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Nowcasting GDP of Singapore through-the-lens of maritime trade and services

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NOWCASTING GDP OF SINGAPORE THROUGH-THE-LENS OF MARITIME TRADE AND SERVICES

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DECLARATION

We certify that all the material in this dissertation that is not our own work has been identified, and that no material is included for which a degree has previously been conferred on us.

The contents of this dissertation reflect our own personal views, and are not necessarily endorsed by the University.



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ABSTRACT

Title of Dissertation: **Nowcasting GDP of Singapore Through-the-Lens of Maritime Trade and Services.**

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Nowcasting can play an important role in giving policy-makers timeline insights regarding the information published with a significant time lag. Using the nowcasting tool, Dynamic Factor Model (DFM), this dissertation nowcasts the GDP and its components, such as manufacturing, transportation and storage, financial and insurance services, and IIP, through-the-lens of maritime trade and services. This study also represents the first attempt to incorporate 29 high-frequency maritime trade flows (based on real-time AIS data), shipping, port, and logistics data into this model to predict macroeconomic variables.

As a leading maritime nation, this dissertation examines Singapore as a case country because of its thriving economy due to maritime trade and services. It is also strategically recognized for its pro-business policies and as a premier maritime and aviation hub.

The findings reveal that maritime trade flows and shipping activities significantly impact these macroeconomic factors, and the model can provide accurate forecasts. Thus, this dissertation adds value to the maritime and shipping industry. It also showcases the end of period nowcasting of GDP and its core components and IIP, which may be utilised by policymakers, central banks, market watchers, and maritime practitioners to track the state of the economy and develop appropriate policies for future economic development. Similarly, this also provides value to maritime industry stakeholders and policymakers for informed investment decisions.

KEYWORDS: Dynamic Factor Model (DFM), GDP, Maritime trade, Nowcasting, Macroeconomic factors, Singapore.

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LIST OF ABBREVIATIONS

AIS	Automatic Identification System
ASEAN	Association of Southeast Asian Nations
ASF	Asian Shipowners Forum
BIMCO	Baltic and International Maritime Council
BSI	Baltic Exchange Supramax Index
BoP	Balance of Payment
BoT	Balance of Trade
CPI	Consumer Price Index
COVID-19	Coronavirus
DFM	Dynamic Factor Model
DWT	Deadweight tonnage
GDP	Gross Domestic Product
GFC	Global Financial Crisis
ECB	European Central Bank
EXIM	Export-Import
FDI	Foreign Direct Investment
FI	Financial institution
FM	Factor Model
FOREX	Foreign Exchange
FPSO	Floating Production Storage and Offloading
GDFM	General Dynamic Factor Model
H&M	Hull and Machinery
HSFO	Heavy Sulphur Fuel Oil
IACFI	Inter-Asia Container Freight Index
IBIA	International Bunker Industry Association
ICS	International Chamber of Shipping
INTERTANKO	International Association of Independent Tanker Owners
IIP	Index of Industrial Production
IMF	International Monetary Fund
IT	Information Technology
KFS	Kalman Filtering and Smoothening
LIBOR	London Interbank Offered Rate
LSCI	Liner Shipping Connectivity Index
MAS	Monetary Authority of Singapore
MFI	Maritime Finance Incentive
MF-VAR	Mixed Frequency Vector Auto Regressive
MGO	Marine Gas Oil
MIDAS	Mixed Data Sampling
ML	Maximum Likelihood
MPA	Maritime and Port Authority
MTI	Ministry of Trade and Industry
MOT	Ministry of Transport

MoU	Memorandum of Understanding
MVA	Manufacturing Value Added
OECD	Organisation for Economic Co-operation and Development
P&I	Protection and Indemnity
PCA	Principal Component Analysis
pch	percentage change
PCI	Port Congestion Index
PMI	Purchasing Manager Index
PPI	Producer Price Index
PSA	Port of Singapore Authority
PSC	Port State Control
PPP	Purchasing Power Parity
SAARC	South Asian Regional Cooperation Organisation
SCFI	Shanghai Containerized Freight Index
SGD	Singaporean Dollar
SOMS	Straits of Malacca and Singapore
SRS	Singapore registry of Ships
TEU	Twenty-foot equivalent unit
XMPIs	Export and Import Price Indices
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
US	United States
USD	US Dollar
WTO	World Trade Organisation

Chapter One: Introduction

In light of recent events in the world economy, such as market fluctuations, pandemics, etc., it is difficult to ignore the tracking of economic activity through-the-lens of maritime trade and services. However, it is the centre of attention of the policy-makers and economists to be aware of key economic indicators and forecast them accurately, most importantly GDP, which measures the overall health of the economy but is published in a significant delay by the official statistics. In that situation, a real-time nowcasting approach eases sound policymaking by reconstructing GDP and other indicators. This dissertation considers Singapore to nowcast GDP and its core components influenced mainly by maritime trade and services. This country serves as a transhipment hub of most Asian countries, with the second-highest liner shipping connectivity in the world.

However, this chapter attempts to discuss the background of this study by defining the underlying problems of nowcasting GDP. Afterwards, this dissertation's key aims and objectives are presented by answering research questions. Besides, this study's motivation, contribution, and significance have been discussed briefly. Finally, the challenges and limitations of this study have been presented.

1.1 Background of the Study

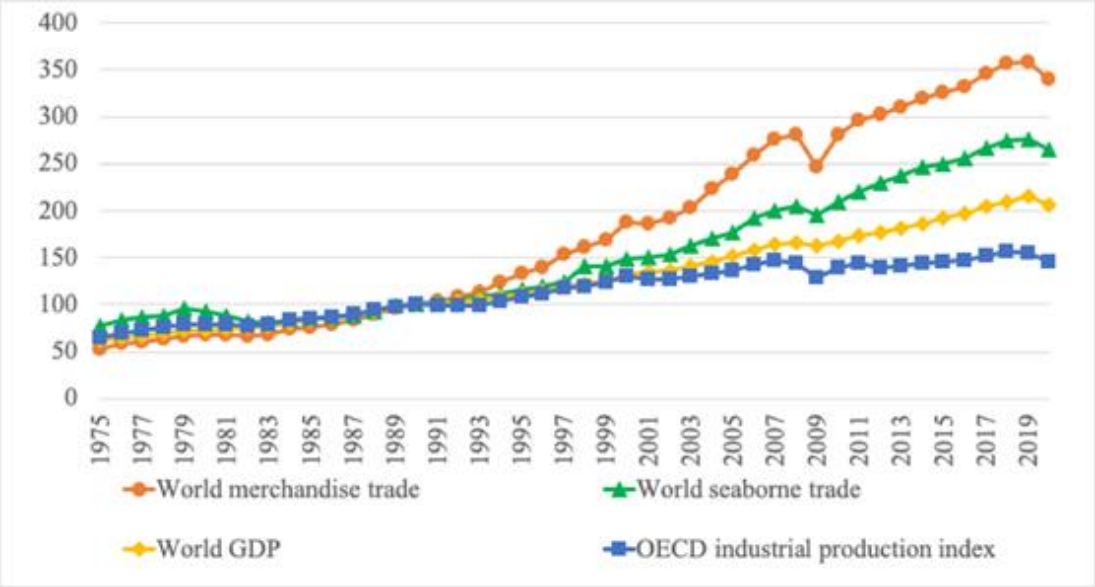
Over the last few decades, international seaborne trade and shipping connectivity have become increasingly important due to globalisation. The global shipping industry contributes to about 85% of the world's trade volume (International Chamber of Shipping [ICS], 2021). The main reasons for the said increase are due to the world's dependence on water as a mode of transportation and the fuel efficiency of seaborne freight (Lane & Pretes, 2020).

Nearly 11 billion tons of cargo were transported by sea globally in 2018 (UNCTAD, 2019). Figure 1's depiction of data from UNCTAD and recent updates reveal that

global commerce, particularly seaborne trade, surpassed two important industrial indices, including the global GDP.

Figure 1.

Share of merchandise trade, seaborne trade, GDP and OECD Industrial Production Index



Note: The data and statistics are from the United Nations Conference on Trade and Development [UNCTAD], (2020)

The relationship between economic growth and industrial activity is shown in the figure above, with the OECD Industrial Production Index, trade in goods, and seaborne shipments serving as the key indicators. Up until 1995, it was observed that global merchandise trade, world seaborne trade, OECD industrial output index, and global GDP all moved in unison. The need for maritime trade and transport services continues to be influenced by global economic growth and the need to convey maritime trade, even though the responsiveness of trade to GDP growth has slowed in recent years. Undoubtedly, the global shipping industry provides the backbone of logistics operations for supply chains and international seaborne trade.

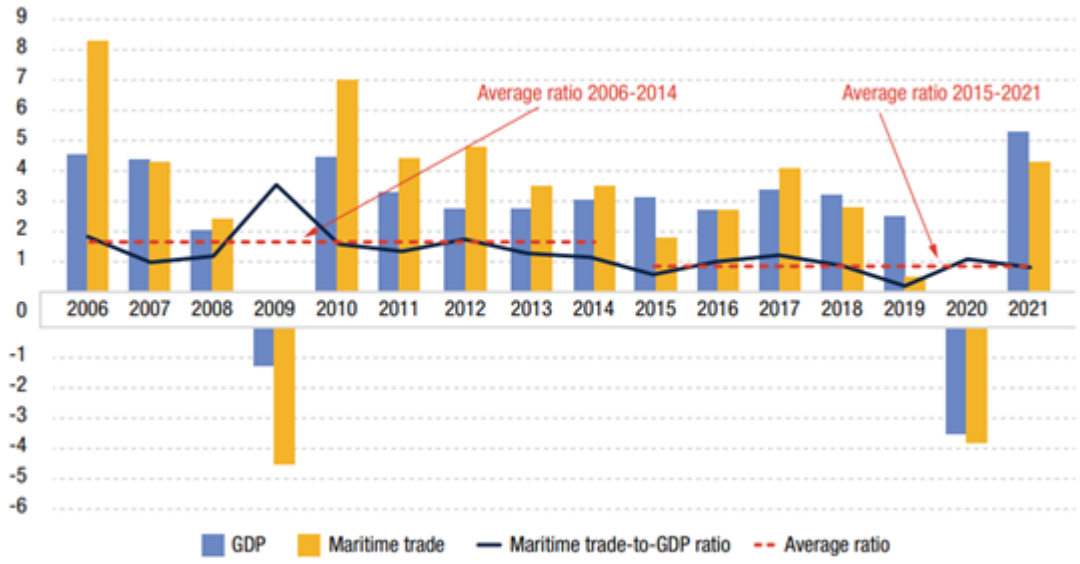
In addition, with the development in the maritime and shipping field, such as the establishment of the Suez and Panama canals, maritime shipping has taken global

trade to a new level, with nearly every part of the world now connected and nations being more deeply integrated.

Figure 1 also showed that the world economy and the global trade system reached a turning point in 2008, as the GFC that had started in the US deepened and entered a more severe phase, making the world economy's growth abruptly decelerated during the last part of 2008 (UNCTAD, 2009). This crisis continued the following year, when global trade volume experienced its greatest decline. UNCTAD (2010) even reported the year 2009 as the worst year for economic contraction in over seven decades. In line with the economy's collapse, international seaborne trade declined by almost five percent in the same year. To make things worse, even during the said recession, the shipping industry continued to see a surge in oversupply and falling charter and freight rates as the industry's capacity grew.

Figure 2.

International maritime trade to world GDP ratio from 2006 to 2021



Note: The data and statistics are from the United Nations Conference on Trade and Development [UNCTAD] (2021). Review of Maritime Transport 2021. (https://unctad.org/system/files/official-document/rmt2021ch3_en.pdf)

As the debates continued regarding the status of the economy as uneven and fragile; the global recovery began early in 2010, which was sparked by fast-growing

economies like China. In most advanced economies, the weak economic conditions and potential winding down of stimulus packages posed challenges to the sustainability of the recovery. After the financial crisis, the following years saw trade recovery in general. However, overcapacity issues in shipping remained, and then came the emergence of COVID-19 in 2020. Interestingly, the disruption caused by the pandemic did not appear to have negative effects on maritime transport as it may be observed that the volume decline was less dramatic than expected in 2020 and had begun to rebound by the end of the year, laying the groundwork for the transformation of global supply chains and a new pattern of maritime trade (UNCTAD, 2021). While looking at the international maritime trade to world GDP ratio, it can be seen that the year 2021 has increased and remained positive compared to 2020 (Figure 2) despite supply chain disruptions, pandemic-induced logistics operations, port congestions, changes in globalisation patterns, soaring freight rates and surcharges (UNCTAD, 2021).

Over the last few decades, a growing number of researches have been conducted for nowcasting GDP using the DFM, such as Stock & Watson (2002), Forni et al. (2004, 2005), and Giannone et al. (2008), among others and made notable improvements. The difficulty of condensing several variables for forecasting and other applications has recently received attention in the econometric literature (Bragoli & Fosten, 2018).

The DFM discussed will be utilised to nowcast Singapore's GDP. The researchers have concentrated on this country not only because it is considered one of the fastest-growing economies in the world, but also because the government of Singapore is interested in disclosing information about its GDP and other economic indicators, such as indices. Singapore's GDP is only released to the public once every three months after a six-week delay and frequently after significant changes. To provide the most accurate and timely tracking of the economic situation, the policymakers must have a precise and timely estimate of GDP for the current to upcoming quarter.

Recognising the massive impact from the maritime trade perspective on GDP, it is increasingly vital to observe GDP through-the-lens of maritime and shipping. This dissertation applies the nowcasting approach from a maritime trade perspective.

1.2 Problem Statement

GDP is affected by considerable uncertainty around the global macroeconomic outlook, such as geopolitical risks, with the trajectory of the pandemic that could manifest through supply chain disruptions in maritime trade and shipping activities. As a result, nowcasting the GDP is a frequently stated problem in macroeconomics. Singapore has weathered through the financial crisis of 1997 and 2008 and the worst COVID-19 surge in 2020, but suffered economically because they failed to forecast the economic activity accurately. Being an export-oriented country, the economy of Singapore is mainly driven by merchandise exports of electronics & machineries, manufacturing, transportation and storage, port activities, financial services, and tourism activities.

While looking into the macroeconomic issues from the maritime viewpoint, monitoring the trade activity in real-time and forecasting the maritime trade flows is beneficial to the country. There is an urgent need to address these concerns by monitoring the macroeconomic factors from the maritime trade perspectives that significantly impact any economy, such as Singapore.

Furthermore, new challenges such as the persistent increase in inflation rate and slowing down of economic recovery will keep eyes focused on how the macroeconomic policy of Singapore reacts. Market watchers and investors are also observing how macroeconomic policies can address long-term challenges such as climate change, income inequality, and supply chain disruptions that negatively affect the reputation of the nation's pro-business environment and financial stability.

1.3 Research Questions

In view of making effective policy decisions, a real-time evaluation of the state of the economy is required. A successful policy is made depending on how well the information available at the moment is used. Utilising the current information flow is

also crucial to creating a policy that focuses on the future (Bhadury et al., 2019). To address the issues mentioned above, this dissertation attempted to find the answers to the following questions:

1. What are the end-of-period nowcasting information for macroeconomic factors (i.e., GDP, IIP, manufacturing, transportation and storage, financial and insurance services) for Singapore?
2. What are the critical maritime trade factors, and how much do they impact these macroeconomic variables?

3. How can relevant stakeholders of the Singaporean economy make policy decisions based on this nowcast information?

1.4 Objectives of the Study

Nowcasting or forecasting the GDP is of great interest among economists and policymakers in assessing the current economic climate for crafting an optimal monetary policy.

The general objective of this dissertation was to nowcast GDP and its core components such as manufacturing, transportation and storage, financial and insurance services as well as the Index of Industrial Production (IIP) of Singapore through-the-lens of maritime trade, and services.

Specifically, this study aimed to:

1. Identify and estimate the key maritime trade flows, shipping, port, and logistics-related variables that are either positively or negatively influencing the macroeconomic factors;
2. Explain the impact of maritime trade on the macroeconomic factors of Singapore to facilitate policy decisions; and,
3. Discuss how to maximise the use of end-of-period nowcasting information for appropriate policy decisions.

1.5 Motivation for this study

Even though many nowcasting studies concentrate on developing nowcasting models for GDP, no one has used data from the maritime and shipping industry. This dissertation assesses a DFM from the standpoint of the maritime, shipping, and port industry. It presents a chance to use maritime data to get a head start in understanding physical trade in commodities. Before official economic development or trade statistics are released, ship movements, schedules, and port traffic data are frequently accessible at short notice (UNCTAD, 2020). The goal of using the timeliness and actual informational content in some economic variables to anticipate others is what typically connects the many approaches to solving the nowcasting challenges.

With 85% of the world's share, maritime trade and services remain the backbone of economic prosperity from the dawn of civilization. Although in the earlier times, it was impossible to track the economic activity accurately from the lens of maritime trade and services due to a lack of real-time data. Voyages of cargo ships carrying most of the international trade are now easier to follow, trace and monitor the trade flows in real-time using the Automatic Identification System (AIS). This technology generating big data can help with policymaking through supporting official statistics based on conventional data sources and surveys in terms of timeliness, granularity, and, in some situations, correctness.

Furthermore, this dissertation is primarily looking at the macroeconomic factors of Singapore because it is a small economy with a stable GDP growth rate and substantial maritime trade, port, and shipping business exposure. Additionally, from ancient times, Singapore has served as a vital sea lane for international maritime trade in the Straits of Malacca and Singapore (SOMS) because of its strategic and economic importance in the Southeast Asian region. It provides unparalleled connections for passengers and cargoes and is particularly advantageous for accessing Asian economies. Lastly, its unique capabilities and expertise make Singapore an attractive business location globally. Hence, shipping companies and shipping-related businesses (e.g., ship financing, ship broking, risk management,

and marine insurance) are encouraged to set up their headquarters in the country, which indirectly affects its GDP (Maritime Singapore, 2022).

As a result, it will be interesting to observe how the changes in trade, shipping, logistics, and port industries influence Singapore's macroeconomic factors, which may be positive or negative.

1.6 Contribution of this study

The economy of Singapore as a case country for monitoring the macroeconomic situation through a nowcasting tool remains the scope of this dissertation. The importance and originality of this study is nowcasting the GDP of Singapore and its key components such as manufacturing, transportation and storage, and financial and insurance services, as well as the IIP that are mostly influenced by the maritime trade flows, shipping, port, and logistics activities. Various high-frequency indicators are applied in this study, separated into four main groups: maritime trade, shipping, port, logistics, and others.

There are some key areas where this dissertation will contribute. Firstly, this will be the first ever contribution of nowcasting the macroeconomic variables through-the-lens of maritime trade and services for Singapore. It employs DFM using a dataset of high-frequency potential predictors from the AIS real-time data which are privately available sources of information for analysing the maritime trade patterns of a country from scratch. Additionally, it combines it with other economic and financial variables available in different databases such as SingStat, IMF, data.gov.sg, etc. This can improve the timeliness and reliability of official trade statistics and may even reveal the emerging pattern of international trade in a country.

Secondly, the experimental work presented here provides one of the first investigations into how these maritime and shipping indicators from the dataset are useful for nowcasting the GDP, its components, and the IIP. Nowcasting results of different macroeconomic factors will also sharpen the ability of the policymakers to identify the emerging market risks in maritime trade flows. Moreover, the results of may also serve as an early yardstick or indicator for the probable investing countries

and the host countries to decide on which sector to invest in and how much to invest depending on expected growth prospects.

Thirdly, this study nowcasts the macroeconomic factors of Singapore and benchmarks the end-of-period nowcasting results against the actual official data release. As a result, this study shows the impacts of maritime trade and shipping variables on these macroeconomic factors. It would also be most helpful in determining the business cycles, fluctuations, and market volatility, especially for the small open economies such as Singapore that heavily depend on seaborne trade and maritime activities. Hence, the investors can use the advanced nowcasting results of finance and insurance components and place their investing decisions well in advance.

Finally, this dissertation suggests some interesting implications for industry practitioners and literature, such as contributing to a nascent and growing literature that uses AIS data to monitor maritime trade activity in real time.

1.7 Challenges and Delimitations

The main limitation of this study is that it encompasses the observed macroeconomic factors, such as the GDP and its subcomponents, from an economic perspective in general. Into the bargain, it can also be observed from a different lens, such as agriculture, manufacturing, or services. Still, this dissertation is focused only on nowcasting these factors through-the-lens of maritime trade and services.

In addition, due to practical constraints in terms of finding relevant literature in maritime fields, wherein most of the articles discuss only the GDP of a country as a whole without using maritime data, the reader should bear in mind that the dissertation will be unable to provide a comprehensive review of literature in that area.

While examining the AIS data about maritime factors concerning vessel calls, the input data is available almost weekly, daily, and even hourly. Such information is

being updated on a real-time basis, which would offer more accurate and timely results. However, this dissertation has considered only monthly frequency data to observe quarterly variables. Furthermore, accessing all the AIS data was impossible due to time constraints and the inaccessibility of different maritime databases.

For nowcasting macroeconomic variables, nowcasters need to consider many variables that arrive sequentially. Thus, when new information becomes available throughout the quarter, they can adjust the information from data releases and revisions. However, this model would produce accurate and reliable nowcasts if more high-frequency indicators (i.e. weekly, daily or hourly) could be incorporated into the model. Still, due to the unavailability of sufficient maritime trade and shipping data, this study does not incorporate these data.

1.8 Disposition

The overall dissertation structure takes the form of seven chapters and the structure is organised as follows (in Figure 3).

Chapter 1 provides the introduction and background for this dissertation regarding nowcasting the GDP of Singapore using maritime trade and services. This is followed by the discussion of the problem statement, objectives, research questions, significance and the challenges and/or limitations of this dissertation.

