/R/VPS_Fuel_Analysis")
pdf(paste0('HFOSGSIN_HK.pdf'))

plotFulePricesWW <- function(){
  #  load('~/R/csv/VPS/FuelPriceHFO380WW.RData') #http://www.bunkerindex.com/prices/bixfree_1712.php?priceindex_id=2
  FuelPriceHFO380       <-  read.csv2("daniel_wu_bix_wwfuelprice_2018-12-20.csv", sep=";", header = T)
  FuelPriceHFO380$Date <-  as.Date(FuelPriceHFO380$Date,format='%d.%m.%Y',tz='UTC')
  names(FuelPriceHFO380)[2] <- 'IFH380_Price'

  load('~/R/csv/VPS/rawOilBrentEurope.RData')#https://fred.stlouisfed.org/series/DCOILBRENTEU
  names(oilPrice)[2] <- 'Crude_Price'
  z <- merge(oilPrice,FuelPriceHFO380,by='Date',all=T)
  #z <- z[which(!is.na(z$Price_Bunker_USD)),]
  names(z)[c(2,3)] <-c('Price_Crude_USD','Price_Bunker_USD')
   txt <- paste('Normalized prices: HFO380-Bunker (blue) and Crude oil (Brent Europe, red)')

  #normized prices
  plot(FuelPriceHFO380$Date,(FuelPriceHFO380$IFH380_Price-min(FuelPriceHFO380$IFH380_Price,na.rm=T))/max((FuelPriceHFO380$IFH380_Price-min(FuelPriceHFO380$IFH380_Price,na.rm=T)),na.rm=T),pch=19,cex=0.4,t='b',col='blue',main=txt,xlab='',ylab='rel')
  points(oilPrice$Date,(oilPrice$Crude_Price-min(oilPrice$Crude_Price,na.rm=T))/max((oilPrice$Crude_Price-min(oilPrice$Crude_Price,na.rm=T)),na.rm=T),pch=19,cex=0.4,t='b',col='red')
  grid(NULL,NULL)
  maxHFO     <- max(FuelPriceHFO380$IFH380_Price,na.rm=T)
  minHFO     <- min(FuelPriceHFO380$IFH380_Price,na.rm=T)

  maxCrude <- max(oilPrice$Crude_Price,na.rm=T)
```

```
  minCrude <- min(oilPrice$Crude_Price,na.rm=T)
  mintxt <- paste('Min: HFO=',minHFO,'$','\nCrude=',minCrude,'$',sep='')
  maxtxt <- paste('Max: HFO=',maxHFO,'$','\nCrude=',maxCrude,'$',sep='')
  text(max(FuelPriceHFO380$Date),0.9,maxtxt,adj=1)
  text(min(FuelPriceHFO380$Date),0.1,mintxt,adj=0)
  lines(c(min(FuelPriceHFO380$Date),max(FuelPriceHFO380$Date)),c(1,1),col='grey',lty
     =2)
  lines(c(min(FuelPriceHFO380$Date),max(FuelPriceHFO380$Date)),c(0,0),col='grey',lty
     =2)


  # Bunk vs crude
  txt <- 'Crude vs Bunker prices'
  plot(z$Price_Crude_USD,z$Price_Bunker_USD,pch=19,cex=0.4,t='b',col='orange',main=
     txt,xlab='Crude [$]',ylab='HFO30 [$]')
  grid(NULL,NULL)

  #fraction
  z$fract <- z$Price_Bunker_USD/z$Price_Crude_USD
  txt <- paste('Relationship between Bunker and Crude prices (Bunker$ = factor *
     Crude$)')
  plot(z$Date,z$fract,pch=19,cex=0.4,t='b',col='skyblue',ylab='Bunker/Crude',xlab=''
     ,main=txt)
  grid(NULL,NULL)

   return(z)
}
wwprice <- plotFulePricesWW()
bunkerPrice <- function(wwprice){
price_ifo380           <- read.csv("~/R/VPS_Fuel_Analysis/price_ifo380.csv",sep=';')
price_ifo380$Date_hk   <- as.POSIXct(price_ifo380$Date_hk,  format='%d.%m.%Y',tz='
    UTC')
price_ifo380$Date_sing <- as.POSIXct(price_ifo380$Date_sing,format='%d.%m.%Y',tz='
    UTC')

sing <- price_ifo380[,c(1,2)]; names(sing)<-c('Date','Sing')
hk   <- price_ifo380[,c(3,4)]; names(hk)  <-c('Date','HK')

index <- which(!is.na(sing$Date));sing <- sing[index,]
index <- which(!is.na(sing$Sing));sing <- sing[index,]

index <- which(!is.na(hk$Date));hk <- hk[index,]
index <- which(!is.na(hk$HK));   hk <- hk[index,]

price        <- merge(sing,hk,by='Date')
price$Date   <- as.Date(price$Date)
price        <- merge(price,wwprice,by='Date',all=T)
price$delta <- price$HK-price$Sing

plot(price$Date,price$HK,main='HK (black), Sing (blue), WW (orange) IFO price',ylab=
```

```
    '$',xlab='',t='b',pch=19,cex=0.3);grid(NULL,NULL)
points(price$Date,price$Sing,t='b',pch=19,cex=0.3,col='blue')
points(price$Date,price$Price_Bunker_USD,t='b',pch=19,cex=0.3,col='orange')

price$WWSG <- price$Price_Bunker_USD-price$Sing
price$WWHK <- price$Price_Bunker_USD-price$HK
plot(price$Date,price$WWSG,t='b',pch=19,cex=.4,col='blue',ylab='diff in $',
    ylim=range(price$WWSG,price$WWHK,na.rm=T),main='Price difference WW-SG (blue)
    and WW-HK (orange)')
points(price$Date,price$WWHK,t='b',pch=19,cex=.4,col='orange')
grid(NULL,NULL)

plot(price$Date[price$Date>'2017-01-01'],price$WWSG[price$Date>'2017-01-01'],t='b',
    pch=19,cex=.4,ylab='diff in $',col='blue',ylim=range(price$WWSG[price$Date>'
    2017-01-01'],price$WWHK[price$Date>'2017-01-01'],na.rm=T),main='Price difference
     WW-SG (blue) and WW-HK (orange)')
points(price$Date[price$Date>'2017-01-01'],price$WWHK[price$Date>'2017-01-01'],t='b'
    ,pch=19,cex=.4,col='orange')
grid(NULL,NULL)

price$diffHKSG <- price$WWHK-price$WWSG
plot(price$Date[price$Date>'2017-01-01'],price$diffHKSG[price$Date>'2017-01-01'],t='
    b',pch=19,cex=.4,ylab='diff in $',col='blue',main='(WW-HK) - (WW-SG)')
abline(0,0,col='red',lty=2)
grid(NULL,NULL)


plot(price$Date,price$delta,main='HK-Sing price difference',ylab='$',xlab='',t='b',
    pch=19,cex=0.3,col='blue');grid(NULL,NULL)
abline(0,0,col='red')

par(mfrow=c(1,2))
i_const <- which(price$Date>='2013-04-15' & price$Date<'2014-08-01' & !is.na(price$
    delta))
plot(price$Date[i_const],price$Sing[i_const],t='b',pch=19,cex=0.3,col='blue',ylab='
    price in SGSIN [$]',main='Near constant price regime');grid(NULL,NULL);abline
    (0,0)

plot(price$Date[i_const],price$delta[i_const],t='b',pch=19,cex=0.3,col='blue',ylab='
    price diff [$]',main='Near constant price regime');grid(NULL,NULL);abline(0,0)
z <- lm(price$delta[i_const] ~ price$Date[i_const])
lines(price$Date[i_const],fitted(z),col='red',lty=2)
summary(z)
par(mfrow=c(1,1))


par(mfrow=c(1,2))
i_decrease <- which(price$Date>='2014-09-01' & price$Date<'2016-01-01' & !is.na(
    price$delta))
plot(price$Date[i_decrease],price$Sing[i_decrease],t='b',pch=19,cex=0.3,col='blue',
```