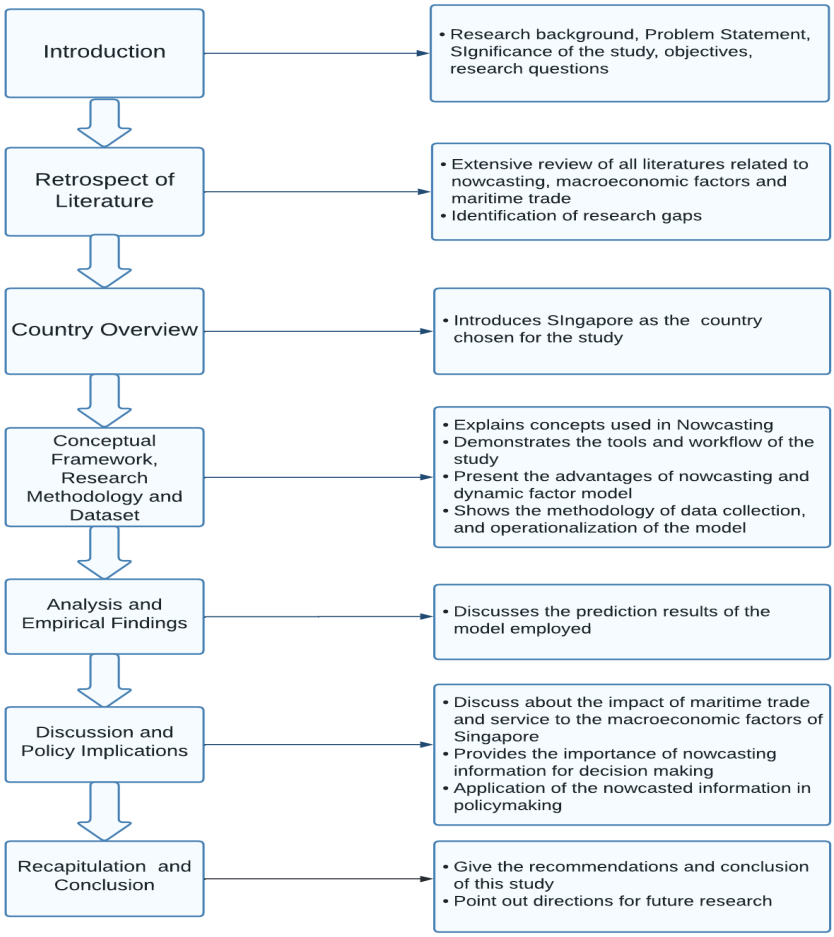
Chapter 2 presents an in-depth review of the relevant literature regarding nowcasting macroeconomic factors from different perspectives, as well as the relationship between maritime trade and services and these factors to find the gaps.

Chapter 3 explains why Singapore is chosen for study, with a brief overview of the country from a maritime perspective. It emphasises how overall maritime activities contribute to its economic growth.

Chapter 4 begins by laying out the conceptual framework to understand better how the maritime trade data can help policymakers make sound policy decisions for a country's economic growth through nowcasting. In addition, this chapter is concerned with the methodology, specifically the Dynamic Factor Model (DFM). Lastly, the dataset, including both dependent and independent variables, are presented into categories to simplify the analysis.

Figure 3.

Dissertation structure



Note: Developed by the Authors

In Chapter 5, the operationalisation of the DFM and nowcasting were conducted. An analytical framework is also presented to explain the key steps of nowcasting. This

chapter also presents the findings addressing the key aims and objectives of the study.

Chapter 6 discusses the impact of maritime trade and services data from Singapore's perspective using nowcasting. In addition, it provides the importance of nowcasting for decision-making and how this data can be applied for making a sound policy decision by various stakeholders of the Singaporean economy.

Chapter 7 presents the recapitulation and conclusions of the study. It also provides potential research in maritime fields or room for further improvements that can be conducted using the findings of this paper.

Chapter Two: Retrospect of Literature

From the dawn of civilization, maritime trade remained the backbone of international trade despite the expeditious development of global air transport (Lee, 2018). Maritime transport services generally grow in tandem with maritime trade and receive a boost from the fragmentation and globalisation of international production (Valentine et al., 2013). However, in the last two decades, due to fluctuations in trade, economic growth, and significant adverse economic shocks, it is increasingly important to monitor macroeconomic indicators such as the GDP growth rate on a real-time basis.

Maritime trade is affected by fluctuations, shocks, and geopolitical events. Relatively, trade wars and the recent pandemic have necessitated economists to project and accurately predict GDP growth rate and other macroeconomic factors under the rapidly changing economic uncertainties. The question is, “What macroeconomic indicators should be analysed to judge how the business cycle is developing?” It is an essential question for policymakers who make policies based on economic conditions and market situations (Caruso, 2018). Utilising the data present in macroeconomic variables, which are more timely and prevalent than the target variables (e.g., GDP) is the approach to assessing the current state of the economy in real-time as macroeconomic data is released and updating the forecasts accordingly. Policy organisations, central banks, and ministries constantly require determining their policies without deep insight into the economy’s current state and, in some instances, even without proper judgement of the recent past due to publication delays in economic data. Institutions have practically overcome this issue by generating forecasts for the upcoming or past quarter using judging procedures or straightforward univariate models. Given this, nowcasting is a valuable tool for closely monitoring the state of the economy. Nowcasting is also claimed to be a handy tool compared to other forecasting techniques for policymakers to get real-time, reliable information for monitoring economic variables (Cheng et al., 2021). While this may be true, there has been limited research conducted on nowcasting the macroeconomic factors based on maritime trade.

In light of the above discussion, this chapter tries to identify the gaps in the literature by presenting proper justification and evidence about the relationship between macroeconomic factors and maritime trade, as well as a suitable model for nowcasting these factors to get the most accurate results. This section exhibits the relationship between macroeconomic factors, maritime trade, and its impact. Later on, major macroeconomic factors such as GDP, industrial production, manufacturing, transportation, and financial services have been identified, influenced mainly by maritime trade. To observe these factors, existing literature on relevant models has been considered.

2.1 Relationship between maritime trade and macroeconomics

Maritime trade is one of the greatest economic success stories of the last 50 years. Since the Second World War, there has been a significant increase in the volume of trade and geographical coverage. This expansion has been unprecedented during the past decades. It shows no signs of slowing down, meaning that the world economy is evolving fast, and the maritime trade network we have now is simply a snapshot of that trend. The rapid changes in technology, from the steam engine to the latest technology of containerisation, can be a key factor as to why economies today are more interconnected than before. Given recent trends towards globalisation and regionalisation, the influence of tariff and non-tariff barriers on trade has decreased and thus resulted in better integration of the nations. With this, even the maritime and port industries have experienced substantial pressure from the rise in commerce, and these businesses have responded with innovations, investments, and higher productivity.

In this context, the traditional dichotomy between international trade and open economy macroeconomics can be viewed as an organising device (Jones et al., 1997). Since international trade and maritime trade are synonymous, it is essential to understand international trade factors to comprehend maritime trade (Blonigen & Wilson, 2013).

Numerous studies that examined the connection between economic growth and trade emphasised the significance of maritime trade for global trade, wealth, and

economic growth. For evidence, Stopford (2013) demonstrated the dynamic connection between seaborne trade and economic expansion. Furthermore, Rahman et al. (2013) also mentioned the presence of a direct correlation between world trade, international freight transportation, and the overall GDP, as well as the current developments in the growth's local, regional, and international economies of that freight flow. Using UNCTAD's three categories (dry cargo, crude oil, and petroleum products), Michail et al. (2020) evaluated the relationship between global macroeconomic conditions and seaborne transport, finding that GDP shocks are positive across all categories.

In terms of connectivity and GDP, a study conducted by Saeed et al. (2021) explored the complex relationship between bilateral trade, bilateral maritime connectivity, and industrial production. This was quantified by GDP per capita, and it was discovered that maritime distances between trading partners negatively affect exports and imports. Maritime trade is crucial to bring in global capital as well as for the ability of a nation to engage in international trade. This being the case, their study revealed a significant correlation between maritime dependency and GDP per capita (Lane & Pretes, 2020).

Aside from the GDP discussed above, different works of literature also suggest a close association between maritime trade and other macroeconomic factors such as IIP, manufacturing, transportation and storage, finance and insurance, unemployment rate, inflation rate, foreign exchange (forex) rates, interest rates, CPI, and balance of payments (BoP).

Stopford (2013) confirmed a close correlation between the growth rate of sea trade and industrial production over thirty years (1963-95). As per Korkmaz (2012), the total trade and industrial production indexes are positively and statistically significantly impacted by the general rise in ship transportation.

The increase in maritime trade reflects the exponentially growing demand for raw materials like coal and iron ore used as inputs in steelmaking and industrial activity, particularly in large developing regions like China, India, and oil-rich Western Asian nations that are heavily investing in infrastructure development. Oil imports have

surged due to the rapid industrialization and economic growth of developing countries like China and India, with Africa and Latin America increasingly meeting China's key commodities needs (Valentine et al., 2013). Moreover, Diks & Panchenko (2006) have shown that industrial production fluctuations also directly affect how many containers are moved through ports.

According to UNCTAD (2019), while investigating the relationship between manufacturing and international trade, it appeared that supply chains for manufacturing continue to be supported by maritime transport. According to Rodrigue (2020), maritime transportation has been crucial to trade for millennia, demonstrating the interdependence of trade, shipping services, and the supply chain.

In essence, exchange rate changes significantly influence international trade, the balance of payments, and economic growth (Abbas et al., 2020). Policymakers can limit expenditure and imports while promoting exports, investment, and economic growth by preventing the exchange rate from appreciating by building foreign exchange reserves. The trade ratio to GDP has a negative correlation with domestic to foreign prices and a positive correlation with the growth of foreign exchange reserves. It can be shown that nations with significant foreign exchange reserves exhibit faster rates of economic expansion (Krušković & Maričić, 2015). Also, external debt and exports being a part of international trade considerably impact foreign exchange reserves (Borchert et al., 2021).

Under the interest rates, the LIBOR rates do directly impact the sea trade towards the infusion of vessels in the market. The significant roles and contributions demonstrate that ship finance loans have contributed to the growth of maritime transportation, new port facilities, and expanding maritime fleets. Accordingly, Vu (2016) has confirmed a solid correlation between interest rates (LIBOR), global sea trade, global GDP, and the world's merchant fleet.

Looking at the balance of trade, it has been noted that the success of countries exports and imports forms the basis of their international trade. Shahbaz & Rahman (2014) claimed that exports might improve GDP. Similarly, Li & Cheng (2007) also

observed that international trade and shipping are closely related, and one of the most significant measures of it is the balance of payments (BoP), which is heavily influenced by marine trade.

Another essential factor is Foreign Direct Investment (FDI) which has a bidirectional impact on the volume of international trade. Both these factors are complementary to each other (Henry, 1994). One school of thought suggested that FDI might induce trade (Yamawaki, 1991), while other studies suggest the relation to be the opposite (Eaton & Tamura, 1994). For a country with an open economy like Singapore, investment comes from domestic savings and international capital inflows like FDI. With the aid of FDI, the host nation can reach investment levels that exceed its capabilities for boosting GDP and economic expansion. A certain level of financial sector development is a significant prerequisite for FDI investment in a country, which will also positively affect economic growth.

Consumer Price Index (CPI) serves as an immediate price inflation indicator for various flows of goods and services (Statistical Office of the European Communities, 2009), thus developing a relationship with international trade. As an illustration, over the past twenty-five years, the decrease in consumer price inflation seen in all the OECD economies has corresponded with a sharp rise in trade between OECD and non-OECD economies (Pain et al., 2008).

For the unemployment rate, Fratila et al. (2021) showed that within the blue economy, maritime transport and its associated industries such as repairs, shipbuilding, and port activities, account for about 24% of employment and 40% of value-added.

After evaluating the existing literature regarding the relationships between maritime trade and macroeconomic variables, it can be known that seaborne trade and economic development go hand in hand. It is also evident that the two have a close relationship (i.e., maritime trade and GDP and its different components), specifically in industrial production, manufacturing, transportation, and financial services. The later sections will discuss these relationships separately with proper justification and evidence.

2.1.1 Gross Domestic Product (GDP)

Among all the macroeconomic factors, gross domestic product (GDP) is influenced mainly by maritime trade. The first and foremost indicator of the growth of an economy is its GDP as it provides a true picture of the economic performance of a country that estimates the level of production for the market of a country, so if the economists are failing to portray this true scenario, then all the economic policies go in the wrong directions. In other words, it is the total monetary worth of all finished products and services produced within a country's boundaries over a specific time, typically a year or quarter. GDP is a flow that includes all finished products and services produced over a given period and are evaluated at market rates (Mitchell et al., 2019). Its core components are aggregate investment, consumption, government purchase, and exports. These components are directly or indirectly influenced by maritime trade and services. However, while analysing the relationship between GDP and maritime trade from existing literature, Valentine et al. (2013) established a tight connection between global GDP, international trade in goods, and seaborne shipments between 1970 and 2012. Whereas Park et al. (2019) have differentiated that maritime transport has a positive correlation with the economic development of the countries while other modes of transport such as air or land transport have either zero or negative impact on economic growth.

Furthermore, according to Cariou (2020), the extent of relationships between world population, GDP growth rate, and international trade has changed over time and is expected to change further in the future. At the same time, in the period between 1970 and 2017, it is observed that there was a strong relationship between GDP per capita and seaborne trades. Besides, focusing on the main drivers of future maritime trade and proposed long-term seaborne trade will be driven by changes in GDP per capita with its related effect like the need for industrial production.

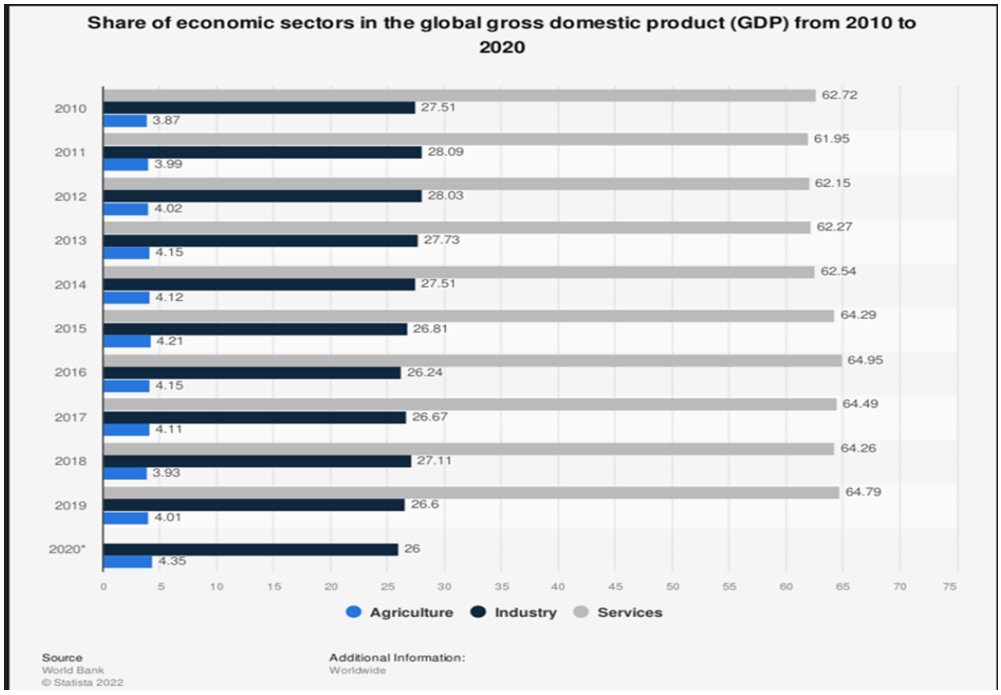
GDP is composed of three key components such as agriculture, industry, and services sectors. Different countries have different sectoral drivers or sectoral break-ups of their GDP depending on their natural resources, nature of the economy, starting with agriculture, industry, and lastly, service sectors. It is also equally true that the economy of any country moves from an agricultural background to an

industrial one during its journey from an underdeveloped to a developing or a developed country. However, the study will only focus on sectors heavily influenced by maritime trade and services.

In February 2022, the World Bank calculated the contribution of each economic sector to the global GDP from 2010 to 2020. In 2019 agriculture made up 4.01% of the global GDP, the industry made up roughly 26.6%, and services made up roughly 64.79% as shown in Figure 4.

Figure 4.

Share of economic sectors in the global GDP, 2010-2020



Note: The data and statistics are from World Bank and is adopted by Statista (https://www.statista.com/statistics/256563/share-of-economic-sectors-in-the-global-gross-domestic-product/)

Moving forward, the study of different sectors which form part of GDP and their impact on the overall GDP of different economies also becomes crucial. This section will also bring out the relationship between these sectors and international trade.

2.1.1.1 Agriculture

International trade of agricultural products can spur economic growth, particularly in emerging nations where agriculture accounts for many exports and foreign revenues. The study of global trade in food and agriculture has grown considerably during the past several years on a global scale (Josling et al., 2010). On a country level, interactions exist between the agricultural sector on one side and other sectors on the other. The main economic activity that dominates the manufacturing sector and the per capita GDP in some nations, like India, is identified as agriculture by analysing cross-sectoral interactions (Singariya & Sinha, 2015).

Concerning maritime trade, agricultural products are transported in various ways, including bulk vessels for commodities like grains and some oilseeds or containers for most manufactured commodities and processed agricultural products. The costs of seaborne transport also vary widely depending on the type of commodities and sea routes. According to the newly created OECD Maritime Transport Costs database, they are noticeably higher for particular agricultural items, such as grains and oilseeds (Korinek & Sourdin, 2010).

2.1.1.2 Manufacturing

Manufacturing has always been essential to the growth of developing nations' economies. The development of the manufacturing sector tends to speed the rate of technological advancement of the economy as a whole, partly due to the absorption of surplus labour (Kaldor, 1967) and the development and spread of innovation through linkage effects in particular industries (Marconi et al., 2016). The influence of manufacturing on productivity levels across the entire economy can be used to explain the relationship between industrial growth with GDP increase (Libanio & Moro, 2006). Empirical research on the manufacturing industry's dominant impact on economic growth was also conducted by Kaldor (1967). He presented several arguments for the distinctive growth role that manufacturing plays, including the industry's high productivity, linkage effects, and demand effects. Further discussions concerning some Asian countries and growing economies support the same.

At current and constant prices, China's Manufacturing Value Added (MVA) share exceeds 30%, while the average for emerging nations is between 11% and 14% (Haraguchi et al., 2017). Thus, China has emerged as a nation that has achieved extraordinary achievements in recent years concerning the manufacturing sector.

Given that it has contributed the maximum to real GDP per capita over the past thirty years, manufacturing is the most yielding industry in India (Hussin & Yik, 2012). Elhiraika (2008) explores how structural dynamics and change, especially in the form of a higher manufacturing share in total output, might accelerate growth and reduce growth volatility in Africa. The research suggests that a more significant manufacturing component in overall production would increase GDP growth and reduce growth volatility.

Looking at the pivotal importance and contribution of the manufacturing sector to the GDP of various countries in terms of export and import being the main components of maritime trade, forecasting the GDP of manufacturing industries is also gaining importance in optimal decision formulae for the government and industrial sector in recent times.

2.1.1.3 Transportation and Storage

The globalisation and transport revolution, logistics integration, and the following growth of the marine industry have redefined the functional role of ships and ports in global logistics and supply chains (Song & Panayides, 2012). Tovar et al. (2007) stated that because ports are a crucial component of the logistics chain, the performance of ports directly influences critical economic variables like export competitiveness and ultimate import pricing, which in turn influence economic growth. The maritime industry encompasses a wide range of port services, including pilotage, towing and tug assistance, emergency repairs, anchorage and berthing services, and auxiliary services, including storage and warehousing, maritime processing goods, and customs clearing services (Dwarakish & Salim, 2015).

Since the economic and social development of the country has proliferated, transportation has become one of the most important factors contributing to its economic development. In recent years, it has grown into an essential service

industry. Technological advancements in transportation and management are enabling the transportation system to become more efficient, resulting in the same benefit being produced for a lesser cost or a more significant benefit for the same amount of money. Additionally, it has been shown that the growth of the transportation sector both predicts the direction of economic development and reflects cyclical fluctuations in the overall economy (Gao et al., 2016).

Lloyd et al. (2019) assessed the contribution maritime transportation has made to Nigeria's economy in terms of GDP output. According to the study, the economy may be impacted by three different events: induced, indirect, and direct. While the indirect influence is caused by purchases made as a result of direct requests for the goods and services the sector needs, the direct impact can be quantified in various ways, including the value contributed to GDP, revenue, and profit for the industry, etc. The last impact or the induced occurs when an economic sector increases the purchasing power of citizens employed by it, thereby creating a multiplier effect in the larger economy.

In research, Han & Fang (2000) studied the four transportation measures and their importance in the economy. Based on his analysis, the transportation-driven GDP is the only one that can assess the contribution of transportation to the economy and provides an in-depth analysis of the interconnection between the transportation industry and other sectors of the economy. Hence, the share of transportation in the GDP is a standard indicator of the importance of transportation to the economy and the benefits it brings.

2.1.1.4 Financial and Insurance Services

Generally, the financial sector's function in all economies is to direct resources from savings into investment initiatives. The financial industry is significant because financial intermediaries manage resource distribution. Financial intermediaries that perform well boost capital allocation efficiency, promote saving and increase capital formation.

The growing attention of the economics profession in financial organisations results from the compelling evidence that financial development leads to growth (Wachtel,

2003). However, it is pertinent to note that the link between finance and growth varies systematically among nations according to their features. For example, there is less evidence of financial effects in rich countries than in less developed countries. Nevertheless, sufficient empirical support demonstrates that the expansion of the financial sector encourages economic growth.

Following the global economic crisis in 2008, the financial sector has become more involved in world economic affairs since the global economic crisis of 2008. Therefore, it is now more important than ever to have a thorough awareness of financial concerns and how they affect transportation operations. Shipping and port operations became a more profitable industry with the expansion of global trade, if not necessarily in terms of rate of return, then most definitely in terms of the amount of this return. Financial institutions place importance on this for no other reason than the fact that they see transport infrastructure, such as port terminals, as an investment class that belongs in a diversified global portfolio. Banks, insurance firms, and even pension funds are among these entities. Approximately 90% of all global trade transactions are currently financed by large commercial banks (De Monie et al., 2011). Moreover, the formation and expansion of a paper market on shipping freight have been facilitated by the high level of market volatility in the shipping sector, as seen by abrupt swings and extreme variations. To promote the expansion of shipping, complicated financial products and derivatives have been devised (Kavussanos & Visvikis, 2006).

2.1.2 Industrial Production

The industrial sector's output, which includes manufacturing, utilities, mining, and, to some extent, construction, is reflected in industrial production. Similarly, industrial production is defined as a tool for measuring economic activity involving sectors highly impacted by consumer demand, explicitly mining and manufacturing.

The index of industrial production (IIP) is described by Brunhes-Lesage & Darné (2012) as the most important and widely observed index due to its significance to the manufacturing activity and its role as an indicator (in volume terms) of the overall business cycle. In other words, the percentage variation in industrial production

represents the change in the volume of industrial production over time. Further, most countries use the IIP as a key variable to forecast short-run GDP growth.

It can also be noted that industrial production offers insight into the state of the economy because, in times of recession, manufacturing of consumer durables and capital goods is likely to decrease. Despite making up a relatively smaller percentage of an economy's total output, the industrial sector is considered a key measure of economic development and success due to its sensitivity to consumer demand and interest rates.

In the fact that industrial production is one of the significant determinants of sea transport demand through world trade, a positive relationship should also be observed between global industrial production and international shipping stock returns. Umoru & Eborieme (2013) showed a positive and significant relationship between industrial growth and trade liberalisation in Nigeria. In the country, industrial sub-sectors are considered to play an integral role in growth by increasing production and exports, reducing unemployment and rural-urban drift, and reducing poverty. In addition, industrial production and the explanatory variables formed a unique co-integral relationship.

Korkmaz (2012) investigated whether maritime transport impacts several economic indicators in Turkey. With this, he utilised the data on the number of ships coming in and out of Turkish ports and explored if it affected the industrial production index and total trade. As a result, it revealed that the increased number of ship transportation in Turkey positively impacts the industrial production index and total trade.