```r
    ylab='price in SGSIN [$]',main='Decreasing price regime');grid(NULL,NULL);abline(0,0)
plot(price$Date[i_decrease],price$delta[i_decrease],t='b',pch=19,cex=0.3,col='blue',ylab='price diff [$]',main='Decreasing price regime');grid(NULL,NULL);abline(0,0)
z <- lm(price$delta[i_decrease] ~ price$Date[i_decrease])
lines(price$Date[i_decrease],fitted(z),col='darkgreen',lty=2)
summary(z)
par(mfrow=c(1,1))
d <-price$delta[i_decrease]  - fitted(lm(price$delta[i_decrease] ~ price$Date[i_decrease]))
p <- price$Sing[i_decrease] - fitted(lm(price$Sing[i_decrease] ~ price$Date[i_decrease]))


par(mfrow=c(1,2))
i_increase <- which(price$Date>='2016-01-01' & !is.na(price$Sing))
plot(price$Date[i_increase],price$Sing[i_increase],t='b',pch=19,cex=0.3,col='blue',ylab='price  [$]',main='Increasing price regime');grid(NULL,NULL);abline(0,0)
plot(price$Date[i_increase],price$delta[i_increase],t='b',pch=19,cex=0.3,col='blue',ylab='price  [$]',main='Increasing price regime');grid(NULL,NULL);abline(0,0)
z <- lm(price$delta[i_increase] ~ price$Date[i_increase])
lines(price$Date[i_increase],fitted(z),col='red',lty=2)
summary(z)
par(mfrow=c(1,1))



return(price)
}
price <- bunkerPrice(wwprice)


HFO380_SGSIN <- read.csv("HFO380_SGSIN.csv",stringsAsFactors = F)
HFO380_HKHKG <- read.csv("HFO380_HKHKG.csv",stringsAsFactors = F)

#delta - density
Fuel_comparison <- function(Fuel,dRange =c(988,991),txt='XXX',txtparameter='deltaDensity', H1='dd_is_less'){
  deltaDens_com <- function(Fuel, densityRange =c(989.5,989.6),para =txtparameter){
    i_post   <- which(Fuel$Date >='2017-01-01' )
    i_pre    <- which(Fuel$Date < '2016-01-01' )
    d_post   <- Fuel$density[i_post]
    d_pre    <- Fuel$density[i_pre ]
    dd_post <- Fuel[i_post,which(names(Fuel)== para)]
    dd_pre   <- Fuel[i_pre, which(names(Fuel)== para)]
    x <- data.frame(d=c(d_pre,d_post),dd=c(dd_pre,dd_post), ind=c(rep('pre',length(dd_pre)),rep('post',length(dd_post)) ))
    x <- x[order(x$d),]
    x <- x[which(!is.na(x$d)),]
```

```
  x <- x[which(!is.na(x$dd)),]

  y <- x[which(x$d> densityRange[1] & x$d<=densityRange[2]),]
  dd_pre    <- y$dd[y$ind=='pre']
  dd_post   <- y$dd[y$ind=='post']
  n_pre     <- length(dd_pre)
  n_post    <- length(dd_post)

 m_pre  <- mean(dd_pre)
 m_post <- mean(dd_post)

  sd_pre  <- sd(dd_pre)
  sd_post <- sd(dd_post)
# m              <- m_post-m_pre
# conf_interval <- c(round(m + 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3),round(m - 1.96*sqrt(sd_pre^2/n_pre+sd_pre^2/n_post),3))
# conf_interval <- sort(conf_interval)
  tTest          <- t.test(dd_post, dd_pre)
  conf_interval <- tTest$conf.int
 m <- diff(rev(tTest$estimate))

  # wilcoxson test of difference in mean
  if(H1=='dd_is_less') H1='less' else if(H1=='dd_is_greater') H1='greater' else H1="two.sided"
  dat     <- data.frame( allData = c(dd_post,dd_pre), dataClasses = c(rep("post",length(dd_post)),rep("pre",length(dd_pre))) )
 if(sd_pre==0 & sd_post==0){
   W_diffInDD    <- round(m_post-m_pre,3)
   W_confInt     <- rep(W_diffInDD,2)
 }else{
   W       <- stats::wilcox.test(allData ~ dataClasses, data = dat,conf.int = T, correct = T, exact = F, conf.level = .95)#,alternative =H1)
  W_diffInDD    <- round(W$estimate,3)
  W_confInt     <- round(W$conf.int,3)
 }