Thus, we can comfortably conclude that the ups and downs of maritime trade do have an impact on industrial production in quite various ways. For instance, trade may bring in raw materials, spare parts, and semi-manufactured goods and thus add to industrial production and vice versa, finally impacting the country's GDP.

2.1.3 Balance of Trade vs GDP

Improved knowledge of the underlying relationship between the balance of trade situation and a country's GDP is urgently needed in the globalisation period due to ongoing global macroeconomic crises and changes in the international trade pattern.

The balance of trade (BoT) is the difference between the exports and imports of a country over a given period. A balance of payments is primarily based on the trade balance since it measures all international transactions. A country is said to have a positive trade balance if its exports exceed its imports (trade surplus). On the other hand, when a nation purchases more from other nations than it exports, the trade balance is negative (trade deficit). Thus, these fluctuations in the trade balance affect a country's GDP either favourably or unfavourably. Under these circumstances, it is a significant concern for the economies and is expected to examine the relationship between the trade balance and GDP. As a result, several research studies examine the connection between the trade balance and GDP and find that GDP significantly improves the trade balance. For instance, Falk (2008) examined the factors that affect trade balance and found that real foreign GDP per capita has a significant positive correlation with trade balance as a proportion of GDP. In contrast, real domestic GDP per capita negatively correlates with the trade balance. Likewise, Weerasinghe & Perera (2019) has indicated that GDP, inflation rate, and import volumes significantly impact the trade balance of Sri Lanka.

However, the trade balance is significantly impacted by GDP; when GDP rises, imports also rise, resulting in a negative trade balance (Rahmawati, 2014). Sari (2017) also connected GDP to consumption. People's consumption will inevitably increase when GDP rises, leading to an increase in imports and a consequent decline in the performance of the trade balance. In addition, other studies also suggest that the quicker growth in imports relative to exports could significantly affect the trade balance, limiting economic growth in some developing economies (Parikh & Stirbu, 2004). The findings, which were supported by Tung (2018), also showed that yearly GDP per capita growth has negatively affected the trade

balance, suggesting that rising income levels may cause an imbalance in trade between nations by driving up import prices.

On the other hand, the growth in exports will boost GDP by bringing in more foreign currency. Sheehey (1990) showed that exports and GDP growth positively. The analysis of further studies states that causal relationships exist between two countries, Canada and the US. Their study found that GDP, exports, and imports growth variables are closely related, and that causality is established in every possible direction in Canada. However, the results for the US showed that only exports have a causal relationship with GDP (Zestos & Tao, 2002). A study by Kristjanpoller & Olson (2014) on countries in Latin America showed that higher growth in exports results in higher growth in these countries' GDP.

From the above discussion, it can be concluded that the connection between the BoT and a country's GDP depends on the volume of exports and imports—the more the exports, the better the trade balance and vice versa. However, the types of economies, whether developing or developed, also play a significant role in the impact of the trade balances.

2.2 Nowcasting as a tool

Stopford (2009) discussed some sophisticated market forecasting tools that divide trade into different categories and commodities to forecast each commodity trade using a set of equations. In theory, it is generally believed that more information should lead to better and more accurate results. The only danger is that it takes much time and might quickly generate so much information that the forecast's primary rationale is lost. Finding a considerable degree of detail to work on is the main challenge. Additionally, sensitivity assessments can be created using forecasting models to examine how much the forecast changes in response to a modest change in one of the assumptions. Peng & Chu (2009) showed that simple, classical decomposition models perform well. It does not, however, adhere to formal statistical theory. On the other hand, complex or sophisticated models do not necessarily provide more reliable and accurate forecasts than simpler models.

The emergence of Giannone et al. (2008)'s work stimulated the curiosity of economists and researchers to nowcast the GDP and other macroeconomic factors using high-frequency data to get the most reliable forecasts. The nowcasting process goes beyond just producing an early estimate because it effectively necessitates evaluating how new data will affect future forecast revisions for the target variable. As a result, nowcasting is a dynamic tool for monitoring economic variables. It makes a clear connection between the updates in succeeding data releases and the subsequent forecast adjustments. Nowcasting is especially important for critical macroeconomic indicators infrequently gathered, usually once every three months, and released with a significant delay (Banbura et al., 2010).

Due to the lengthy delays in delivering many crucial macroeconomic indicators, nowcasting is crucial in economics. Nowcasting aims to identify significant facts regarding the status of the economy before official data is made public. Because nowcasting is urgent, nowcast models must use all recent, high-frequency data. Forecasts generated by nowcasts ought to be able to be updated continuously in reaction to any new data releases (Marcellino & Schumacher, 2010).

2.2.1 Relevance of nowcasting

In the 1960s and 1970s, methods for nowcasting thunderstorm locations were developed by extrapolating radar echoes (Wilson et al., 1998). The term 'nowcasting' was employed for the first time in meteorology to forecast the weather. The method gained popularity over time, and several academic fields, including economics, began to use it in their research.

Real-time monetary policy decisions in macroeconomics are based on predictions about past, present, and future economic conditions. Forecasting and evaluating the quarter's conditions are crucial tasks for policy institutions because most statistics are released with a lag and then changed. Because they are issued earlier than other variables or because they are closely related to a variable that the banks want to forecast, it pays additional attention to some data releases. However, in theory, any release, regardless of how frequently it occurs, may impact the accuracy of current-quarter projections. From the perspective of the short-term forecaster, there

is no reason to discard any data. However, it is essential to know how accurate each release is as a reflection of the state of the economy today. Forecasters at many central banks and other institutions utilise nowcasting models extensively, as they are increasingly well-liked tools for reducing some of this uncertainty (Giannone et al., 2008).

However, while reviewing literature regarding nowcasting techniques, different researchers have nowcasted several macroeconomic variables by employing various econometric models with different datasets of various frequencies for different economies. For instance, Evans (2005) was the first to explore the issue of estimating the GDP in real-time using Kalman Filtering equations.

Meanwhile, Clements & Galvao (2008) introduced the MIDAS method to the macroeconomic forecast literature to forecast a low-frequency variable, like quarterly GDP, using a limited number of high-frequency variables. Numerous studies have discussed the advantages of using MIDAS regressions to improve quarterly macroeconomic predictions using monthly data, or to improve quarterly and monthly macroeconomic predictions using a limited collection (often one or a few daily financial series).

In a paper, the 'bridging with factors' technique put forth by Giannone et al. (2008) evaluated the backcast, nowcast, and short-term forecasts of quarterly GDP growth in the euro area. Following the release of both "soft" and "hard" data, the factor model was revised several times throughout the month. The factor model is a valuable new tool for short-term analysis, since the results show that it outperforms the pool of bridge equations (Angelini et al., 2011).

A technique for assessing the marginal influence of intra-monthly information releases on current-quarter estimates (nowcasts) of real GDP growth was created by Giannone et al. (2008). The statistical approach is foundational in the nowcasting field and can handle big data sets with staggered data-release dates. The work mentioned above has been a starting point for many scholars conducting more nowcasting research.

In an experiment that began in 2003, the Federal Reserve Board of Governors initially used the Giannone et al. (2008) model to forecast GDP. Since then, several

variations have been created for various economies and put into use by other central banks, such as the European Central Bank and other organisations, such as the International Monetary Fund (IMF).

Banbura et al. (2010, 2013) argued that the process of nowcasting goes beyond the simple production of the early estimates, and it requires the assessment of the impact of data releases and revisions of the target variables as well as applied DFM for nowcasting the euro area GDP for the Q4 in 2008. In the same vein, a DFM was estimated by Chernis & Sekkel (2017) to nowcast Canada's GDP using a combination of soft and hard indicators, and it was demonstrated that the DFM outperformed univariate benchmarks as well as other widely used nowcasting methods like bridge equations and MIDAS. Similarly, Ajevskis & Dāvidsons (2008) studied the GDP of Latvia using a large panel of data by applying the Stock–Watson factor model and the GDFM.

Amstad & Fischer (2009) used weekly data to forecast the Swiss core inflation rate and demonstrated that updating the forecast at least twice a month is beneficial. They also recommended that policymakers take full advantage of the real-time flow of information resulting from data releases and revisions to economic series. Reijer & Johansson (2019) evaluated the pseudo-real-time out-of-sample nowcasts for Swedish GDP using factor models and mixed-data sampling regressions with a single predictor variable.

Miller & Chin (1996) initially improved their quarterly model estimates by using monthly data. The forecasting accuracy of bridge models for GDP growth in the euro region was studied by Baffigi et al. (2004). The bridge model "bridges the gap" between the delayed (but more complete) data and the data content of timely updated pointers.

Aastveit et al. (2014) developed combined density nowcasts for U.S. quarterly GDP growth using a density combination approach. Bridge equation models, FMs, and MF-VARs- three popular model classes for short-term forecasting—were combined. It was found that the density combination approach outperformed a straightforward model selection strategy and performed better in point forecast evaluation than conventional point forecast combination methods.

Similarly, Glocker & Kaniovski (2020) estimated a cluster DFM that considers frequency mismatch and data with ragged edges. He utilised it to forecast variables related to employment, actual private household consumption, and real goods exports. According to this study, it enhances forecasts in a (pseudo) real-time framework.

Alkhareif & Barnett (2022) created monthly GDP nowcasts for Saudi Arabia that can mimic the country's non-oil GDP growth rates by using the Generalised Dynamic Factor Model (GDFM) on a panel of 272 variables from January 2010 to June 2018. The researchers asserted that their model fared better than more conventional models in terms of following the business cycle.

Matsumura et al. (2021) nowcast the manufacturing activity in Japan with a high level of precision from labour-intensive industries using high-frequency mobility data and suggested that mobility data are helpful input for nowcasting macroeconomic activity.

Nowcasting the macroeconomic indicators through the lens of maritime trade flows and vessel traffic information is gaining popularity because of its high-frequency real-time AIS data availability. For example, Arslanalp et al. (2019) used AIS-based big data about vessel traffic and port calls using Malta as a benchmark for forecasting real-time trade activity. They tested the quality of the official trade statistics and maritime statistics. Besides, Arslanalp et al. (2021) also proposed an approach to track the merchandise trade using shipping data for the case of Pacific island countries to get the early warning signs of economic activity turning points. Correspondingly, Cerdeiro et al. (2020) built indicators of world maritime trade using raw data from the radio signals that vessels emit by different machine learning methods for estimating the trade volumes.

However, it is crucial to select the best econometric model to manage this challenging task, and current developments in modeling, possibly a considerable amount of mixed frequency datasets, can be helpful. In actuality, using current information found in more frequent macroeconomic or financial indicators, like surveys or spreads, or alternative data, such as internet searches or traffic data, can

be valuable for keeping track of the state of the economy (Marcellino & Sivec, 2021).

In light of the above discussion, it is evident from different works of literature that nowcasting is a dynamic approach to observing macroeconomic variables. DFM is currently a popular choice of economic nowcasting that provides the most accurate nowcasts rather than commonly used nowcasting tools.

Therefore, recent nowcasting literature focuses on developing macroeconomic nowcasting models that exploit timely information to provide early estimates of GDP and other key economic indicators before the data become available. As a result of indicator availability at a variety of frequencies, asynchronous release dates and publication lags, and changes in the economy, nowcasting models are faced with unique challenges that require superior solutions that are specially tailored for this literature.

2.3 Research Gaps and Literature Contribution

After critically reviewing the existing contributions from works of literature regarding the relationship between maritime trade and macroeconomy, it is evident that international seaborne trade is intertwined with overall macroeconomic activity (i.e. GDP, industrial production, manufacturing, transportation and storage, financial and insurance services). Nevertheless, market situations and fluctuations in maritime trade and shipping activities can reflect the changes in these indicators. Besides, shipping is regarded as the backbone of international trade; many other industries strongly rely on it, since it is used to transport a variety of commodities to and from manufacturing centres. Most of these researches focused on nowcasting GDP using economic and financial indicators. However, they ignored the maritime trade flows and shipping indicators, as well as other subcomponents of GDP that reflect more explicit pictures of economic activity influenced by maritime trade. As a result, policymakers and industry practitioners often fail to track these macroeconomic variables to craft monetary policy or informed investment decisions.

However, in the field of maritime economics and finance, to the best of our knowledge, this dissertation is distinct from existing contributions in terms of

macroeconomic indicators that are influenced mainly by maritime activities. Furthermore, this dissertation will develop a sophisticated nowcasting model for employing high-frequency maritime trade flows and shipping data for observing macroeconomic activity through the lens of maritime trade and services.

Chapter Three: Country Overview of Singapore

Due to world economic shocks and uncertainty in past years, it is increasingly essential for the fastest growing economies like Singapore to monitor the macroeconomic variables on a real-time basis to formulate their national policies to remain competitive. The Straits of Malacca and Singapore (SOMS) have served as important sea lanes for international trade for hundreds of years. Singapore is regarded as one of the world's market-oriented and open economies, with a major maritime and aviation hub.

As a significant business and global maritime hub, Singapore has a proactive maritime business environment, including efficient transport and shipping services and the global transhipment hub port. This chapter attempts to provide a brief synopsis of Singapore and describe the exposure and importance of maritime trade and services to its economic growth. In this study, Singapore is considered for nowcasting its macroeconomic factors as a case country for a wide variety of reasons.

3.1 Country Profile: Singapore

Before and during the age of European dominion, trade, shipping, colonisation, and the struggle for political and economic supremacy had a long and continuous history surrounding the SOMS (Rusli et al., 2014). As a part of the long-term process of evolution, ancient Singapore played an essential function in the overall development of maritime trade in Asia (Miksic, 2013). The economy and maritime profile of Singapore are highlighted in the following sections.

3.1.1 General Profile

As a small state, Singapore has an area of only 719 square km (278 mi2) and a coastline of 193 km (119.9 mi) in South East Asia, as shown in Figure 5. This land area is approximately 0.9 times the size of New York City. Singapore is the 52nd-smallest country in the world and the third-smallest country in Asia by area after

Macau and Singapore. With 8,358 people per square kilometre, it is also the third most populated country in the world, behind Macao and Monaco.

Figure 5.

Map of Singapore

The persistent humidity in Singapore and its marine location help to keep maximum temperatures reasonable. The degree of urbanisation in the country has reached such a level that all residents are now considered urban residents. Because of its advantageous location in the middle of Asia at the crossroads of East-West trade and within a seven-hour flying distance of the rapidly increasing Asian market, enterprises can reach this market. Its prominence at the southernmost point of the Malay Peninsula, where it rules the Strait of Malacca that separates the Indian Ocean from the South China Sea, is to credit its development and wealth. The general overview of the country is shown in Table 1.

Table 1.

Singapore's Data and Statistics

Capital	Singapore city
Land Area (km²)	719 km² (278 mi2)
Coastline (km)	193 km (119.9 mi)
Population (as of latest census)	5,943,567
Population growth rate (as of latest census)	0.81%
Population density(as of latest census)	8,358 per km² (21,646 people per mi2)
Climate	Average monthly temperature: 81° F (27° C) in June; 77° F (25° C) in January Average daily range: 13° F (7° C)

Note: The data and statistics for Singapore are from Britannica (https://www.britannica.com/place/Singapore)

3.1.2 Economy Profile

Singapore's lack of natural resources or lack of land in no way restricts the dynamic expansion of international trade in commodities. In addition to production and services, this country's trade is a significant economic sector due to its natural deep-water ports and strategic location at the intersection of major sea routes. (Mindur, 2020). Singapore has the most vibrant economy in the world with a highly developed free-market economy with characteristics of dirigisme. This country enjoys an atmosphere of corrupt-free, stable prices, a low unemployment rate, and a healthy trade balance. In terms of purchasing power parity (PPP), this nation has the second-highest per capita GDP in the entire world. The export of manufactured goods, petroleum products, medicines, and chemicals, a thriving transhipment port, maritime transportation, financial and insurance services, and other logistics-related activities, are significant drivers of Singapore's economy. The brief economic profile of Singapore for the year 2021 is shown in the table below.

Table 2.

Economic Statistics of Singapore, 2021

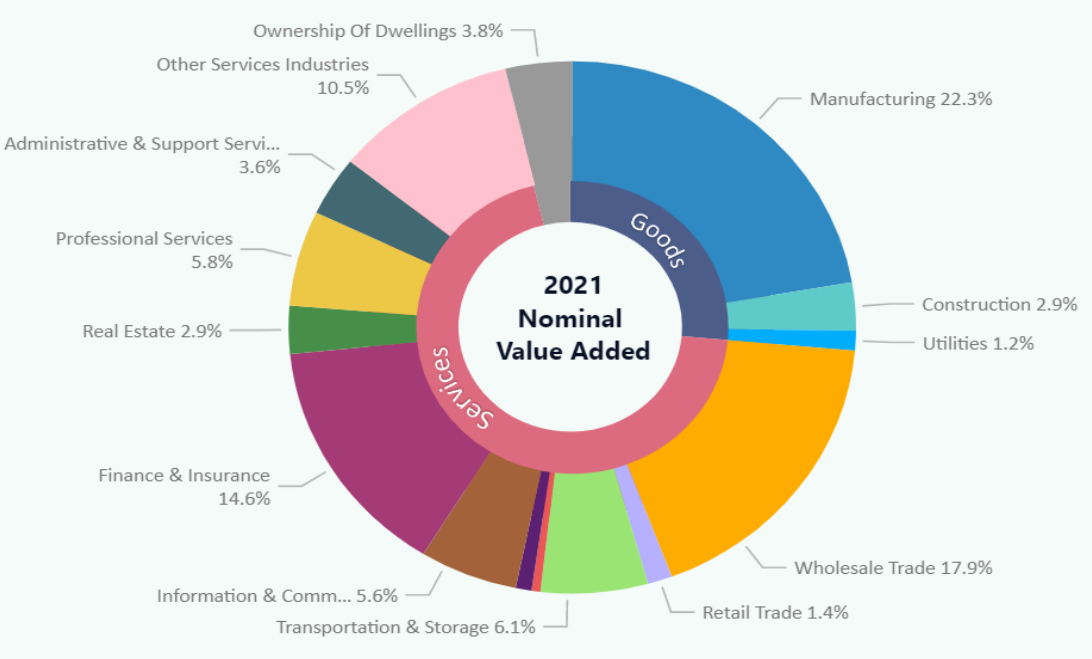
Economic Indicator	2021
GDP per capita (USD)	66,176.39
GDP (USD bn)	396.99
Economic Growth (GDP, annual variation in %)	4.8
Consumption (annual variation in %)	5.2
Investment (annual variation in %)	2
Manufacturing (annual variation in %)	22.3
Retail Sales (annual variation in %)	5.1
Unemployment Rate	2.6
Public Debt (% of GDP)	99.5
Inflation Rate (CPI, annual variation in %, eop)	-0.6
Inflation Rate (CPI, annual variation in %)	-0.5
Inflation (PPI, annual variation in %)	-15.3
Policy Interest Rate (%)	0.88
Current Account (% of GDP)	18.7
Current Account Balance (USD bn)	57.6
Total Merchandise Trade (USD billion)	1160
Total Exports (USD billion)	614.1
Total Imports (USD billion)	545.9
Trade Balance (USD billion)	68.2
Total International Trade in Services	609.2
Total Service Exports (USD billion)	308.8
Total Service Imports (USD billion)	300.4
Stock of FDI in Singapore (2020) (USD billion)	2141.8
International Reserves (USD)	248
External Debt (% of GDP)	429

Note: The data and statistics for Singapore are from Focus Economics (*https://www.focus-economics.com/countries/singapore)*

Singapore has experienced exceptionally rapid growth since attaining independence in 1965 with an enviable trade balance and low inflation. Real GDP per capita has grown at an average annual rate of 7% to 14% over the years, reaching USD—14,482 in 1992. The GDP of Singapore has increased 12 times since 1960. However, there has been considerable variation in sectoral development, with manufacturing and financial services recording the most rapid growth (Bercuson, 1995). Figure 6 shows the sectoral breakdown of the GDP of Singapore in 2021, exhibiting that transportation and storage, manufacturing, finance, and insurance contribute to Singapore's GDP by approximately 43%, significantly impacting maritime trade and shipping.

Figure 6.

The Contribution of Different Sectors to the GDP of Singapore in 2021



Note: The data and statistics are from Singapore Department of Statistics, 2021

However, other components of GDP, such as wholesale and retail trade, construction, and other service industries, are indirectly related to maritime trade and services.

3.1.3 Maritime Profile

To serve as a hub for entrepot trade, the British East India Company established the current Port of Singapore in 1819. The port primarily acted as a regional hub for cargo distribution from and going to the Malayan interior. In the 1960s, Singapore recognized the potential to play a significant role in maritime trade. Thus, in addition to processing local cargoes, the port started to concentrate on establishing itself as a transhipment hub for international cargoes. As a result, in addition to local traffic from Malaysia and the nearby Indonesian islands, the port's hinterland now also includes cargo that is being transshipped through it from Europe, East Asia, Australasia, and the Indian Subcontinent (Lam, 2016).

Singapore offers shipping businesses seamless worldwide trade connectivity thanks to its location at the hub of a network of trade routes and its connections to 600 ports in more than 120 nations. The range and depth of services provided by Singapore's hub port is unmatched by many other global ports. On the average, there are about 1,000 vessels in the Port of Singapore, and a ship comes or departs a port every two to three minutes, earning it the title of "World's Busiest Transhipment Hub". There are about 13,000 ship calls in Singapore annually, while the number of cruise vessels touching Singapore is around a million. More than 5,000 maritime establishments employ over 160,000 personnel (Maritime Singapore, 2022). The prominent Maritime Key Figures of Singapore, 2021 are presented below:

Table 3.

Maritime Statistics of Singapore, 2021

Fleet National Flag (in DWT)	136,330; (6.382% of the world's total)
Singapore Registry of Ships	92,336.0
Ship building (in GT)	7,725.0
Total Cargo (in thousand tonnes)	599,642.7
Cargo (General) (in thousand tonnes)	385,317.1
Cargo (Bulk) (in thousand tonnes)	214,325.6
Container port throughput (in TEUs)	37,467.6
Number of seafarers	6,000
Number of port calls	50,731
Ship recycling	-
Liner Shipping Connectivity Index (LSCI) ranking (as of the latest census)	2nd in rank (with a value of 113.78)
Liner Shipping Bilateral Connectivity Index (LSBCI)	Malaysia (0.588); China (0.568); Korea (0.521); Hong Kong (0.502); Belgium (0.479)

Note: The data and statistics of Singapore are from UNCTAD and Department of Statistics Singapore

A few statistics about Singapore's maritime industry are shown in Table 3. The national flag fleet of the country contributes to more than 6% of the world and its registry accounts for over 90,000. Meanwhile, its total cargo volume is almost 600,000, consisting of general and bulk cargo. Another figure is its container port throughput, which is around 37,000 TEUs. Singapore also has 6,000 seafarers (both officers and ranking). On the other hand, the number of port calls will be more than 50,000 in 2021. Hence, it can be concluded that the Maritime industry is the

country's lifeline, supporting other industries such as tourism, finance, banking, and so on.

3.2 Choice of Country

One of the world's busiest and most important waterways is the Strait of Malacca and Singapore (SOMS). As the primary marine channels of communication in this part of the world, these straits are significant economically and strategically for the nations in Southeast Asia and the surrounding Asia-Pacific region. It is beyond dispute that Singapore and the Straits of Malacca are crucial to maritime trade (Rusli et al., 2021). The SOMS ranks among the most important shipping routes in the world from an economic and strategic standpoint (Qu & Meng, 2012). Every year, around 25% of the world's trade in goods transported by sea moves through these straits (Lee, 2018).

Moreover, Singapore is one of the top three maritime cities in the world due to the existence of container shipping firms and container terminal operators (Verhetsel & Sel, 2009). When examining the location of headquarters for marine enterprises, Jacobs et al. (2010) confirmed Singapore's global solid position by placing it second to London. Also, Xinhua-Baltic International Shipping Centre Development Index Report ranked Singapore number one shipping centre for the ninth year running, which genuinely supports Singapore's favourable geographic location for the maritime industry (Osman et al., 2021). Given this, it is clear that the economy of Singapore is highly dependent on maritime trade, which directly and indirectly impacts the country's GDP.

3.3 Impact of maritime trade and services on the economy of Singapore

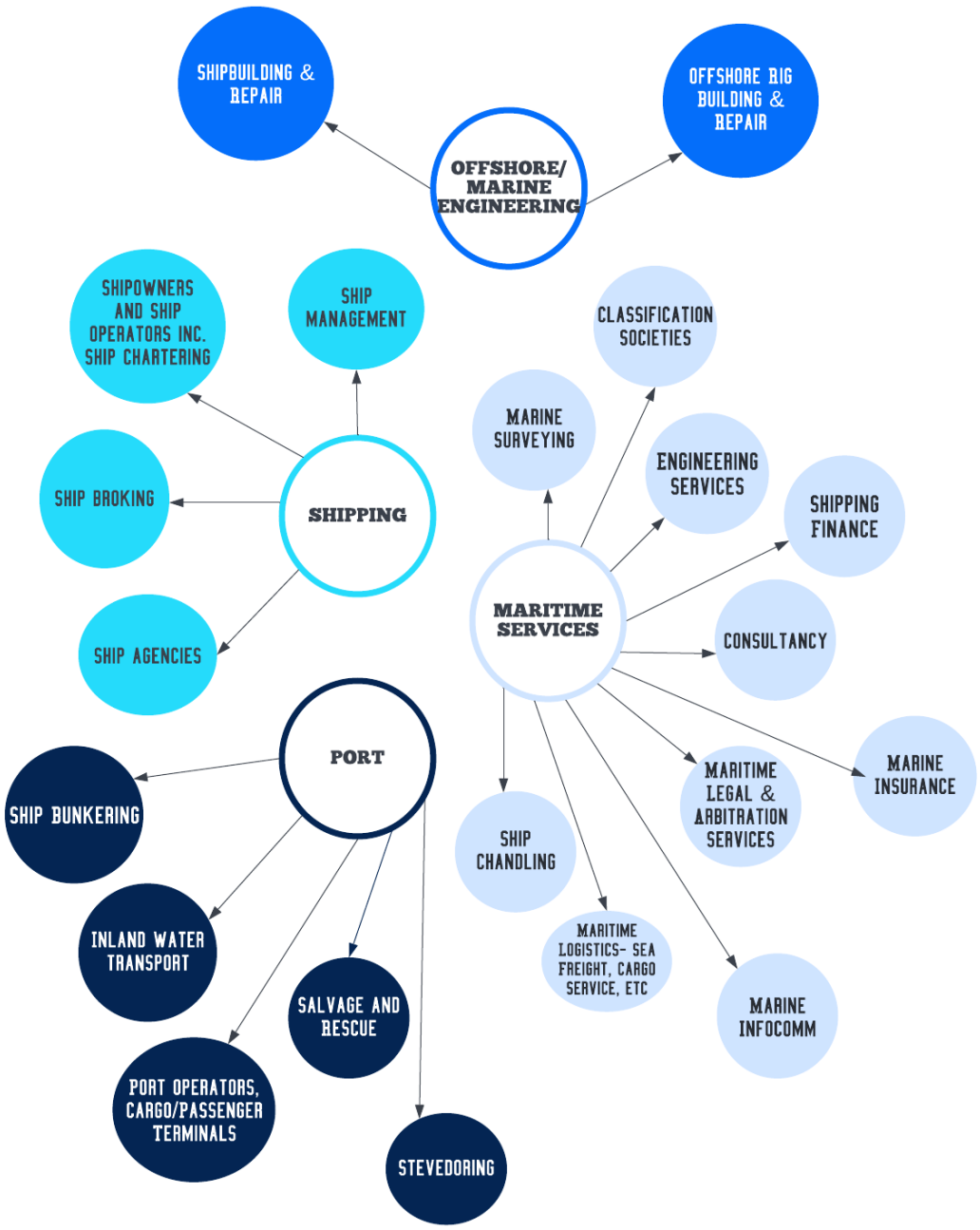
Maritime trade has significantly increased over the past few decades due to globalisation and national economic growth. The long-term viability of the global trading system is aided by maritime transport's effects on nations' economic, social, and environmental well-being. Ports and ships play a significant role as trade facilitators in the global economic system. The port business experienced a massive surge in demand for both physical infrastructure investment and cargo handling in

direct proportion to the development of maritime transport. As containerization has progressed, the port sector and cargo handling techniques have become more consistent and effective. This change speeds up containerised trade growth (Lam, 2016).

Singapore is a city-state that relies significantly on maritime trade to maintain its export-driven economy and hub status in the transhipment and oil refining industries. An extensive investigation into the Singapore maritime cluster was conducted by Wong et al. (2010). These maritime groups were split into two categories. Conventional water transportation industries make up the core maritime sector, sometimes known as the shipping sector. The last one is the marine and offshore engineering and support services and marine and shipping transportation.

Figure 7.

Maritime Ecosystems of Singapore



Note: Author's own elaboration based on Maritime Cluster Information of Singapore

The figure 7 above shows the maritime activities which are carried out in Singapore. From the viewpoint of quantifying the contribution to the national economy of Singapore, the maritime industry is comprising ports, shipping lines, shipping agencies, repair, ship-broking, inland water transport, cruise, chartering, classification society, ship management, maritime logistics, maritime finance and insurance, legal services related to shipping and maritime, maritime education, training and research, maritime related information and technology that contribute to the GDP significantly directly and indirectly (Cullinane et al., 2006). The maritime sector in Singapore contributes about 7% of the country's GDP, which is a significant amount (Parzhytska & Pokrovsky, 2021). The following sections will discuss the impacts of maritime trade and services on the economic growth and prosperity of Singapore.

3.3.1 Seaborne trade exposure

Through its effects on the environment and the economic and social well-being of nations, maritime transport helps ensure the long-term viability of the global trade system. Over the last two decades, the merchandise trade of Singapore has risen significantly, reflecting the importance of maritime trade to the economy of Singapore as a result of globalisation and national economic growth. Moreover, one-third of Singapore's GDP during the British colonial era was generated by entrepot trade (Rodan, 1989).

Lee (2012) analysed the long-run and short-run dynamic interactions between imports, exports, international tourism, and economic growth in Singapore and found that imports have a beneficial effect on growth over time. Further, its trade growth appears more volatile than GDP growth, which is not surprising considering the economy's openness (Lim, 2013). Meanwhile, Khalıd & Ahmad (2017) investigated the connection between trade openness and output growth for Singapore and indicated that greater trade openness is the primary factor driving Singapore's economic expansion.

3.3.2 Shipping services

For a nation to be prosperous, shipping is an essential mode of transportation. It affects how quickly a nation's economy develops. It is the most ideal and economical method of moving many goods. Likewise, it is essential for boosting trade and generating employment. Furthermore, it opens up employment opportunities in various related industries, including but not limited to ship management, ship chartering, shipbuilding, ship breaking, and ship repair. Singapore has taken advantage of its strategic location in Asia as it begins to dominate global trade to develop further the maritime sector that underpins it. In addition, the Singapore Registry of Ships (SRS) is one of the world's largest ten registries. Over 4,500 vessels are currently registered with the SRS. Additionally, Singapore controls roughly 70% of the global floating production storage and offloading (FPSO) platforms market and 70% of the global jack-up rig building industry (Maritime Singapore, 2022).

3.3.3 Port and terminal services

Although loading and unloading containers is a port's primary function, several additional characteristics assist the port in running smoothly and maintaining its competitive edge in Singapore. Moreover, the major Port - PSA, together with other ports, is Singapore's largest owner of warehouse space, overseeing approximately 500,000 m2, further enhancing its storage capabilities. The distriparks in Singapore serve a wide range of freight forwarders, manufacturers, and distribution companies. In addition to its typical Port operations it also aims to generate value by storing goods and empty containers, repackaging, labeling, tagging, sampling and testing, billing, and quality control (Gordon et al., 2005).

Moreover, Singapore, being one of the largest operators of container terminals worldwide, serves as Asia's primary transhipment hub handling through its four container terminals. Singapore's "PSA" is the top transhipment port, not just for its advantageous location but also for its effectiveness. Many exporters and importers feel that transhipping through Singapore is more practical and economical than shipping directly to their final destination. Finally, the new generation terminal of the

port of Tuas, is a further milestone in the maritime history of Singapore. It will be the world's largest container terminal and will be able to handle nearly 65 million TEUs annually. Table 4 provides Singapore's port performance and further insights into the port capabilities.

Table 4.

Singapore's Port Performance, 2021

MEASURE	Median time in port (days)	Average age of vessels	Average size (GT) of vessels	Maximum size (GT) of vessels	Average cargo carrying capacity (dwt) per vessel	Maximum cargo carrying capacity (dwt) of vessels	Average container carrying capacity (TEU) per container ship	Maximum container carrying capacity (TEU) of container ships
All ships	0.7542	11	25,837	237,200	19,312	321,300	5,421	23,964
Liquid bulk carriers	0.6153	11	11,608	170,562	19,582	321,300	..	..
Liquefied petroleum gas carriers	1.0563	13	7,754	48,060	8,796	58,757	..	..
Liquefied natural gas carriers	1.2313	8	96,551	149,367	76,448	122,052	..	..
Dry bulk carriers	0.5122	12	14,201	107,761	23,041	209,756	..	..
Dry breakbulk carriers	0.7806	15	8,107	91,649	10,836	103,652	..	..
Roll-on/ roll-off ships	..	14	54,728	76,420	18,342	43,878	..	..
Container ships	1.0337	13	57,988	237,200	..	..	5,421	23,964
Passenger ships	..	7	79,971	169,379	..	..	..	..

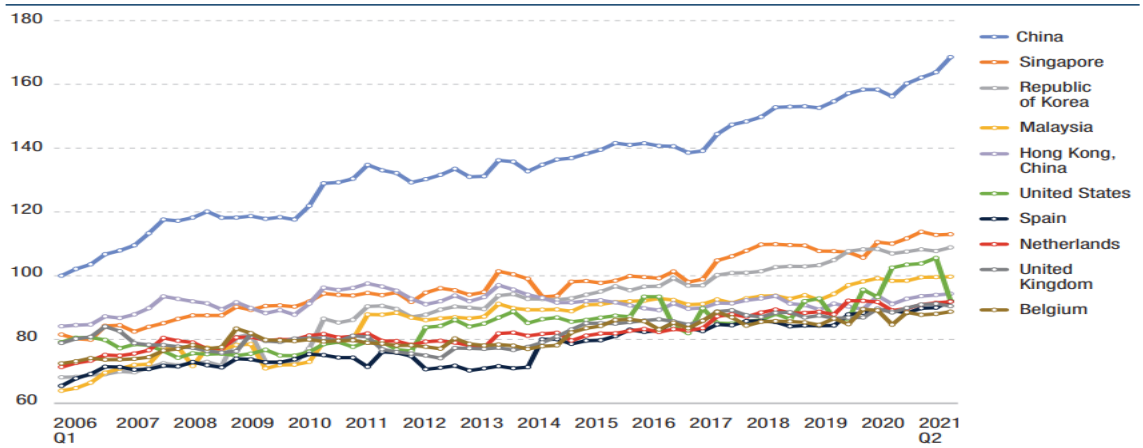
Source: Author's compilation based on UNCTAD Stat

On average, all ships stay in the port for 0.7542 days. Dry bulk spends less time in ports, while LNG carriers stay the longest. The average age of the vessels ranges from 7-15 years old, while the average size ranges from 7,754 GT (LPG) to 96,551 GT (LNG). In addition, the statistics also show that the average cargo carrying capacity in DWT per vessel is 19,312 with LPG having the lowest carrying capacity and LNG the highest (76,448 DWT).

Given the above statistics, it becomes essential to state that a country's location within the world's liner shipping networks is shown by the liner shipping connectivity index (LSCI).

Figure 8.

Liner Shipping Connectivity Index, 2006 Q1 - 2021 Q2

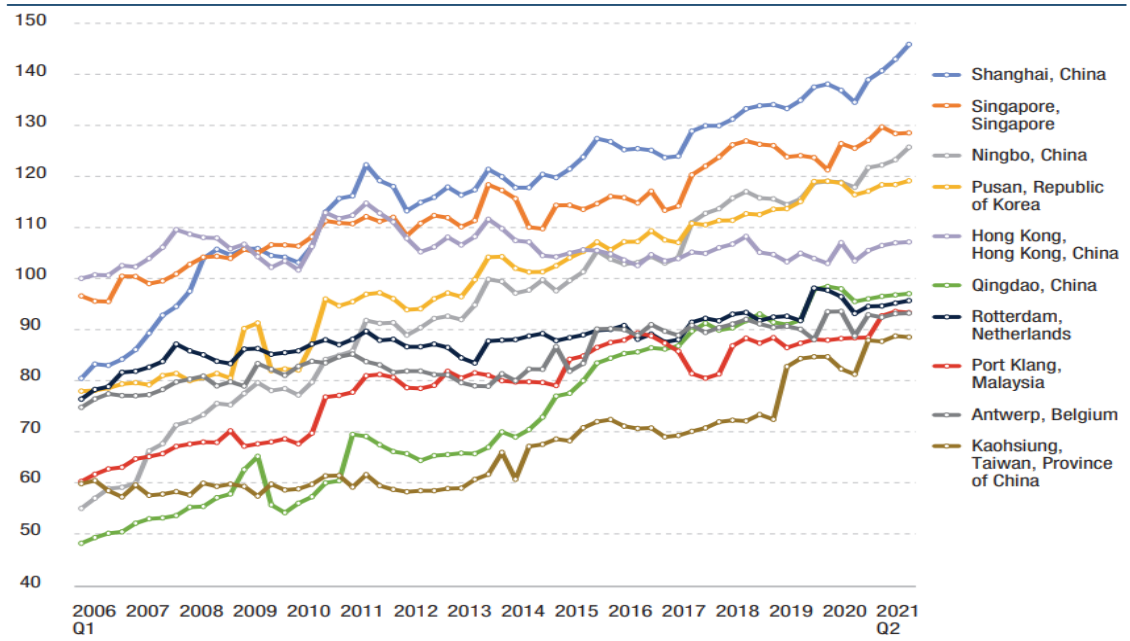


Note: UNCTAD Review of Maritime Transport, 2021

The better liner shipping connectivity reflects better access to overseas markets. It is determined by taking into account the number of calls made by ships, their capacity to transport containers, the number of services and businesses, the size of the largest ship, and the number of other nations connected by direct liner shipping services. In the third quarter of 2021, Singapore was the second-best economy connected to the global liner shipping network, as measured by the LSCI as shown the figure 8. Besides, LSCI at port level Singapore port was also the second-best port in the world, as shown in figure 9.

Figure 9.

Port Liner Shipping Connectivity Index, 2006 Q1 - 2021 Q2



Note: UNCTAD Review of Maritime Transport, 2021

The SRS has expanded alongside AIS expansion. With an average age of 10 years, it is presently the fourth largest in the world and is managed by the MPA. The SRS registered 3843 ships totalling 43.7 million gross tons in 2008, primarily tankers, bulkers, and cargo ships. The Singapore flag also has a reputation for being among the safest. PSC inspection rates are low because it is on the "allowlist" of both the Paris and Tokyo MoU (Vier, 2010).

3.3.4 Maritime Logistics Services

Maritime logistics includes typical logistics functions, including warehousing, storage, distribution centre services, and integrated logistics activities. Maritime logistics includes shipping and ports, including value-added services such as assembly, labeling, and repairing. Most importantly, Singapore is one of the leading bunkering ports in the world, even though it does not produce any oil. In Singapore, bunkers weighing more than 48 million tonnes were lifted in 2016. This would fill more than 17,000 Olympic-sized swimming pools.

Singapore is strategically situated at the main shipping lanes connecting the Indian and Pacific Oceans and has all the required infrastructure support. It boasts good infrastructure, effective telecommunications, a pro-business environment, extensive use of information technology, a wide range of commercial skills, and a talented and disciplined workforce. It also has world-class seaports and airports. Due to these benefits, Singapore has drawn many domestic and foreign businesses. Over 6000 logistics companies operate in Singapore, providing transport, forwarding, warehousing, and distribution services to multinational corporations. Singapore, a significant regional and global logistics hub, generates around 7% of its GDP from the logistics sector (Nam & Song, 2011).

3.3.5 Other Maritime Services

Apart from this, Singapore is a centre for maritime finance, insurance, maritime training and education hub. The government has been coordinating efforts to encourage the growth of various shipping-related services in Singapore since the statement about the intention to enhance Singapore's status as an International Maritime Centre was made in October 2003. These services include ship management, ship/financing and brokering, research and development, training, and maritime arbitration. A core group of shipowners, operators, and marine service providers are sought after by the MPA to establish operations in Singapore.

The middle of the 1960s saw a boom in commerce and services; now, the Singaporean economy is centred on high-value manufacturing, a regional financial hub for business services in East Asia. With the introduction of the Maritime Finance Incentive (MFI) Scheme, Singapore's goal of becoming a central maritime hub was further advanced. (Richardson, 1994).

As per Singapore Maritime Directory, by offering tax exemption for ship investment vehicles and a per cent concessionary tax rate for ship investment managers, it can draw alternative ship financing institutions such as ship leasing companies, shipping funds, and shipping trusts.

With various marine insurers, protection and indemnity (P&I) Clubs, hull and machinery (H&M) insurance, and defence clubs operating there, Singapore also provides a broad and complete range of marine insurance services. Currently, more than 30 marine insurance companies are operating here, providing direct and reinsurance coverage to all facets of the maritime business. There are about 60 licensed insurance brokers, including marine specialists in Singapore, in addition to Lloyd's syndicates and the International Group P&I Clubs, which provide marine hull & liability insurance. Singapore has been home to a branch of Lloyd's Asia, which manages Lloyd's syndicates, since 1999.

Singapore is also quickly becoming Asia's centre for maritime law and arbitration, and it is one of the leading international players in the offshore and marine engineering sectors. The headquarters and representative offices of numerous international maritime organisations and associations, including the Baltic Exchange, ASF, IBIA, INTERTANKO, and BIMCO.

Singapore also has the most technologically sophisticated and practical shipbuilding and ship-repair facilities in Southeast Asia and is the third-largest petrochemical refiner in the world. It controls over 65% of the global floating production storage and offloading (FPSO) conversion industry and around 70% of the global jack-up rig building business.

MPA has collaborated closely with numerous partners to assist projects for workforce development and training as part of their efforts to cultivate talent for the sector. One of the areas of attention is the education of the maritime workforce. To improve professional standards and understanding within the shipping sector, the International Trading Institute at Singapore Management University and the Institute of Chartered Shipbrokers Singapore Branch provide the UCS-ITI Shipping curriculum (Vier, 2010).

In summary, the SOMS has played a vital role in global maritime trade and is unrivalled in this region for its dominance (George, 2008). Given the facts and discussions, it is observed that Singapore, a coastal country, has gained importance

in maritime trade by proving itself to be the world's premier transhipment port. Considering Singapore's economic and strategic importance, it will be attractive to nowcast its GDP and its different components that are greatly influenced by maritime trade and services and quantify these impacts for making informed policy decisions. This study is significant because numerous studies addressed trade's impact on a specific country's GDP. However, in the case of Singapore, they failed to accurately portray the accurate picture describing the impact of maritime trade on the GDP of Singapore based on real-time maritime trade data. However, the world economy is evolving and undergoing dramatic economic changes. Nevertheless, these economic changes affect the macroeconomic policy decisions of Singapore. Therefore, this study focuses on nowcasting the GDP and its subcomponents based on real-time maritime data by employing modern nowcasting techniques DFM for monitoring these macroeconomic factors.

Chapter Four: Conceptual Framework, Research Methodology and Dataset

Before this chapter, an extensive review of the literature regarding GDP nowcasting was conducted to find the relevant gaps concerning the nowcasting macroeconomic variables from the case of Singapore. This study uses only quantitative methods to fill these identified gaps.

Firstly, the chapter provides a conceptual framework for nowcasting macroeconomic variables to make sustainable economic decisions. Secondly, it introduces the method which has gained popularity and has wider acceptance among economists as a nowcasting tool to estimate quantitatively the economic activity of a country in the current period or over the very near future (Dauphin et al., 2022), known as the Dynamic Factor Model (DFM).

In the final section of this chapter, the dataset used for analysis discusses the importance of high-frequency maritime trade flows and shipping data with sources. A brief description of the rationale behind using these indicators with proper justification for each category has also been made.

4.1 Conceptual Framework

In economics and finance, nowcasting is a relatively new concept. Using this section, we develop a framework that can nowcast macroeconomic variables such as GDP using maritime trade and services data. Additionally, DFM is proposed to project the GDP in real time based on data regarding maritime trade and services.

4.1.1 Evolutionary concept of nowcasting

Using more time available information, nowcasting is estimating a target variable's current, or a state that is very similar to it, forward- or backward-in-time condition (Hopp, 2021).

Initially, the nowcasting technique was developed through weather forecasting in the early 1980s. It was described as the projection method for a series of radar pictures

for producing a short-range forecast of forest rainfalls (Wilson et al., 1998). As such, it has been applied in many fields, and the most widespread applications are in meteorological forecasting and financial or macroeconomic variables forecasting. The nowcasting concept has been popular among economists and researchers in recent years. This term is different from forecasting. While forecasting focuses on estimating the future based on data from the past and the present through an in-depth analysis of patterns in the real-time performance of the economy, nowcasting is a technique devised to make very short-term forecasts.

The term 'nowcasting' is a portmanteau of two words, i.e., 'now' and 'forecasting' is a method that can successfully handle this task. It predicts the present, very near future, and very near past (Banbura et al., 2010). It also relies on facts, concentrates on what is known and understandable, and maintains a strategic distance from forecasting. Moreover, it is also defined as the economic discipline that objectively determines a trend or a trend reversal in real-time (Ineichen, 2015).