  #variance test
  p_homogenVarianceTest <-    fligner.test(x=y$dd,g=y$ind)$p.value #http://www.sthda.com/english/wiki/compare-multiple-sample-variances-in-r
  var_post__var_pre      <-    sd_post-sd_pre

  #Normality test
  if(sd_pre==0 & sd_post==0){
    p_shapiroNorm_pre <- 1
    p_shapiroNorm_post <-1
  }else{
  p_shapiroNorm_pre      <-    shapiro.test(y$dd[y$ind=='pre' ])$p.value #http://www.sthda.com/english/wiki/normality-test-in-r
  p_shapiroNorm_post     <-    shapiro.test(dd_post)$p.value
  }
```

```
    if(length(grep('REPORT',para)==1)){
      p_pre      <- length(which(dd_pre  >0.1))/n_pre
      p_post     <- length(which(dd_post >0.1))/n_post
      p_diffConf <- 1.96*sqrt(p_pre*(1-p_pre)/n_pre + p_post*(1-p_post)/n_post )

      p_diff     <- p_post-p_pre
      p_pooled <- ( length(which(dd_pre  >0.1)) + length(which(dd_post >0.1)) )/(n_pre+n_post)
      Z <- (p_diff)/(sqrt(p_pooled*(1-p_pooled))*sqrt(1/n_pre +1/n_post))
      if(is.nan(Z)) Z <- 0
      #http://www.sthda.com/english/wiki/two-proportions-z-test-in-r
      fract_diff   <- p_diff

    }else{
      fract_diff   <- NULL
      p_diffConf   <- NULL
    }

    conf_interval <- c(m,conf_interval,fract_diff,p_diffConf,W_diffInDD,W_confInt,p_homogenVarianceTest,var_post__var_pre,p_shapiroNorm_pre,p_shapiroNorm_post)

    return(conf_interval)
}

Fuel$density      <- as.numeric(Fuel$density)
Fuel$deltaDensity <- as.numeric(Fuel$deltaDensity)



#NAive approach in dd
preDD  <- na.omit(Fuel$deltaDensity[Fuel$Date<'2016-01-01'& Fuel$deltaDensity>-2 & Fuel$deltaDensity<6] )
postDD <- na.omit(Fuel$deltaDensity[Fuel$Date>='2017-01-01'& Fuel$deltaDensity>-10 & Fuel$deltaDensity<6])
pred   <- density(preDD)
postd  <- density(postDD)
plot(pred, col='blue',lwd=2,ylab='',main=paste0(txt,': Density difference \npost (>=2017, red) and pre(<2016, blue)'),xlab='density difference [kg/m^3]')
#polygon(pred, col="red", border="blue")
lines(postd,col='red',lwd=2)
#polygon(postd, col="green", border="blue")
lines(c(0,0),c(0,1),lty=2,col='black')
grid(NULL,NULL)

print('Naive approach: Using ALL data')
tTest <- t.test(preDD,postDD,var.equal = F)
names(tTest$estimate) <- c('meanDD_pre','meanDD_post')
print(tTest)
if(tTest$p.value < 0.05){
```

```
    print('Naive approach (all data): H0: rejected, i.e. there IS a difference in deltaDensity')
    #estimate_x = preDD estimate_y =postDD
    if((tTest$estimate[1]-tTest$estimate[2]) > 0) H1<-"greater" else H1<-"less"  # post-pre
    tTest <- t.test(preDD,postDD,var.equal = F,alternative =  H1)
    if(tTest$p.value < 0.05){
      names(tTest$estimate) <- c('meanDD_pre','meanDD_post')
      print(tTest)
      print(paste0('Mean-density-difference for <2016 is significantly (at 95% conf)',H1,' than after 2017.'))
    }

    }else print('Naive approach (all data): H0: NOT rejected, i.e. there is NO difference in deltaDensity')