The development of a precise analysis of the current status of the economy is considered the first step toward building long-term growth, development, and prosperity (Ferrara & Marsilli, 2019). In economics, it is used to forecast a country's macroeconomic situation for a short period. As a result, nowcasting has become crucial in monitoring the macroeconomic variables released with a substantial degree of delay and collected at a very low frequency, mainly quarterly. This is done by acquiring the early estimates for these macroeconomic variables and applying them by obtaining high-frequency data that are released more timely. The strength of nowcasting is to incorporate the most recent information in a way where data are released non-synchronously and with various publication delays (Banbura et al., 2010).

Researchers and economists are employing different techniques or models for nowcasting the macroeconomic variables for different economies in different years to get the most accurate forecasts shown in the table below.

Table 5.

List of Research regarding nowcasting through different techniques (2003-2022)

No.	Author	Year	Title	Model Employed
1	Bilek-Steindl, S., Url, T.	2022	Nowcasting and monitoring SDG 8	DFM
2	Anesti, N., Galvão, A.B., Miranda-Agrippino, S.	2022	Uncertain Kingdom: Nowcasting Gross Domestic Product and its revisions	Release- augmented dynamic factor model (RA-DFM)
3	Bragoli D., and Fosten, J.	2018	Nowcasting Indian GDP	DFM
4	Caruso, A.	2015	Now-casting Mexican GDP	DFM
5	Ba´nbura, M., Giannone, D., Modugno, M., Reichlin, L.	2011	Nowcasting with daily data	DFM
6	Ba´nbura, M., D. Giannone, and L. Reichlin	2011	Nowcasting	Dynamic Factor Model
7	Doz, C., D. Giannone, and L. Reichlin	2011	A two-step estimator for large approximate dynamic factor models based on Kalman filtering	DFM
8	Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L., Rünstler, G.	2011	Short-term forecasts of euro area GDP growth	Bridge Equation, bridging Factor Model
9	Marcellino, M., and C. Schumacher	2010	Factor MIDAS for Nowcasting and Forecasting with Ragged- Edge Data: A Model Comparison for German GDP	MIDAS
10	Aruoba, S., F. X. Diebold, and C. Scotti	2009	Real-Time Measurement of Business Conditions	Dynamic Factor Model
11	Giannone, D., L. Reichlin, and S. Simonelli	2009	Nowcasting Euro Area Economic Activity in Real Time: The Role of Confidence Indicators	Simple Vector Autoregressive Model (VAR)
12	Giannone, D., L. Reichlin, and D. Small	2008	Nowcasting: The real-time informational content of macroeconomic data	Factor Models
13	Doz, C., D. Giannone, and L. Reichlin	2006	A Maximum Likelihood Approach for Large Approximate Dynamic Factor Models	DFM
14	D'Agostino, A., Giannone, D.	2006	Comparing alternative predictors based on large-panel dynamic factor models.	DFM
15	Evans, M. D. D.	2005	Where Are We Now? Real-Time Estimates of the Macroeconomy	DFM, MIDAS
16	Forni, M., Hallin, M., Lippi, M., Reichlin, L.	2005	The generalized dynamic factor model: one-sided estimation and forecasting	DFM
17	Baffgi, A., Golinelli, R., and Parigi, G.,	2004	Bridge models to forecast the euro area GDP	Bridge Models
18	Forni, M., M. Hallin, M. Lippi, and L. Reichlin	2003	Do financial variables help forecasting inflation and real activity in the euro area?	AR, SW, FHLR
19	Mariano, R., and Y. Murasawa	2003	A new coincident index of business cycles based on monthly and quarterly series	Factor Model
20	Stock, J. H., and M. W. Watson	2003	Macroeconomic forecasting in the Euro area: country specific versus area-wide information	Autoregression; vector autoregressions (VARs), DFM

By analysing different researches from Table 5, it is evident that nowcasting techniques were used in economics which were the simplest, and the earlier versions of nowcasting tools are bridge equations and MIDAS. However, recently

statistical tools have been developed to overcome the inherent problems of the earlier nowcasting tools. The high dimension problem of extracting common factors from large sets of indicators is addressed by dynamic factor models, which are implemented through the estimation of principal components or a state space representation (Evans, 2005; Giannone et al., 2008; Arouba et al., 2009). The mixed-frequency problem is solved via Mixed Data Sampling (MIDAS) equations and state space representations of DFMs. They have all shown to be successful at forecasting short-term developments. Additionally, especially in a volatile situation, they appear to outperform univariate statistical models regarding prediction effectiveness.

The nowcasting tool focuses on predicting the current value of the observed variables, such as GDP, which gives a transparent means of reading the flow of data releases. The benefits of nowcasting include the following: it is judgement free, contains no behavioural biases, is high-frequency, and therefore timely and transparent is that providing a quantitative way of reading the news flow (Reichlin et al., 2011). Besides, Giannone et al. (2008) highlighted the fundamental advantages of nowcasting that uses a large number of a dataset from various sources and frequencies, updates the estimates according to a real-time data release calendar, and bridges the monthly data releases with the quarterly data.

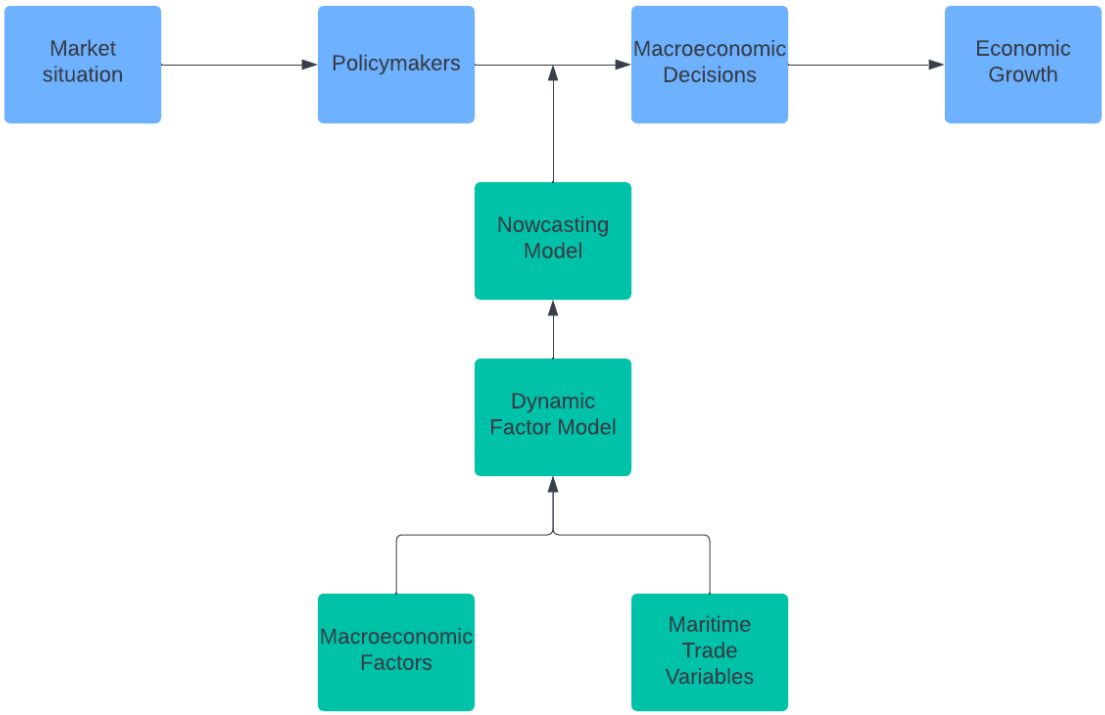
In this study, the DFM has been used to get reliable nowcasts of GDP, industrial production, manufacturing, transportation and storage, and financial and insurance services for Singapore. This workhorse and natural model has been successfully applied in many countries for nowcasting macroeconomic conditions such as GDP to capture the co-movement among numerous variables that allows exploiting the more timely variables for predicting the variable that releases with a longer delay. However, nowcasting is very complex. As Mark Twain mentioned, "Prediction is challenging, especially if it is about the future."

4.1.2 Conceptual Framework for nowcasting the GDP using real-time maritime trade and services data

The conceptual framework for nowcasting the GDP in real-time is designed to understand better the phenomena linked to maritime trade and macroeconomic variables, as well as how macroeconomic policy decisions affect the economic growth of a country. Besides, the process of nowcasting with the application of DFMs has been presented to get reliable and timely forecasts.

Figure 10.

The conceptual framework for nowcasting the GDP based on maritime trade and services



Note: Developed by the Authors

The conceptual framework shown above (in Figure 10) illustrates two things: 1) the traditional way in which knowledge regarding the current market situation can influence how the policymakers make a macroeconomic decision to help achieve

growth of one's economy, and 2) how these professionals may use the nowcasting technique to provide accurate and sound decisions and arrive at the same goal of improving a country's economy. Relatively, these market situations, whether natural or man-made phenomena such as economic shocks, fluctuations, geopolitical events, etc., negatively influence international trade and a country's economic growth in general. Moreover, publication lags make it difficult for policymakers to issue accurate policies or decisions. This may lead to variations in macroeconomic factors such as GDP.

In light of Stopford's (2013) finding that seaborne trade has a dynamic relationship with economic growth, maritime trade disruption may affect overall economic factors' values. To help the researchers explain how the two are related, it is relevant to emphasise that maritime trade is the backbone of any economy and is highly influenced by shipping, port and logistics and other related activities such as financial and insurance services, legal services, etc.

At present, advanced technologies for acquiring data, especially in the maritime sector, enable real-time data to be utilised. In this study, the researchers employ maritime trade data, as it provides 'high-frequency' data, meaning the data is released daily, weekly, monthly, or quarterly. With the help of the developed framework, nowcasting the macroeconomic factors (e.g., GDP) makes it easier to make accurate policy decisions. It can also mean that they provide real-time data, making it possible to nowcast the GDP of Singapore accurately.

Under the proposed framework, the workhorse model 'Dynamic Factor Model' (DFM) has been employed to obtain the most accurate forecasts of Singapore's current quarter GDP growth by using a large dataset. This model is based on the use of the Kalman filter to deal with mixed frequencies and imbalanced datasets, and DFM cast in the state-space representation. This framework can accommodate a potentially massive number of variables while avoiding the so-called 'curse of dimensionality' by condensing the data into a small number of common elements. In addition to predicting variables of interest in real-time, this framework enables forecasters to evaluate and discuss the causes of changes in the forecasts. This

adds a narrative element and deepens the forecast's understanding, which policymakers value almost as highly as the forecast's accuracy. Most of the statistical models currently employed for short-term projections lack these features (Rusnák, 2016). As a result, utilising this technique will allow us to predict more reliable macroeconomic variables, which will, in turn, help policymakers make sound judgments and policy decisions relevant to the economy's current situation.

Accordingly, this conceptual framework has been employed for the study of nowcasting the GDP, together with its components such as industrial production, transportation, manufacturing, and financial and insurance services that are directly influenced by the maritime trade and services. These have been considered using real-time, high-frequency maritime data with the application of DFM to get reliable forecasts. However, in future research, this conceptual framework can be used for nowcasting other macroeconomic variables of Singapore or other economies with a large dataset by application of practical models.

4.2 Research Methodology

Platforms for real-time forecasting that integrate formal models for huge data and filtering into nowcasting have been made possible in recent decades thanks to new approaches in time-series econometrics. The components impacting the macroeconomic model are quite complicated, and the accuracy provided by basic single-series prediction is not good enough. So, in this section, a nowcasting strategy based on maritime data and a DFM is suggested. In a nutshell, the goal is to assess the real-time maritime activity for the current quarter and how it affects macroeconomic variables based on the flow of information available during the quarter.

4.2.1 Nowcasting Approach using Dynamic Factor model

The development of automated platforms for real-time macroeconomic monitoring has been made possible by new time-series econometrics approaches that have emerged during the past 20 years. By merging large data models and filtering procedures, Giannone et al. (2008) created the first formal and internally consistent

statistical framework of this kind. They called it "nowcasting," a word initially used in meteorology to forecast the weather for the present and the next few hours because of the focus on the present.

4.2.1.1 Dynamic Factor Model

Large macroeconomic data sets have been widely analysed using DFMs. These data sets frequently include hundreds of series with hundreds of observations. They have shown promise in combining data from variables observed at various frequencies, estimating the latent business cycle, nowcasting and forecasting, and estimating the likelihood of recessions and turning points (Doz & Fuleky, 2020).

Strict or exact factor models are the name given to the first generation of DFMs. The DFM can handle data with varied frequencies and jagged edges and links output growth to the evolution of a small subset of monthly variables in the context of GDP nowcasting. A monthly frequency of maximum likelihood estimation is used to estimate the model built up in state space. The Kalman filter is used to filter the common latent factor. GDP is only tracked for one month of each quarter, with the other two months being considered empty. As an alternative, GDP can be extrapolated from a quarterly to a monthly frequency using traditional statistical techniques. In addition to the consensus among experts that monthly data are helpful, several studies of GDP nowcasting (see, for instance, the review paper by Banbura et al., 2013) have demonstrated that the time information present in monthly indicators reduces the out-of-sample forecast errors of GDP models.

The term "approximate" or "static factor models" refers to the second generation. Typically, estimating such a model entails two steps. First, the principal component analysis estimates the common factors among the indicators. Second, a linear OLS equation connects the anticipated variable to the elements from the first stage. This method was developed to handle large datasets with dozens or even hundreds of indicators. However, empirical studies typically reveal that increasing the number of variables in a model to above 30 to 40 does not typically increase the model's forecasting accuracy. The static specification of components and the way mixed frequencies and ragged edges of data are handled are a few of this approach's

primary drawbacks. The latter issue is often resolved by aggregating and realigning the data, although this may skew the correlation between the monthly series and GDP.

Factor models are now in their third generation to capitalise on the advantages of the first two generations. The capacity to manage huge datasets with uneven publication lags and heterogeneous frequency distributions can be summed up as a benefit (Toth, 2017).

In the present study, DFM is applied with some minor modifications. The same is modified in the view of a relatively large dataset, while the variables also have different frequencies (weekly, monthly, and quarterly). As a result, this model can benefit from a state-space model's ability to mix various data frequencies elegantly and handle missing values brought on by publishing lags.

Since the study's goal is regularly updating GDP nowcasts, the model's capability is quite advantageous. When fresh advance maritime data becomes available, GDP nowcasts can be updated on a roughly weekly basis given the range of variables taken into account, delivering a significant time benefit.

4.2.1.2 Mathematical Expressions

While DFM assumes that many observed variables $y_{1,t}$, … … … … . . $y_{n,t}$ are driven by a few unobserved dynamic factors $f_{1,t}$, … … … … . . $y_{r,t}$, while the features that are specific to individual series, such as measurement errors, are captured by idiosyncratic errors $e_{1,t}$, … … … … . . $e_{n,t}$

The empirical model can be summarised in the following equation.

$$y_{1,t} = \lambda_{i,1} f_{i,t} + \cdots + \lambda_{i,r} f_{r,t} + e_{i,t}, (where\ i = 1, \ldots, n) \qquad \textbf{(1)}$$

which means the observed variables $y_{1,t}$ depend on unobserved factors $(f_{1,t} \ldots\ldots\ f_{r,t})$ through factor loadings $\lambda_{i,1}, \cdots + \lambda_{i,r}$, while the

idiosyncratic component $e_{1,t}$ captures the movements or shocks specific to each variable *i.*

All together, they give the common component $\sum_{j=1}^{r} \lambda_{i,1} f_{j,t}$

As discussed in the literature review chapter, factor models had an evolving history in the literature related to econometrics. However, Giannone et al. (2008) observed that the dynamic factor models are particularly well suited for nowcasting and monitoring macroeconomic situations in real-time was not made until 2008. This is so that inference can be carried out using Kalman filtering techniques since these models are naturally cast in a state-space form. The common factors and the idiosyncratic components are treated as autoregressive processes, which account for their serial correlation and persistence, to conduct inference in DFMs using Kalman filtering techniques.

$$f_{j,t} = a_j f_{j,t-1} + u_{ij,t}, u_{ij,t}, \sim^{iid} \mathrm{N}(0, \sigma_{\varepsilon i}^2), where\ j = 1, \ldots, r \qquad \textbf{(2)}$$

$$e_{i,t} = \rho_i e_{i,t-1} + \epsilon_{i,t}, \epsilon_{i,t}, \sim^{iid} \mathrm{N}(0, \sigma_{\varepsilon i}^2), where\ j = 1, \ldots, n \qquad \textbf{(3)}$$

Equations 1, 2, and 3 create a state space model in which the idiosyncratic elements and common factors are unobserved states. The measurement equation, or equation 1, connects the data to the unobserved states. Equations 2 and 3, also referred to as transition equations, define the system's behaviour. The idiosyncratic component of the variables is expected to follow an AR (1) process (3). We add our shocks to persistence, so these shocks are not impulsive. It implies that these shocks do not occur continuously. In terms of cross-section and time series dimensions, they are uncorrelated.

Quarterly series

Quarterly series are incorporated into the model by expressing them in terms of their partially observed monthly counterparts, as in Mariano & Murasawa (2003). There

are five quarterly variables used in this model and each of them can be expressed as the sum of their unobserved monthly contributions. For example, GDP (GDP_t^Q) is expressed as the sum of their unobserved monthly contributions (GDP_t^M)

$$GDP_t^Q = GDP_t^M + GDP_{t-1}^M + GDP_{t-2}^M \quad (for\ t = 3, 6, 9) \qquad \textbf{(4)}$$

4.2.1.3 Kalman Filtering and Smoothening

Accordingly, the significant components of the DFM – Kalman filtering and Principal Component Analysis are replicated in this model too. Recently, COVID-19 or the ongoing geopolitical issues have severely impacted trade worldwide. This proves a solid basis for using Kalman techniques to smoothen such noises and disturbances in the data set. As per Nowcasting during the COVID-19 pandemic, we find that the dynamic factor model reacted much more than any other model. In many different fields and application areas, using PCA to achieve this goal has become a popular strategy (Curran et al., 2015; Jolliffe, 2002).

Given measurements taken over time, Kalman filtering is a technique that produces estimates of some unknown variables. Applying the Kalman filter and smoother, which models the variance of missing values as infinite, allows for handling jagged edges. By using the below steps, the same is applied in the model.

Prediction estimates the current value of the latent factor based on its past values and the current value of the observed based on the current value of the latent factor.

Correction updates the current value of the latent factor based on the error of the estimated observed and the actual observed. The effect of the error depends on Kalman gain, which is the relative of the measurement's variability vs. the state's variability. If the variability of the measurement is relatively more considerable, there is lower confidence in the estimates, and the effect of the error will be weaker.

Forecasting is also the Nowcasting step, where it estimates the currently observed value based on the current latent factor.

Smoothening goes back to updating past estimates of the latent factor with the entire data in retrospect, based on how well it eventually estimated the latent factors at each of the next steps.

4.2.1.4 Principal Component Analysis

Maritime data is quite volatile and also witnesses multiple shocks and crises. Furthermore, because of the relatively large dataset employed, the models are more likely to become complex, which increases the risk of under or over-specifying important patterns. A threat known as the "curse of dimensionality" is also posed by such a high number of variables. Essentially, it is a trade-off between excessive complexity and simplicity, which can result in misspecification (leading to instabilities). The factor models aim to approach such a problem sparingly (Bok et al., 2018).

Choosing between principal component analysis and common factor analysis in a model for illustrating the connection between a group of measured variables is frequently portrayed as having minimal substantial effects on data presentation and understanding (Velicer & Jackson, 1990). Both types of analysis produce a reduced rank representation of the relationships between a collection of measured variables. Based on the Monte Carlo research, it is also asserted that common factor analysis and principal component analysis offer equivalent solutions for a particular collection of data (Velicer, 1977; Velicer et al., 1982).

Thus, Principal Component Analysis is a dimensionality-reduction technique that is used to reduce the dimensionality of large data sets. Hence, this analysis technique forms an intrinsic part of this model to overcome such issues. This model's various maritime factors (high-frequency variables) are divided into Maritime, Shipping, Port, and Logistic & Others for ease of handling the data.

In summary, to consolidate the huge collection of variables into a smaller one that still contains the majority of the data in the larger set, principal component analysis is carried out.

The steps followed for Principal Component Analysis are summarised as below:

1. Standardize the range of continuous initial variables Z= $\frac{value-mean}{standard\ deviation}$ **(5)**

2. Compute the covariance matrix to identify correlations

$$\begin{matrix} Cov(x,x) & Cov(x,y) & Cov(x,z) \\ Cov(y,x) & Cov(y,y) & Cov(y,z) \\ Cov(z,x) & Cov(z,y) & Cov(z,z) \end{matrix}$$

(6)

(for a 3-dimensional data set with 3 variables x, y, and z, the covariance matrix is a 3×3 matrix)

3. Compute the eigenvectors and eigenvalues of the covariance matrix to identify the principal components.
4. Create a feature vector to decide which principal components to keep.
5. Recast the data along the axes of the principal component.

4.2.2 Nowcasting

After estimating the macroeconomic factors using the DFMs, the next step consists of nowcasting the macroeconomic factors of the country on the basis of the resultant estimates presented in the previous step.

To start with, the nowcasting equation can be expressed as follows:

$$\hat{Y}_t = €[Y_t|\Omega] \quad \textbf{(7)}$$

wherein $\hat{Y}_t$ represents the expected value of the dependent variable at time t taking into consideration the information or data available till the previous unit of time for the particular range of the data.

The nowcasting model decomposes the latent factors that drive the movements in the data and nowcasts each macroeconomic variable that it traces when the data for that series is published. The vintage data sets for Q1 of 2022 and Q2 of 2022 refer

to the further published data, which are the inputs in this step for the nowcasting of macroeconomic factors.

This approach includes the first step of following the data releases and secondly, forming expectations regarding them; and finally, updating the estimates (Sebin & Karvan, 2021). The same is expressed by the following equation:

$$E\left[y_t^Q|\Omega_{v+1}\right] = E\left[y_t^Q|\Omega_v\right] + E\left[y_t^Q|I_{v+1}\right] \quad \textbf{(8)}$$

Nowcast = Estimate + Vintage data

where Ωv denotes a vintage of data available at time *v*, where *v* is the date of a specific *Q* data release. The "news," or the unexpected component of the fresh data release, is what caused the nowcast to shift. The news is helpful because the difference between the release and the prior forecast, not the release itself, is what is important in understanding how the nowcast is updated. Consequently, the impact of the news is provided by

$$E\left[y_t^Q|\Omega_{v+1}\right] - E\left[y_t^Q|\Omega_v\right] = \sum_{j\in J_{v+1}} b_{j,t,v+1} \left(x_j\, T_{j,v+1} - E\left[x_j\, T_{j,v+1}|\Omega_v\right]\right)$$

Forecast Revision News (9)

where $b_{j,t,v+1}$ are weights derived from the model estimation and J_{v+1} is the set of new variable. News refers to the difference between actual data releases and the model's forecast. The nowcast revision is a combination of the news for each variable and its relevancy to the variable, which is the weight. The decomposition allows us to trace forecast revisions back to unexpected movements in individual predictors.

Thus, the estimate of macroeconomic variables is updated with the vintage data in this model to nowcast the GDP for 2022 Q3. The latest vintage data available for update pertains to June 2022, and the model nowcasts the GDP for Q3 before the actual publication of the same, which is around six weeks after the end of the quarter. With the help of two sets of vintage data, the model can nowcast the impact

of the updates/releases of the data on each macroeconomic factor, thereby decomposing the impact per data release. The model can also provide a detailed breakup of each variable on the related macroeconomic variable for further analysing the most important and least important maritime variables for the policymakers of the country to look upon.

4.2.2.1 Backcasting

Based on the real-time independent variables of data that are reconstructed to replicate the data as they were then, an extensive backcasting is presented to assess the real-time performance of the model and nowcast for 2022-Q1, taking into account vintage data available till April 2022. Such backcasting also implies the robustness of the model and that the users in the near future can replicate the model.

4.3 Dataset

Official statistics related to macroeconomic factors are produced with substantial delay and time lags. Besides, in times of shocks and crises such as pandemics and wars, it is critical to get access to real-time data to make sound decisions. Consequently, analysts and decision-makers depend on alternative sources of high-frequency data, such as AIS data, that can serve as proxies to estimate various macroeconomic variables. However, new technologies and approaches to data collection in the maritime fields make it easier to access real-time and allow researchers to rely on large datasets. At the same time, with the advancement of modern technologies and improved data collection techniques, it is possible to collect maritime trade, shipping, and port-related data. Maritime trade and shipping data span the statistics related to maritime trade flows, shipping activities, port calls, traffic volumes, maritime logistics, storage, etc.

In this study, the dataset of time series data from secondary sources with both high and low frequencies, including quarterly and monthly, with varying observation periods in different categories contains a diverse mix of a total of 54 independent variables that capture the different aspects of the macroeconomy, finance, maritime

trade flows, shipping, port and logistics of Singapore. This section will discuss the rationale behind using these data and briefly describe the collected variables with proper justification for analysis.

4.3.1 Importance of real-time maritime and shipping data for nowcasting GDP

From ancient times to the current globalised century, international seaborne trade is considered the nerve of economic growth. It was almost impossible to track macroeconomic variables such as GDP-based maritime and shipping data. However, most international trade activity is carried out by ships, and now it is easy to accurately monitor the movement of the ship and export-import activity using the Automatic Identification System (AIS) in real-time and port activities. Due to the emergence of modern technologies, real-time AIS data has become easier to derive for research (Arslanalp et al., 2019). Such AIS-based vessel traffic information and real-time trade activity is a reliable source for nowcasting the macroeconomic variables. In this dissertation, using Singapore as a case study, the maritime trade and shipping indicators have been selected, which is an innovative way to measure global trade activity in real time. Further, it could be facilitated by nowcasting the macroeconomic variables such as GDP, industrial production, etc. There are some fundamental advantages of shipping and port call data over official trade statistics. Firstly, maritime and shipping data can improve the timeliness and are available daily in real-time, while official trade statistics appear monthly. Then, port and shipping data improve the granularity of official trade statistics. In many cases, trade data is not broken according to vessel type, cargo type, or port type (Arslanalp et al., 2019).

4.3.2 Working with unbalanced data

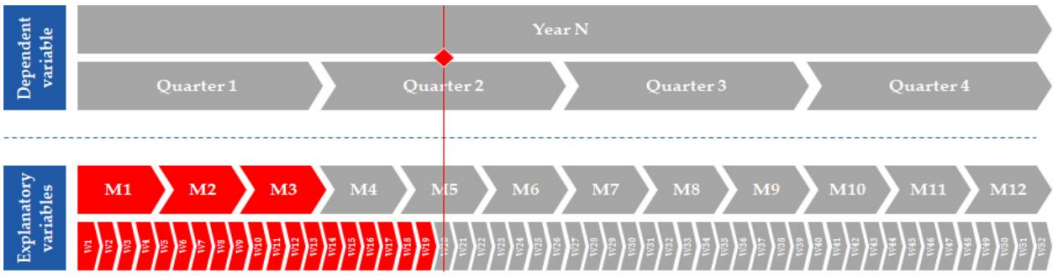
Some series feature data through the current month in real-time at specific publication dates, while the most recent observations are from the previous month for others. The underlying datasets are, therefore, imbalanced. Nowcasting requires proper dealing with this unbalanced part of the data (Zhang, 2020).

4.3.3 Approach to nowcast quarterly macroeconomic variables with high-frequency data

The fundamental assumption underlying the nowcasting technique is to exploit a diverse set of data available before an official release of certain variables, such as GDP. As a result, data selection and transformation are the keys to the success of nowcasting.

Figure 11.

Approach to nowcast quarterly variables incorporating weekly or monthly variables data



Note: Author's illustration

In this dissertation, one of the aims is to assess whether high-frequency maritime trade and services data can be used to forecast the macroeconomic variables in a timely fashion, providing an alternative model for nowcasting GDP from the lens of a maritime perspective. In this study, monthly data are used to nowcast quarterly GDP. The main advantage of high-frequency data is presented in the figure 11 as mentioned above in red squares: weekly data are available up to the preceding week, but in the middle of the month or the middle of the quarter, the data are yet not available. So, the primary rationale behind incorporating high-frequency data is to achieve more timeliness in a nowcasting model (Jardet & Meunier, 2022).

4.3.4 Data Sources

To get the most accurate results, it is necessary to use data that comes from reliable sources. In this study, most of the macroeconomic or maritime data collected were sourced from the Department of Statistics, Singapore, data.gov.sg,

Clarksons, AXS Marine, UN Comtrade, IMF, and the Monetary Authority of Singapore.

4.3.5 Data Description

This study selects the maritime trade and shipping factors as independent variables as input for nowcasting five quarterly dependent variables. A *data vintage* is a date at which a time series of data is observed. For example, the data vintage January 1970 refers to all the macroeconomic time series accessible in January 1970. This study summarises total collected variables in the Appendix-A and the Table 6 presented the final list of dependent and independent variables that has been considered for analysis after correlation test.

Table 6.

List of dependent and independent variables

Variables	Description	Impact / Direction	Formulation	Frequency	Period Covered	Observations	Source
Dependent Variables							
Macroeconomic Variables							
GDP	Gross Domestic Product at current market prices		Million S$	Q	Mar-1975 to Jun-2022	190	SingStat
IIP_SG	Index of Industrial Production		Index	Q	Jan-1983 to Jun-2022	158	SingStat
MFG	Manufacturing		Million S$	Q	Mar-1975 to Jun-2022	190	SingStat
TRANS	Transportation and Storage		Million S$	Q	Mar-1975 to Jun-2022	190	SingStat
FIN_INS	Financial and Insurance Services		Million S$	Q	Mar-1975 to Jun-2022	190	SingStat
Independent Variables							
Maritime Trade							
TMEREXP	Total Merchandise Export	Positive	000'S$	M	Jan-2000 to Jun-2022	270	comtrade.un.org/data
TMERIMP	Total Merchandise Import	Negative	000'S$	M	Jan-2000 to Jun-2022	270	comtrade.un.org/data
RE_EXP	Total Merchandise Re-Export	Positive	US$	M	Jan-2000 to Jun-2022	270	comtrade.un.org/data
RE_IMP	Total Merchandise Re-Import	Negative	US$	M	Jan-2000 to Jun-2022	270	comtrade.un.org/data
DC_LOAD_SG	Dry Cargo loaded (voyage intake)	Positive	Metric tonnes	M	Jan-2013 to Jun-2022	114	AXS Marine
LC_LOAD_SG	Liquid Cargo loaded (voyage intake)	Positive	Metric tonnes	M	Jan-2013 to Jun-2022	114	AXS Marine
DC_DISCH_SG	Dry Cargo discharged (voyage intake)	Positive	Metric tonnes	M	Jan-2013 to Jun-2022	114	AXS Marine
LC_DISCH_SG	Liquid Cargo (discharged voyage intake)	Positive	Metric tonnes	M	Jan-2013 to Jun-2022	114	AXS Marine
Shipping							
SCFI	SCFI Shanghai-SE Asia (Singapore) Container Freight Rate	Positive	USD ($)/TEU	M	Jan-2010 to Jun-2022	150	Clarksons
BSI	Baltic Exchange Supramax Index	Positive	Index	M	Jul-2005 to Jun-2022	204	Clarksons
DRY_LOAD_FROM_SG(LOAD_DURATION)	Dry Cargo Loaded from SG (Load Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
DRY_LOAD_FROM_SG(DISCH_DURATION)	Dry Cargo Loaded from SG (Discharge Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
LIQUID_LOAD_FROM_SG(LOAD_DURATION)	Liquid Cargo Loaded from SG (Load Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
LIQUID_LOAD_FROM_SG(DISCH_DURATION)	Liquid Cargo Loaded from SG (Discharge Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
DRY_DISCH_IN_SG(LOAD_DURATION)	Dry Cargo Discharged in SG (Load Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
DRY_DISCH_IN_SG(DISCH_DURATION)	Dry Cargo Discharged in SG (Discharge Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
LIQUID_DISCH_IN_SG(LOAD_DURATION)	Liquid Cargo Discharged in SG (Load Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
LIQUID_DISCH_IN_SG(DISCH_DURATION)	Liquid Cargo Discharged in SG (Discharge Duration)	Positive	Number of Days	M	Jan-2013 to Jun-2022	114	AXS Marine
DRY_LOAD_VOY_AVG_SPEED	Dry Cargo Loaded from SG (Voyage Average Speed)	Positive	Nautical miles	M	Jan-2013 to Jun-2022	114	AXS Marine
LIQUID_DICH_VOY_AVG_SPEED	Liquid Cargo Discharged in SG (Voyage Average Speed)	Positive	Nautical miles	M	Jan-2013 to Jun-2022	114	AXS Marine
Port							
VSL_CALLS	Vessel Calls	Positive	DWT	M	Jan-1993 to Jun-2022	354	data.gov.sg
VSL_ARVL	Vessels Arrivals (>75GT)	Positive	Number	M	Jan-1995 to Jun-2022	330	data.gov.sg
BULK_CARGO	Cargo (Bulk)	Positive	000'Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
PCI	Port Congestion Index	Negative	Index	M	Feb-2016 to Jun-2022	78	Clarksons
Logistics and Others							
BUNKSALES	Bunker Sales	Positive	000'Tonnes	M	Jan-1995 to Jun-2022	330	data.gov.sg
MGOBUNKER	MGO Bunker Price	Positive	US$/Tonnes	M	Jan-1990 to Jun-2022	378	Clarksons
XRATES	Exchange Rates	Negative	S$ to US$	M	Apr-1991 to Jun-2022	375	Clarksons
LIBOR	Market Interest Rate: US$ LIBOR 6 Months	Negative	%	M	Apr-1989 to Jun-2022	399	Clarksons
INFLATION_RATE	Inflation Rate	Negative	%	M	Jan-1970 to Jun-2022	630	rateinflation.com

4.3.5.1 Dependent variables:

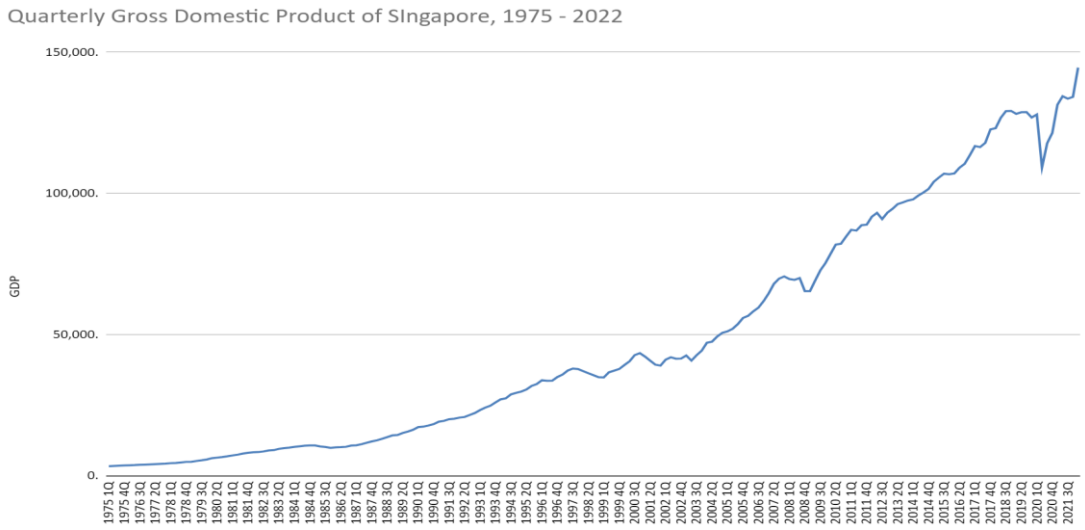
For Singapore, the five key quarterly variables are considered for nowcasting and these are briefly described below.

4.3.5.1.1 Gross Domestic Product (GDP)

GDP is considered the broadest measure of a nation's activity (Evans, 2005). The figure 12 below shows how the GDP behaves per quarter from the years 1975 to 2021. It is observed that the GDP of Singapore depicts a gradual increase till the year 2000 and as steep growth after that. In 1997, Singapore experienced the effect of the Asian financial crisis. A significant downturn is also visible in 2008 and 2020 due to the global financial crisis of the US and worldwide COVID-19, respectively.

Figure 12.

Gross Domestic Product (GDP) for Singapore, 1975-2022

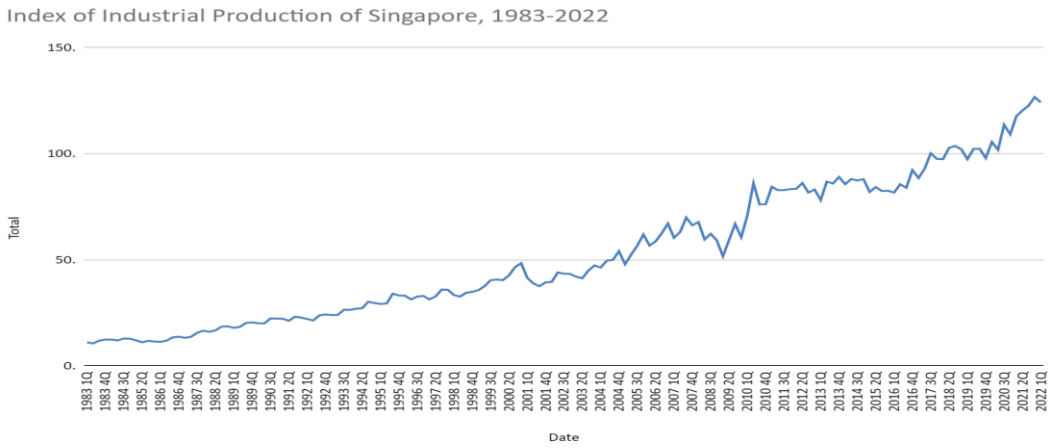


4.3.5.1.2 Industrial Production (IIP)

The industrial production index (IIP) is an economic indicator measuring actual output in the manufacturing, mining, electric, and gas industries relative to a base year. It is published in the middle of every month by the Federal Reserve Board (FRB) and reported on by the Conference Board, a member-driven economic think tank. The FRB also releases revisions to previous estimates at the end of every March. IIP graph (shown in figure 13) is relatively consistent till the year 1999 and 2000. During the 1980s, Singapore began to upgrade to higher-technological industries. The year 2001 registered a drop due to the impact of recession in Asian economies. Further, the 2008 decline was a result of the US Financial crisis. There was also a decline in 2016 since the transport engineering cluster placed a drag on growth.

Figure 13.

Index of Industrial Production for Singapore, 1975-2022

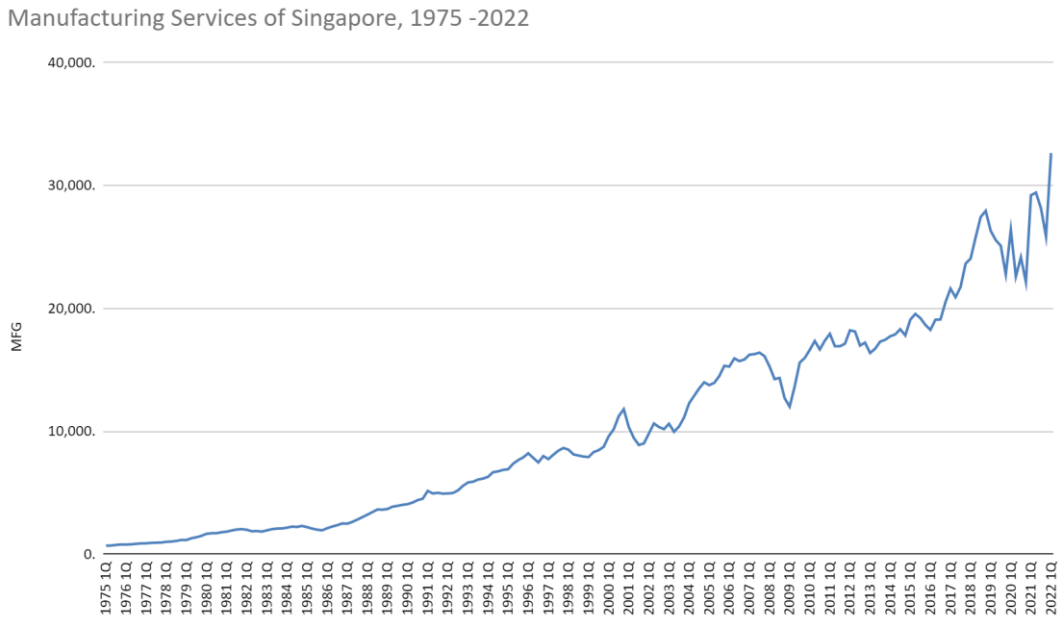


4.3.5.1.3 Manufacturing

Singapore's most prominent industry by far is the manufacturing sector, contributing 20%-25% of the country's annual GDP. As observed in the graph (shown in figure 14), the sector contracted in 2001 due to the adverse impact of lower demand for electronics products and the weak US economy. In contrast, other fluctuations go hand in hand with the 2008 and 2020 worldwide crises.

Figure 14.

Manufacturing Service for Singapore, 1975-2022

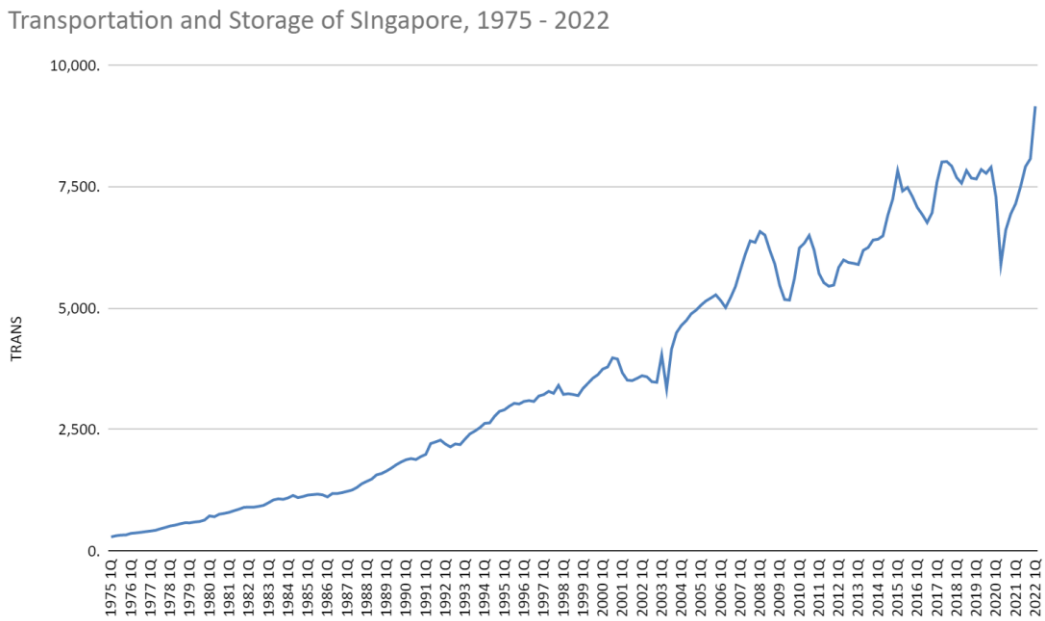


4.3.5.1.4 Transportation and Storage

The transportation and storage sector also follows the same trend as other sectors with respect to the 2008 financial crisis and majorly the COVID-19 pandemic as shown in figure 15.

Figure 15.

Transportation and Storage for Singapore, 1975-2022



4.3.5.1.*5 Financial and Insurance Services*

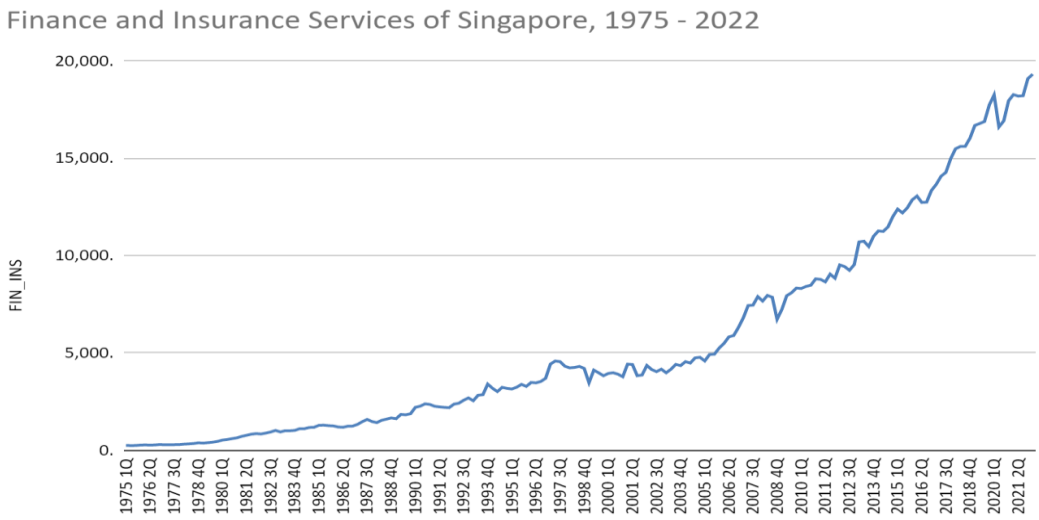
The figure 16 shown below that finance and insurance service in Singapore, in general, has been increasing significantly over time. It can be observed that the growth of this sector is gradual and is impacted by the overall ups and downs of the world economy.

This can be explained by the number of financial institutions and businesses based in Singapore. This is not only because of the ease of doing business in the country

but also because of other factors such as the sound economic and political environment, conducive legal and tax policies, reputation for integrity, and strict regulations against crime and money laundering. These factors have created a vibrant marketplace conducive to trade, business networking, and events.

Figure 16.

Finance and Insurance Services for Singapore, 1975-2022



4.3.5.2 Independent variables

When building a nowcasting model, finding the independent variables that significantly influence the dependent variables and helpful, timely, or real-time, and updated frequency to forecast GDP growth and other macroeconomic variables is essential. For meeting those criteria, shown in the table above by categorising into four main categories: maritime trade, shipping, port and logistics, and others.