  #Naive approach change in nr of SL samples
  if(length(grep('REPORT', txtparameter))==1){
    print('')
    print('Naive approach: Using ALL data')

    preSL  <- Fuel[which(!is.na(Fuel$REPORT_SHORT_LIFT_BENCHMARK) & Fuel$Date<'2016-01-01'),]
    postSL <- Fuel[which(!is.na(Fuel$REPORT_SHORT_LIFT_BENCHMARK) & Fuel$Date>='2017-01-01'),]

    p_pre  <- length(which(preSL$REPORT_SHORT_LIFT_BENCHMARK  >0.1))/nrow(preSL)
    p_post <- length(which(postSL$REPORT_SHORT_LIFT_BENCHMARK >0.1))/nrow(postSL)
    p_diff <- p_post-p_pre
    p_diffConf <- 1.96*sqrt(p_pre*(1-p_pre)/nrow(preSL) + p_post*(1-p_post)/nrow(postSL) )
    print(paste('Difference in fract. of SL samples (post-pre): ',round(p_diff,3) ,', [',round(p_diff - p_diffConf ,3),',', round(p_diff + p_diffConf ,3),'] = 95% conf. interval'))
    print('If conf.intervals contains 0 => no signif. difference in fraction of SL (at 95% level)')
    ci       <- c(p_diff - p_diffConf,p_diff + p_diffConf)
    signDiff <- sum(sign(ci))*prod(ci)

    if(signDiff!=0){
      p_pooled <- (length(which(preSL$REPORT_SHORT_LIFT_BENCHMARK >0.1)) + length(which(postSL$REPORT_SHORT_LIFT_BENCHMARK>0.1)))/(nrow(preSL)+nrow(postSL))
      Z        <- p_diff/(sqrt(p_pooled*(1-p_pooled))*sqrt(1/nrow(preSL) +1/nrow(postSL)))
          if(abs(Z) < 1.64){
            print(paste('Naive approach (all data): No significant difference (',round(p_diff,3),') in fraction,of SL-BM between post and pre at 95% confidence'))
```

```
            }else print(paste('Naive approach (all data): Significant difference (',
    round(p_diff,3), ') in fraction of SL-BM between post and pre at 95% confidence'
    ))
     }



#http://www.sthda.com/english/wiki/two-proportions-z-test-in-r
  }


  #Density distribution all data
  preDD  <- na.omit(Fuel$density[Fuel$Date<'2016-01-01'] )
  postDD <- na.omit(Fuel$density[Fuel$Date>='2017-01-01'])
  pred   <- density(preDD)
  postd  <- density(postDD)
  plot(pred, col='blue',lwd=2,main=paste0(txt,': HFO380 Fuel Density \npre(<2016,
    blue) and post(>=2017, red)'),xlab='Fuel density [kg/m^3]',ylab='')
  #polygon(pred, col="red", border="blue")
  lines(postd,col='red',lwd=2)
  #polygon(postd, col="green", border="blue")
  lines(c(0,0),c(0,1),lty=2,col='black')
  grid(NULL,NULL)




  #restrict to bins with highnumber of samples
  Fuel              <- Fuel[Fuel$density > dRange[1] & Fuel$density <= dRange[2]  ,]
  #Fuel density plot
  bin    <- seq(dRange[1],dRange[2],0.1)
  h_pre  <- hist(Fuel$density[Fuel$Date<'2016-01-01'],breaks = bin,
               main=paste(txt,': Density in kg/m^3'),xlab='density [kg/m^3]',xlim=
    range(bin),col='skyblue',freq = F,plot=F)
  h_post <- hist(Fuel$density[Fuel$Date>='2017-01-01'],breaks = bin,xlim=range(bin),
    add=T,freq = F,plot=F)
  z_pre    <- data.frame(binEnd=h_pre$breaks[-1],Density = h_pre$density,  farge=rep(
    'skyblue'),stringsAsFactors = F)
  z_post  <- data.frame(binEnd=h_pre$breaks[-1],Density = h_post$density, farge=rep(
    'orange'), stringsAsFactors = F)
  z        <- rbind(z_pre,z_post)
  z        <- z[order(z$Density,decreasing = T),]
  z        <- z[order(z$binEnd, decreasing = F),]
  bp <- barplot(z$Density[seq(1,nrow(z),2)]*0.1,col=z$farge[seq(1,nrow(z),2)],main=
    paste(txt,': Density in kg/m^3 (non-stacked)\n blue: <=2015, orange: >= 2017'),
              xlab='',names.arg = z$binEnd[seq(1,nrow(z),2)],las=3)
  bp <- barplot(z$Density[seq(2,nrow(z),2)]*0.1,col=z$farge[seq(2,nrow(z),2)],add=T)
  grid(NULL,NULL)
  text(bp[1],0.05,'influx of lighter fuel \nafter 2017-01-01',adj=0)
```