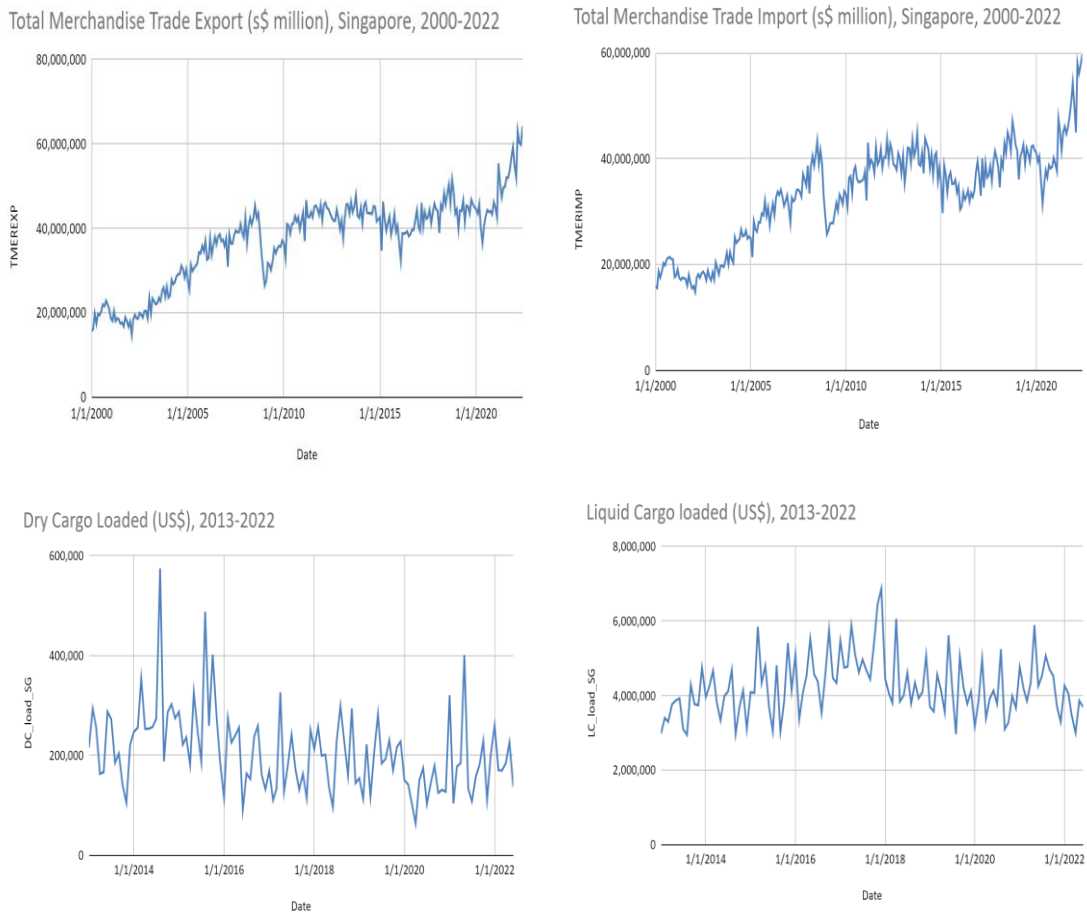
4.3.5.2.1 Maritime Trade flows

The maritime trade flows indicator includes total volume merchandise trade, export, import, re-export, re-imports, and total cargo loaded and discharged by vessels left from and for Singapore that reflects the trade activity in real-time. These indicators directly affect the GDP and show how an economy achieves more robust economic

integration and seamless connectivity to other countries through trade. Demand for imports by individual countries is estimated as a function of real GDP. Exports are estimated similarly as a function of import demand in the rest of the world, with foreign demand weighted by the structure of the country's exports (WTO, 2020). Four leading trade flows indicators are plotted below as shown in figure 17.

Figure 17.

Maritime Trade Flows



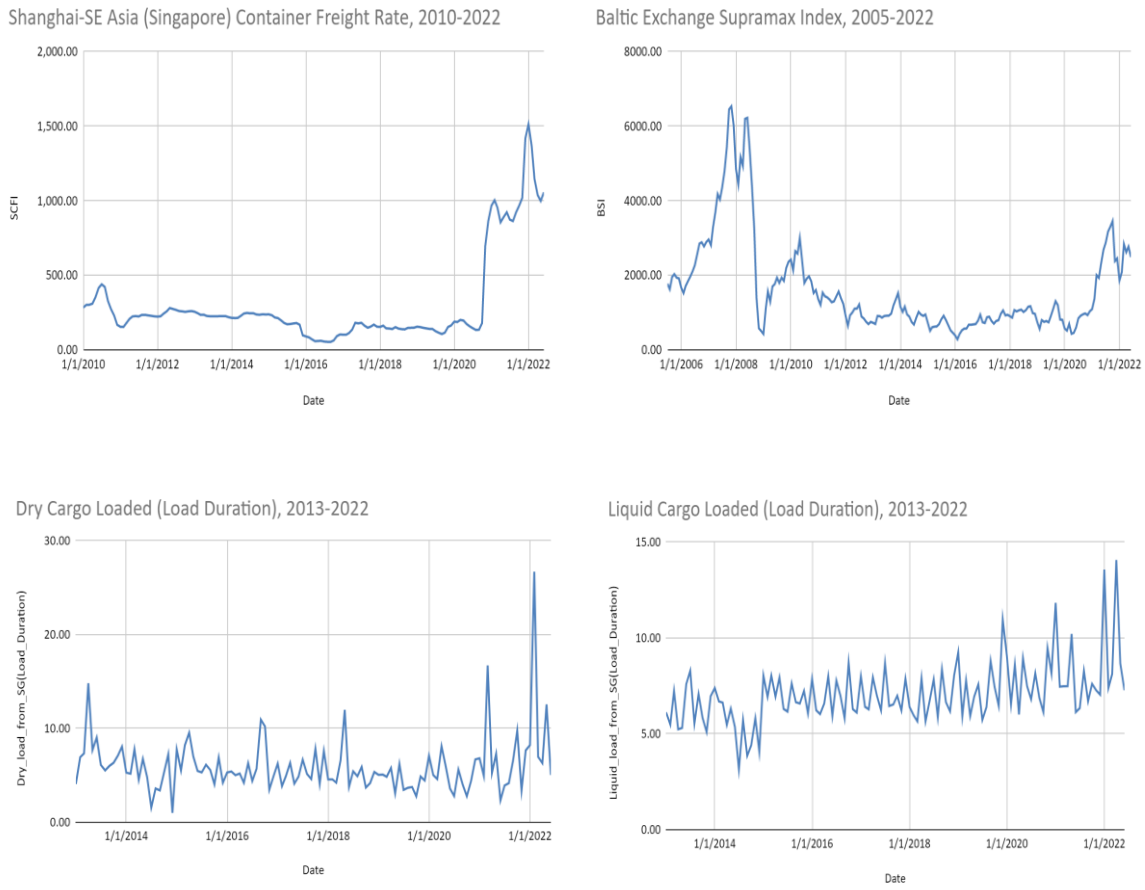
4.3.5.2.2 Shipping

Shipping indicators are insights generated by the physical movement of ships and their prices and freight rate indices that measure the trends of shipping activity. The

shipping indicators include freight indices, vessel deliveries, demolitions, ship registration, vessels' speed, loading and discharging time, etc., that affect the transport costs positively or negatively and thereby increase or decrease the economic output. However, four major shipping indicators data are graphed below, (as shown in figure 18) and the rest are presented in the appendix.

Figure 18.

Shipping factors

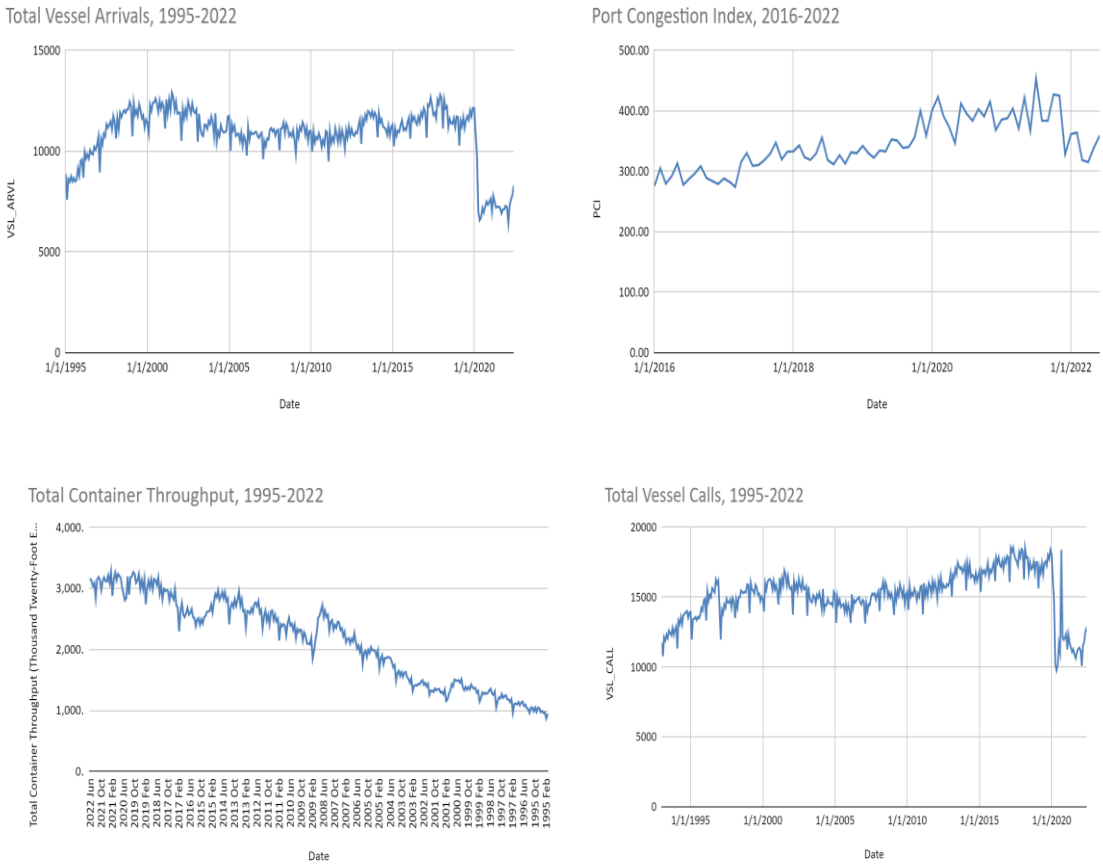


4.3.5.2.3 Port

Port-related indicators determine the performance of the port operations and trade activity that, includes total cargo throughput, including general, bulk, oil, non-oil, and containerised cargo, vessel calls and arrivals, port congestion index, etc. (Loke et al., 2014). Among the four are plotted in the below figure 19.

Figure 19.

Port-related factors



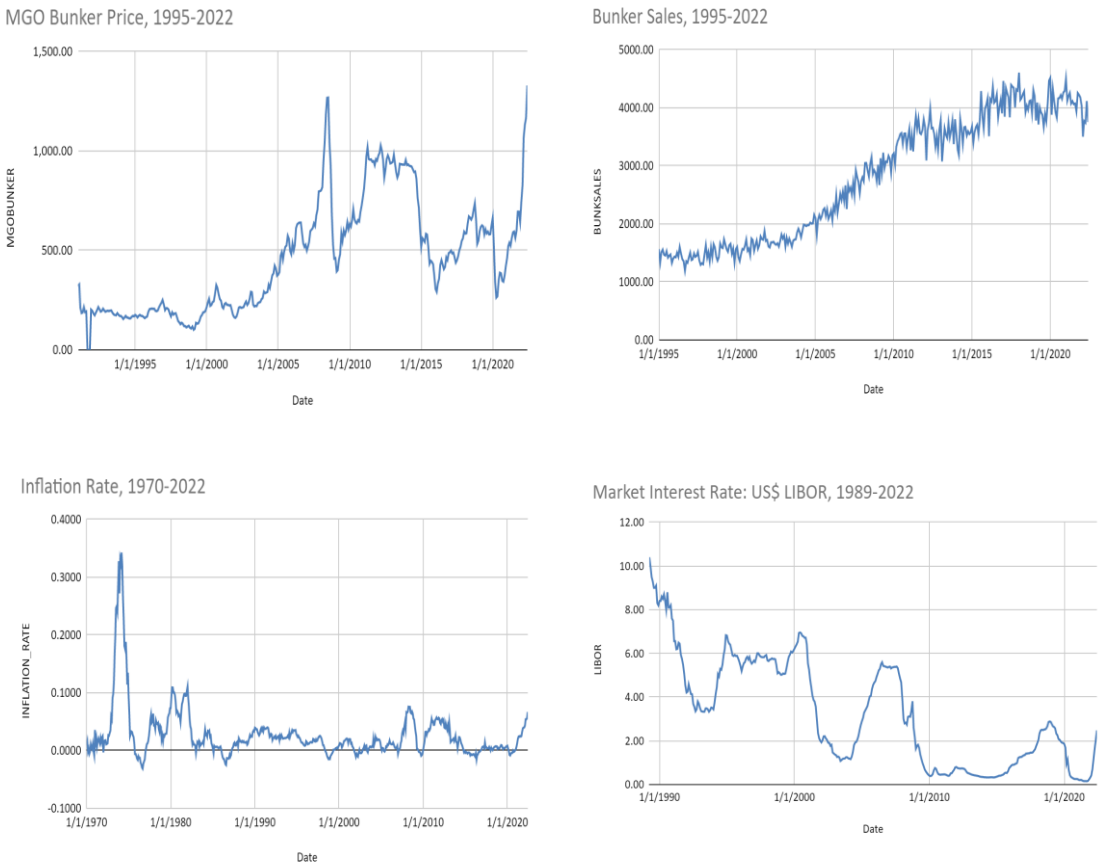
4.3.5.2.4 Maritime Logistics and Others (Economic and Financial)

Maritime logistics-related indicators such as bunker sales in Singapore positively affect GDP and other variables as shown in figure 20.

Economic and financial indicators such as inflation rate, interest rate, CPI, exchange rate, and foreign reserves are considered, affecting the macroeconomic variables either positively or negatively. Below, two line graphs in figure 20 depict the inflation rate of Singapore from 1970 to 2022 and the interest rate (LIBOR) from 1990 to 2022.

Figure 20.

Maritime Logistics and Other factors



Chapter Five: Analysis and Empirical Findings

In connection with research methodology, this chapter attempts to operationalise the Dynamic Factor Model (DFM) towards nowcasting Singapore's macroeconomic factors through the lens of maritime trade and services. Since the maritime trade flows and shipping data show high fluctuations, the model follows the dynamic factor analysis, thus overcoming the dimensionality issue of the data used. The well-known techniques of Kalman filtering and principal component analysis are the next steps, which form the basis of standard factor projections. With the use of vintage data updates, the aim of nowcasting is achieved for 2022 Q3. Nowcasting is a relatively new field in maritime economics, and it is likely to continue to be developed on many fronts. The findings are analysed and discussed at each data point. The chapter is finally concluded by presenting the impact of maritime trade flows and shipping activities on the macroeconomic factors of the economy.

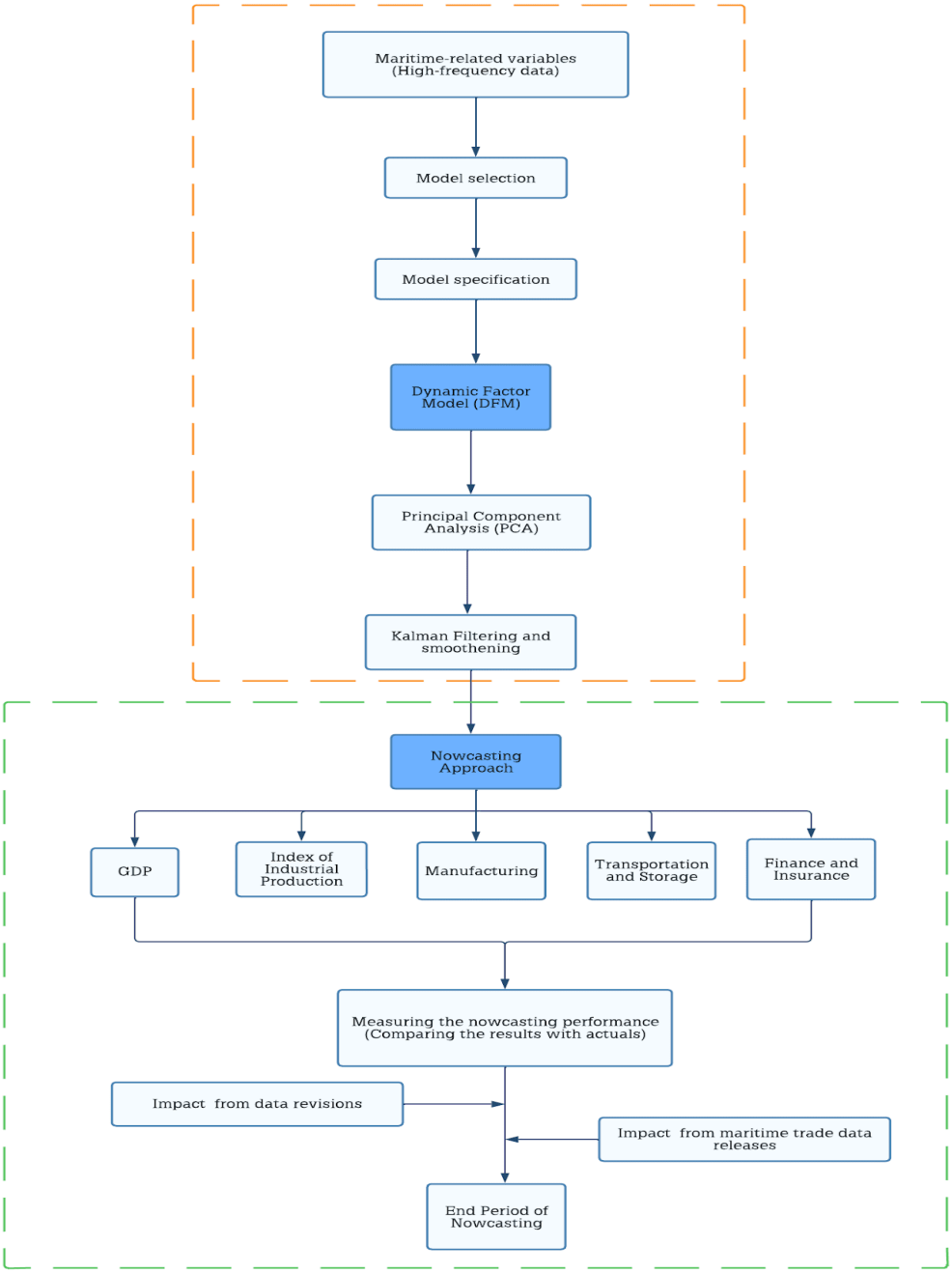
5.1 Analysis

To follow the steps and procedures explained in the methodology chapter, this section of this dissertation presents the key steps of analysis through an analytical framework to nowcast the quarterly macroeconomic variables of Singapore using maritime trade and shipping data.

5.1.1 Analytical Framework:

Figure 21.

Analytical Framework for Nowcasting



Note: Author's illustration

The analytical framework is designed, as shown in figure 21, explained in the research methodology section, to conduct the end-of-period performance of nowcasting quarterly macroeconomic variables.

Building a dataset of maritime industry variables that could theoretically, structurally, and empirically nowcast the target variables is the first step in the process. This allows us to begin with the supposition that these variables could potentially aid in the nowcasting effort. Since the approach relies on indicators that are released before the target variables, these variables should be timely and have a frequency at least as high as the goal indicator (i.e. minimum quarterly in this model). For the model to distinguish between the common factor and the idiosyncratic component, the time series needs to be long enough. Taking into account the said requirements, a final database or a dataset of 29 monthly variables and five (5) quarterly variables for the period from 1970 to recent 2022 was created in this step after the initial correlation analysis.

Real-time macroeconomic condition monitoring is essentially a significant data issue. Indeed, utilising overly simplistic models when working with huge data sets might result in incorrect specifications since crucial aspects are left out (Bok et al., 2018). The concept of a factor model is chosen as the primary model since the nature of the data time series is relatively dimensional and because such a model can handle many variables without running out of degrees of freedom (Breitung & Eickmeier, 2006).

The next step of model operationalisation was achieved with the implementation of model specification by defining the variables - series ID, series name and their unit of measurements. As mentioned, these independent variables have the frequency of monthly and quarterly. These variables enter the model at different times with different units and must be transformed accordingly. The basis of transformation is the main highlight of the model specification, defined as a percentage change at the model specification step.

Taking into account the dynamics of the large data set constructed, which pertains to different periods, the dynamic factor model is introduced as a state-space model in two stages. Firstly, it performs a Principal Component Analysis (PCA) to derive a first estimate of the common factors. At the PCA step, the data is then grouped into smaller sets of data based on maximum variance. Further on, using Kalman filter and smoothening (KFS) techniques, factors are extracted from the DFM.

The fact that the aforementioned methods allow for the Maximum Likelihood (ML) estimate of the model parameters is one of their distinguishing features. Due to KFS's high adaptability, it can easily manage a variety of data properties, such as missing data, mixed frequencies, seasonal dependencies, non-stationarity, or regime-switching nonlinearity. The objective is to use the most recent periods (vintage data) to re-estimate the factors and let the approach handle the issue of missing observations. As a result, Sub-Step 2 provides an updated estimation of the common components that incorporates data from all recent releases of economic data that are now accessible.

The last and final step of the model is to use the nowcasting approach and nowcast the five selected macroeconomic factors, namely - GDP, IIP, manufacturing, transportation and storage, and finance and insurance for 2022-Q3. The process is concluded by presenting the findings for each target variable on the basis of the nowcast impact decomposition table. A glimpse of sensitivity analysis on the basis of the coefficients of the independent variables and their impact on the target macroeconomic variables is also presented at the end.

5.1.2 Descriptive Statistics:

In the first place of this analysis, descriptive statistics summarise and organises information on the characteristics and distribution of values in the dataset used to estimate the DFM. These descriptive statistics will allow a glance at the measurement of central tendency and degree of dispersion of values in the dataset, including the number of variables used, its frequency, mean, standard deviation, minimum, and maximum. Some available monthly and quarterly data collection dates back to the 1970s, primarily macroeconomic variables. In contrast, maritime-

related variables started as early as 1993 (Total Vessel Calls) or as late as 2016 (Port Congestion Index). Meanwhile, the minimum and maximum values were also indicated with their corresponding observation dates. The number of observations ranges from 78 to 621. This shows how diverse the data collection for this study is.

Table 7.