```



 #**********************************
 result <- NULL
 for(i in 1:(length(bin)-1)) result <- rbind(result, c(bin[i],bin[i+1],deltaDens_com(Fuel,densityRange =c(bin[i],bin[i+1]),para =txtparameter)))
 result          <- data.frame(result)
 if(length(grep('REPORT', txtparameter))==1){
       names(result) <- c('densFrom','densTo','meanDiff','lowConfInt','highConfInt','fract_diff','p_diffConf','W_diffInDD','W_lowconfInt','W_highconfInt','homoVar_p','var_post__var_pre','p_shapiroNorm_pre','p_shapiroNorm_post')
 }else names(result) <- c('densFrom','densTo','meanDiff','lowConfInt','highConfInt','W_diffInDD','W_lowconfInt','W_highconfInt','homoVar_p','var_post__var_pre','p_shapiroNorm_pre','p_shapiroNorm_post')
for(i in 1:nrow(result))for(j in 1:ncol(result))if(is.nan(result[i,j])) result[i,j] <- NA
#***************************************



   #difference in number of samples
 if(length(grep('REPORT', txtparameter))==1){
   signMeanDiff <- (sign(result$fract_diff- result$p_diffConf)+sign(result$fract_diff+ result$p_diffConf))/2
   farge <- rep('grey',nrow(result))
   i      <- which(signMeanDiff>0);if(length(i)>0)farge[i]<-'forestgreen'
   i      <- which(signMeanDiff<0);if(length(i)>0)farge[i]<-'red'
     bp<- barplot(result$fract_diff,col=farge,ylab='difference in fraction',main=paste0(txt,': Difference in fraction of ocurrence of \n',txtparameter,'>0.1 between post(>=2017) and pre(<2016)'))
   grid(NULL,NULL)
   arrows(x0 = bp,
          y0 = result$fract_diff- result$p_diffConf,
          x1 = bp,
          y1 = result$fract_diff+ result$p_diffConf,
          lwd= 1.5,angle=90,code=3,length=0.05,col='blue')
 }

 #Normal based conf interval
 result$signMeanDiff <- (sign(result$lowConfInt)+sign(result$highConfInt))/2
 farge <- rep('grey',nrow(result))
 i      <- which(result$signMeanDiff>0);if(length(i)>0)farge[i]<-'forestgreen'
 i      <- which(result$signMeanDiff<0);if(length(i)>0)farge[i]<-'red'

 bp <- barplot(result$meanDiff,col=farge,names.arg =bin[-1],las=3,ylab='diffference in mean',xlab='',ylim=range(result$lowConfInt,result$highConfInt,na.rm=T),
                 main=paste0('Difference in mean ',txtparameter,' for ',txt,' based on t-test \nbetween post (>2017) and pre (<2016), grey= non-signif. (@ 5%level)'))
 points(bp,result$meanDiff,pch=19,cex=0.4,col=farge)
```

```
grid(NULL,NULL)
arrows(x0 = bp,
        y0 = result$lowConfInt,
        x1 = bp,
        y1 = result$highConfInt,
        lwd= 1.5,angle=90,code=3,length=0.05,col='blue')

#wilcoxson based densdiff estimate
signMeanDiff <- (sign(result$W_lowconfInt)+sign(result$W_highconfInt))/2
farge <- rep('grey',nrow(result))
i      <- which(signMeanDiff>0);if(length(i)>0)farge[i]<-'forestgreen'
i      <- which(signMeanDiff<0);if(length(i)>0)farge[i]<-'red'
bp <- barplot(result$W_diffInDD,col=farge,names.arg =bin[-1],las=3,ylab='difference in mean',xlab='',ylim=range(result$W_lowconfInt,result$W_highconfInt),
              main=paste0('Difference in mean ',txtparameter,' for ',txt,' based on Wilcinson test \nbetween post (>2017) and pre (<2016), grey= non-signif. (@5%level)'))
points(bp,result$W_diffInDD,pch=19,cex=0.4,col=farge)
grid(NULL,NULL)
arrows(x0 = bp,
        y0 = result$W_lowconfInt,
        x1 = bp,
        y1 = result$W_highconfInt,
        lwd= 1.5,angle=90,code=3,length=0.05,col='blue')



par(mfrow=c(3,1))
#Normality test of data per bin based on Shapiro testen
farge <- rep('grey',nrow(result))
i  <- which(result$p_shapiroNorm_pre < 0.05);if(length(i)>0) farge[i]<-'red'
bp <- barplot(result$p_shapiroNorm_pre,col=farge,main=paste0(txt,': Shapiro test for H0: normality in ',txtparameter,' < 2016 \n if p< 0.05 (red) => not normal distributed'),
              names.arg =bin[-1],las=3,ylab='p-value',xlab='' )
points(bp,result$p_shapiroNorm_pre,pch=19,cex=0.4,col=farge)
if(length(i)>0) text(bp[i],0.05, round(result$p_shapiroNorm_pre[i],3),col='red',srt=90,adj=0)
abline(0.05,0,col='red',lty=2)

#Normality test of data per bin based on Shapiro testen
farge <- rep('grey',nrow(result))
i      <- which(result$p_shapiroNorm_post < 0.05)
if(length(i)>0) farge[i]<-'red'
barplot(result$p_shapiroNorm_post,col=farge,main="Shapiro-Wilk Test (Normality): Hong Kong",
        names.arg =bin[-1],las=3,ylab='p-value',xlab='' )
points(bp,result$p_shapiroNorm_post,pch=19,cex=0.4,col=farge)
if(length(i)>0) text(bp[i],0.05, round(result$p_shapiroNorm_post[i],3),col='red',
```

```
    srt=90,adj=0)
  abline(0.05,0,col='red',lty=2)

  #Test of same variance data per bin based on fligner testen
  farge <- rep('grey',nrow(result))
  i     <- which(result$homoVar_p < 0.05)
  if(length(i)>0) farge[i]<-'red'
  bp <- barplot(sign(result$var_post__var_pre),col=farge,main=paste0(txt,': Fligner
    test for H0: same variance (var_post - var_pre = 0) in ',txtparameter,'\n if p<
    0.05 (red) => not same variance'),
                names.arg =bin[-1],las=3,ylab='var_post - var_pre',xlab='density bin
    ')
  points(bp,result$var_post__var_pre,pch=19,cex=0.4,col=farge)
  if(length(i)>0) text(bp[i],0.05, round(result$homoVar_p[i],3),col='black',srt=90,
    adj=0)
  abline(0.05,0,col='red',lty=2)

  par(mfrow=c(1,1))

  return(result)
}

rSGSIN <- Fuel_comparison(HFO380_SGSIN,txt='SGSIN',txtparameter='deltaDensity')
rHKHKG <- Fuel_comparison(HFO380_HKHKG,txt='HKHKG',txtparameter='deltaDensity')


#shortliftingBM
rSGSIN <- Fuel_comparison(HFO380_SGSIN,txt='SGSIN',txtparameter='REPORT_SHORT_LIFT_
    BENCHMARK')
rHKHKG <- Fuel_comparison(HFO380_HKHKG,txt='HKHKG',txtparameter='REPORT_SHORT_LIFT_
    BENCHMARK')

rSGSIN <- Fuel_comparison(HFO380_SGSIN,txt='SGSIN',txtparameter='REPORT_MAX_SHORT_
    BENCHMARK')
rHKHKG <- Fuel_comparison(HFO380_HKHKG,txt='HKHKG',txtparameter='REPORT_MAX_SHORT_
    BENCHMARK')
dev.off()
```

Daniel Wu

Investigation of the Effects of Mass Flow Meters on the Singaporean Bunker Industry

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