Descriptive Statistics of quarterly dependent variables

	GDP	*IIP_SG*	*MFG*	*TRANS*	*FIN_INS*
Mean	48,226.45	52.30	10,232.55	3,693.54	5,552.65
Standard Error	2,982.94	2.53	579.69	180.81	379.33
Median	36,991.40	43.41	8,308.70	3,287.30	3,942.40
Standard Deviation	41,008.70	31.76	7,969.39	2,485.67	5,214.89
Kurtosis	-0.77	-0.94	-0.57	-1.26	0.12
Skewness	0.73	0.48	0.63	0.28	1.09
Range	141,197.80	116.02	31,941.30	8,867.90	19,075.20
Minimum	3,292.10	10.62	690.80	289.70	235.60
Maximum	144,489.90	126.64	32,632.10	9,157.60	19,310.80
Sum	9,114,798.90	8,262.89	1,933,952.60	698,078.20	1,049,451.30
Count	189.00	158.00	189.00	189.00	189.00

The above table 7 shows the descriptive statistics of all the quarterly macroeconomic variables that will be nowcasted. Among them, the average GDP of Singapore is SGD 48,226.45 within the observed period 1975 to 2022, with a maximum of SGD 144,489.90 and a minimum of only SGD 3,292.10 which shows a considerable fluctuation in this period. Since other variables also follow similar trends, for the sake of brevity, the discussion is limited to the GDP only.

Table 8.

Descriptive Statistics of monthly independent variables (Maritime Trade flows)

	TMERIMP	*TMEREXP*	*RE_EXP*	*RE_IMP*	*DC_load_SG*	*LC_load_SG*	*DC_Disch_SG*	*LC_Disch_SG*
Mean	33,499,428.34	37,282,118.91	492,968,470.18	12,720,836.16	207,294.33	4,237,341.18	1,560,956.91	10,728,036.92
Standard Error	559,293.37	619,006.09	29,965,261.01	1,420,785.93	7,571.79	74,512.73	89,395.51	175,813.10
Median	35,317,008.50	39,817,725.50	496,146,887.50	7,621,746.00	190,621.00	4,128,399.50	1,189,123.00	10,483,780.00
Standard Deviation	9,190,127.81	10,171,308.00	492,379,481.93	23,302,621.85	80,844.58	795,578.28	954,482.88	1,877,170.27
Kurtosis	-0.30	- 0.28	- 0.97	135.60	3.75	0.61	0.25	-0.25
Skewness	-0.25	- 0.45	0.45	10.10	1.36	0.73	1.01	0.36
Range	44,880,294.00	49,549,733.00	2,063,928,420.00	334,129,251.00	511,027.00	3,925,649.00	4,256,298.00	8,769,615.00
Minimum	14,816,724.00	14,710,314.00	789,164.00	837.00	63,774.00	2,947,615.00	84,561.00	6,865,056.00
Maximum	59,697,018.00	64,260,047.00	2,064,717,584.00	334,130,088.00	574,801.00	6,873,264.00	4,340,859.00	15,634,671.00
Sum	9,044,845,653.00	10,066,172,106.00	133,101,486,948.00	3,421,904,928.00	23,631,554.00	483,056,894.00	177,949,088.00	1,222,996,209.00
Count	270	270	270	269	114	114	114	114

Table 9.

Descriptive Statistics of monthly independent variables (Shipping)

	Dry_load_from_SG(Load_Duration)	*Dry_load_from_SG(Disch_Duration)*	*Liquid_load_from_SG (Load_Duration)*	*Liquid_load_from_SG (Disch_Duration)*	*Dry_Disch_in_SG (Load_Duration)*	*Dry_Disch_in_SG(Disch_Duration)*	*Liquid_Disch_in_SG(Load_Duration)*	*Liquid_Disch_in_SG(Disch_Duration)*	*Dry_Load_voy_Avg_speed*	*Liquid_Dich_voy_Avg_speed*	*SCFI*	*BSI*
Mean	5.99	9.92	7.09	8.87	14.01	11.99	9.77	7.38	45.10	52.92	301.76	1,652.10
Standard Error	0.29	0.38	0.15	0.16	0.35	0.24	0.17	0.12	0.65	0.64	24.35	90.48
Median	5.31	9.36	6.90	8.64	13.35	11.71	9.79	7.03	43.52	48.94	215.63	1,104.43
Standard Deviation	3.08	4.07	1.60	1.75	3.79	2.52	1.78	1.24	6.92	6.88	298.22	1,292.33
Kurtosis	18.86	3.49	5.01	1.79	4.23	0.05	0.83	0.57	0.39	-0.31	4.31	3.49
Skewness	3.43	1.58	1.46	1.16	1.57	0.26	0.69	0.40	0.67	0.87	2.26	1.90
Range	25.70	23.11	10.93	9.21	23.80	14.22	10.06	7.15	36.08	27.25	1,460.05	6,251.63
Minimum	1.00	3.23	3.14	5.83	5.24	4.94	5.79	3.92	32.38	45.65	53.20	280.14
Maximum	26.70	26.34	14.07	15.04	29.04	19.16	15.85	11.07	68.46	72.90	1,513.25	6,531.77
Sum	682.32	1,130.40	807.69	1,011.73	1,597.07	1,367.27	1,113.91	841.24	5,141.08	6,032.57	45263.27	337,028.64
Count	114	114	114	114	114	114	114	114	114	114	150	204

From the descriptive statistics of maritime trade flows variables shown in Table 8 table, it is observed that total re-exports and re-imports register the highest standard deviation, thereby depicting that this data is quite spread out and varied. In contrast, others are more clustered towards the mean, like dry cargo loaded from Singapore in a million tonnes, since it has the lower standard deviation.

Next, descriptive statistics about shipping factors conveying the commercial aspects of the shipping business are presented in Table 9.

Moving forward, the standard deviation of the duration for loading and discharging, both dry and liquid cargo, averages around 3-5 days, which reflects that there is not much variation, as presented in the above table. The speed of the vessels also remains at seven nautical miles.

Table 10.

Descriptive Statistics of monthly independent variables (Port)

	VSL_CALL	*BULK_CARGO*	*PCI*	*VSL_ARVL*
Mean	15,145.62	14,908.67	344.17	10,825.71
Standard Error	93.65	184.91	4.84	74.99
Median	15,305.50	14,653.05	333.81	11,079.00
Standard Deviation	1,761.95	3,359.09	42.77	1,362.35
Kurtosis	0.31	-0.86	-0.52	1.81
Skewness	-0.60	0.34	0.41	-1.47
Range	8,800.00	14,054.00	179.24	6,472.00
Minimum	9,768.00	8,914.40	274.34	6,440.00
Maximum	18,568.00	22,968.40	453.58	12,912.00
Sum	5,361,549.00	4,919,859.50	26,844.89	3,572,483.00
Count	354	330	78	330

The above table summarises the descriptive statistics about port factors, specifically Total Vessel Calls, Bulk Cargo, PCI, and Total Vessel Arrival. The observations range from 78 (lowest) to 354 (highest). The bulk cargo and total vessel calls recorded the highest average and standard deviation. Since Singapore is considered a transhipment hub with low bunker prices, most ships would want to dock in their ports. Besides, Singapore is the busiest port in the world regarding shipping tonnage, with more than 130,000 vessel calls annually.

Table 11.

Descriptive Statistics of monthly independent variables (Logistics, economic and financial)

	BUNKSALES	MGOBUNKER	XRATES	INFLATION_RATE	LIBOR
Mean	2,802.19	572.57	1.48	0.03	3.24
Standard Error	58.24	15.73	0.02	0.00	0.12
Median	2,922.25	550.88	1.43	0.02	2.74
Standard Deviation	1,057.98	258.49	0.29	0.05	2.49
Kurtosis	-1.58	-0.48	78.50	19.07	-0.80
Skewness	-0.02	0.46	-7.16	3.88	0.49
Range	3,414.90	1,168.69	3.61	0.37	10.25
Minimum	1,190.70	160.75	-1.77	-0.03	0.15
Maximum	4,605.60	1,329.44	1.84	0.34	10.40
Sum	924,723.80	154,592.87	554.02	17.09	1,294.73
Count	330	270	375	630	399

The descriptive statistics of logistics and financial variables shown in the above table 11 bunker sales in Singapore have a high standard deviation due to differences in the supply and demand of bunker, as well as MGO bunkers price, which also deviated between SGD 1329 to SGD 160. Since economic and financial variables also follow the usual economic trends, for the sake of brevity, the discussion is limited only.

5.1.3 Correlation Analysis

The objective of correlation analysis is to measure the relationship between two variables. A correlation coefficient between two variables indicates that one variable changes in values and the other variable tends to change in a specific direction. There is a chance of some correlation between the series observations because time series data are continuous and chronologically ordered. Analysing the relationship between a series and its lags is essential because some of the historical lags may contain information that may be used to anticipate future events in the series. To avoid multicollinearity between the input variables, the dependent variables will be assessed in the correlation test and will be judged to be eliminated if the coefficient of the two dependent variables is more significant (Gujarati , 2021).

Hence, the correlation analysis between the original data set of 49 variables, including the monthly independent variables, is carried out, and the initial correlation table is presented in Appendix B. This process assists in identifying and quantifying

the correlation between or among variables that are correlated with less than 90%, used in the next analysis steps. Based on such correlation, the results, the final dataset consisting of 29 independent variables, are finalized after due reasoning out of the correlated variables. After removing the highly correlated variables, the below table shows the final dataset.

Table 12.

Correlation table containing variables after removing highly correlated variables

	TMERIMP	TMEREXP	BUNKSALES	MGOBUNKER	XRATES	RE_EXP	RE_IMP	BULK_CARGO	LIBOR	SCFI	INFLATION_RATE	BSI	Ship_Delv_Dwt	Ship_Deliveries	DC_load_SG	Dry_load_from_SG(Load_Duration)	Dry_load_from_SG(Disch_Duration)	LC_load_SG	Liquid_load_from_SG(Load_Duration)	Liquid_load_from_SG(Disch_Duration)	DC_Disch_SG	Dry_Disch_in_SG(Load_Duration)	Dry_Disch_in_SG(Disch_Duration)	LC_Disch_SG	Liquid_Disch_in_SG(Load_Duration)	Liquid_Disch_in_SG(Disch_Duration)	Dry_Load_voy_Avg_speed	Liquid_Dich_voy_Avg_speed	VSL_CALL	VSL_ARVL
TMERIMP	1																													
TMEREXP	0.99	1																												
BUNKSALES	0.84	0.86	1																											
MGOBUNKER	0.77	0.73	0.66	1																										
XRATES	-0.36	-0.35	-0.34	-0.37	1																									
RE_EXP	0.58	0.61	0.77	0.39	-0.33	1																								
RE_IMP	0.24	0.26	0.36	0.03	-0.10	0.38	1																							
BULK_CARGO	0.72	0.74	0.90	0.51	-0.29	0.69	0.33	1																						
LIBOR	-0.42	-0.44	-0.74	-0.57	0.22	-0.61	-0.20	-0.61	1																					
SCFI	0.65	0.69	0.09	0.19	0.03	-0.44	-0.11	-0.20	-0.27	1																				
INFLATION_RATE	0.39	0.33	0.13	0.48	-0.18	-0.02	-0.18	-0.01	0.09	0.38	1																			
BSI	0.03	0.00	-0.50	0.31	0.33	-0.61	-0.23	-0.44	0.52	0.71	0.46	1																		
Ship_Delv_Dwt	-0.06	-0.05	-0.23	-0.01	0.05	-0.17	-0.05	-0.21	0.07	-0.07	-0.09	0.20	1																	
Ship_Deliveries	0.16	0.16	0.12	0.32	-0.09	0.08	-0.01	0.05	-0.19	-0.03	-0.02	0.01	0.34	1																
DC_load_SG	-0.13	-0.14	-0.27	0.18	-0.26	0.23	0.07	-0.18	-0.18	-0.06	-0.04	-0.09	-0.11	0.04	1															
Dry_load_from_SG(Load_Duration)	0.17	0.22	-0.12	0.19	-0.09	-0.03	0.04	-0.18	-0.12	0.35	0.27	0.21	-0.05	-0.05	0.03	1														
Dry_load_from_SG(Disch_Duration)	-0.03	-0.05	-0.13	0.29	-0.26	0.00	0.01	-0.14	-0.01	0.05	0.14	-0.01	-0.03	0.09	0.24	0.19	1													
LC_load_SG	-0.22	-0.15	0.36	-0.30	0.28	0.23	0.18	0.42	0.13	-0.12	-0.24	-0.02	-0.05	-0.04	0.13	0.06	0.09	1												
Liquid_load_from_SG(Load_Duratior	0.23	0.26	0.36	-0.07	0.30	-0.32	-0.03	0.11	0.08	0.40	0.18	0.25	-0.03	-0.09	0.06	0.16	0.12	0.24	1											
Liquid_load_from_SG(Disch_Duratio	0.00	0.03	0.05	0.01	0.02	0.01	-0.02	-0.09	-0.12	0.06	0.06	0.03	-0.12	0.06	0.22	0.14	0.14	0.41	0.39	1										
DC_Disch_SG	-0.26	-0.31	-0.52	0.32	-0.52	0.51	0.03	-0.31	-0.40	-0.28	-0.12	-0.31	0.07	0.07	0.52	0.00	0.23	-0.01	-0.27	0.17	1									
Dry_Disch_in_SG(Load_Duration)	0.01	0.03	0.27	-0.12	0.06	-0.19	-0.01	0.12	0.09	0.21	-0.03	0.07	-0.10	-0.04	0.26	0.06	0.16	0.33	0.45	0.25	-0.08	1								
Dry_Disch_in_SG(Disch_Duration)	-0.02	0.00	0.31	-0.26	0.34	-0.01	0.10	0.25	0.09	0.18	-0.09	0.09	0.02	-0.09	0.11	0.12	0.08	0.44	0.62	0.45	-0.07	0.47	1							
LC_Disch_SG	-0.36	-0.34	0.21	-0.32	0.31	0.30	0.06	0.32	0.20	-0.28	-0.37	-0.31	-0.09	-0.11	0.17	0.05	0.11	0.60	0.33	0.40	0.12	0.31	0.47	1						
Liquid_Disch_in_SG(Load_Duration)	-0.12	-0.08	0.17	-0.17	0.13	-0.07	0.06	0.07	0.02	-0.06	-0.14	-0.02	-0.08	-0.01	0.15	-0.04	0.03	0.44	0.33	0.30	-0.09	0.20	0.44	0.36	1					
Liquid_Disch_in_SG(Disch_Duration)	-0.03	0.01	0.38	-0.25	0.37	-0.05	0.20	0.15	0.15	0.11	-0.08	0.07	-0.08	-0.04	0.11	0.16	0.16	0.47	0.67	0.53	-0.20	0.41	0.68	0.57	0.51	1				
Dry_Load_voy_Avg_speed	0.13	0.12	0.07	0.06	-0.04	-0.06	0.02	-0.11	-0.15	0.20	0.10	0.07	-0.14	-0.04	0.08	0.21	0.14	0.01	0.20	0.12	0.01	0.07	0.08	0.15	0.02	0.14	1			
Liquid_Dich_voy_Avg_speed	0.02	-0.01	0.12	-0.07	0.07	0.02	0.14	0.08	-0.03	0.01	-0.07	-0.01	-0.04	0.01	0.06	0.05	0.12	0.20	0.20	0.15	0.09	0.11	0.12	0.30	0.03	0.20	0.76	1		
VSL_CALL	-0.03	-0.04	0.22	0.22	-0.13	0.42	0.18	0.31	-0.16	-0.75	-0.22	-0.33	0.00	0.11	0.20	-0.21	0.10	0.15	-0.30	-0.03	0.39	-0.03	-0.04	0.30	-0.05	-0.05	-0.09	0.04	1	
VSL_ARVL	-0.41	-0.44	-0.17	-0.09	0.11	0.03	-0.02	-0.07	0.13	-0.75	-0.21	-0.16	0.04	0.03	0.20	-0.18	0.11	0.17	-0.32	-0.05	0.43	-0.03	-0.08	0.31	-0.04	-0.08	-0.09	0.05	0.82	1

In the correlation test, 20 variables are removed from the dataset because these variables are correlated with others at a degree of more than 90%. The initial correlation table is shown in the appendix-B and the final correlation table is shown in Table 13. For instance, total merchandise trade is 100% correlated with total merchandise export and import. In that case, the total merchandise trade is removed because it shows the total exports and imports. Whereas for Intra Asia container freight rate index is highly correlated with SCFI, then IACFI is removed because SCFI is more relevant and applicable to Singapore. For bunker prices in Singapore, HSFO is highly correlated with MGO bunkers, then HSFO is removed because HSFO bunker price has less number of observations. In the case of vessel arrivals, tanker arrivals and calls in Singapore port in terms of both number and deadweight tonnes are highly correlated. So, the tanker arrivals in numbers and vessel calls in DWT are removed because both indicate and measure the port performance.

5.1.4 Model Specification

After variables selection that is listed in the descriptive statistics and removing the highly correlated variables, model specification in the DFM will improve the prediction efficiency. Although some variables are collected weekly, these variables are adjusted monthly for this study. However, they enter different units in the model, such as total merchandise export and imports at SGD units, while SCFI and Port Congestion index enter at the index level. Transformation is required to better deal with such different units of data and unobserved and missing data, mixed frequencies, seasonality, high fluctuations, non-stationarity or regime-switching, non-linearity, and multicollinearity. Table 13 shows the transformations applied (PCH) to the dataset. Some of the resultant plots are also presented just below.

Table 13.

Model specification for monthly variables

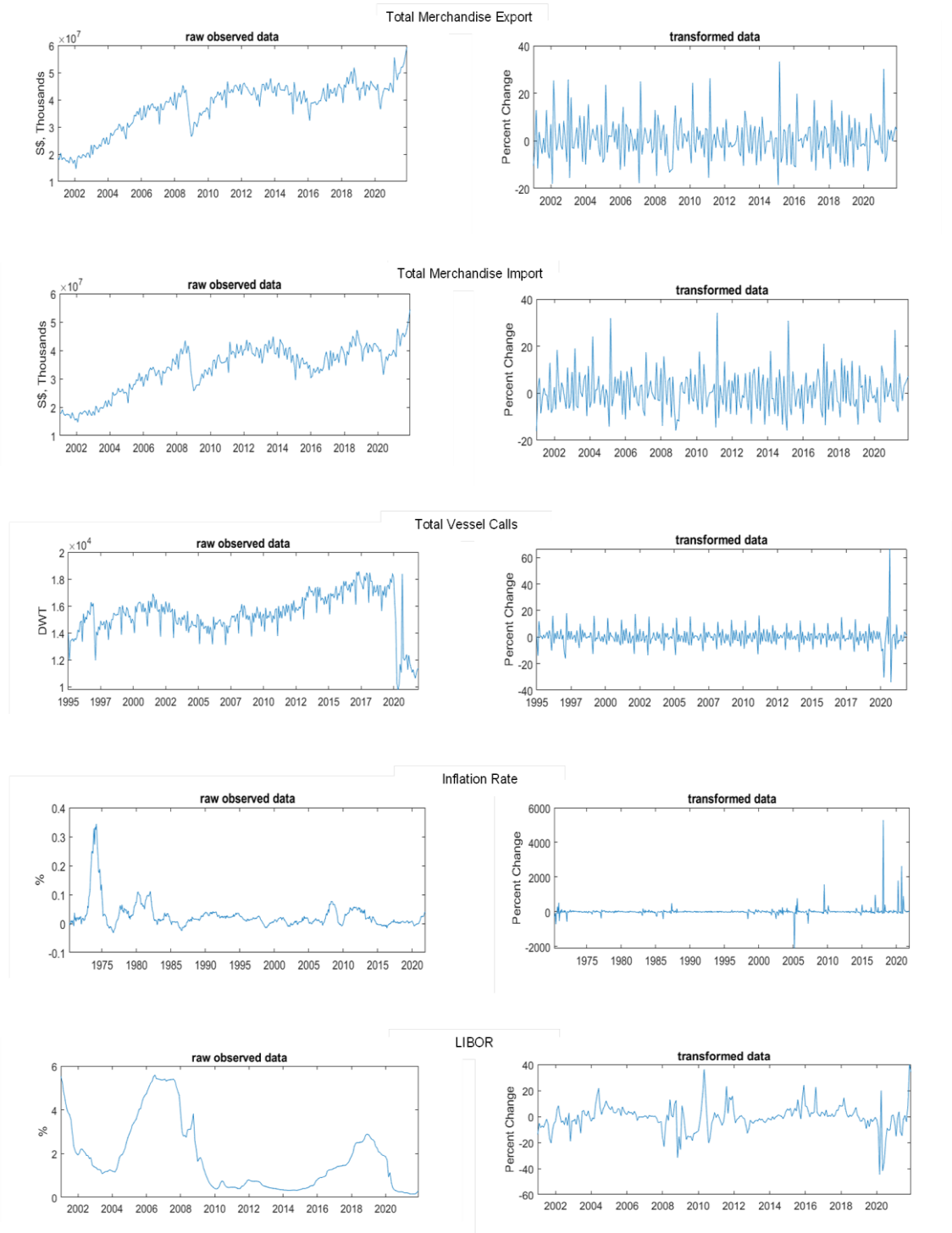
Series ID	Series Name	Units	Transformation
MARITIME TRADE			
TMEREXP	Total Merchandise Export	000'S$	pch
TMERIMP	Total Merchandise Import	000'S$	pch
RE_EXP	Total Merchandise Re-Export	US$	pch
RE_IMP	Total Merchandise Re-Import	US$	pch
DC_LOAD_SG	Dry Cargo loaded (voyage intake)	Metric Tonnes	pch
LC_LOAD_SG	Liquid Cargo loaded (voyage intake)	Metric Tonnes	pch
DC_DISCH_SG	Dry Cargo discharged (voyage intake)	Metric Tonnes	pch
LC_DISCH_SG	Liquid Cargo discharged (voyage intake)	Metric Tonnes	pch
SHIPPING			
SCFI	SCFI Shanghai-SE Asia (Singapore) Container Freight Rate	USD ($)/TEU	pch
BSI	Baltic Exchange Supramax Index	Index	pch
DRY_LOAD_FROM_SG(LOAD_DURATION)	Dry Cargo Loaded from SG (Load Duration)	Number of Days	pch
DRY_LOAD_FROM_SG(DISCH_DURATION)	Dry Cargo Loaded from SG (Discharge Duration)	Number of Days	pch
LIQUID_LOAD_FROM_SG(LOAD_DURATION)	Liquid Cargo Loaded from SG (Load Duration)	Number of Days	pch
LIQUID_LOAD_FROM_SG(DISCH_DURATION)	Liquid Cargo Loaded from SG (Discharge Duration)	Number of Days	pch
DRY_DISCH_IN_SG(LOAD_DURATION)	Dry Cargo Discharged in SG (Load Duration)	Number of Days	pch
DRY_DISCH_IN_SG(DISCH_DURATION)	Dry Cargo Discharged in SG (Discharge Duration)	Number of Days	pch
LIQUID_DISCH_IN_SG(LOAD_DURATION)	Liquid Cargo Discharged in SG (Load Duration)	Number of Days	pch
LIQUID_DISCH_IN_SG(DISCH_DURATION)	Liquid Cargo Discharged in SG (Discharge Duration)	Number of Days	pch
DRY_LOAD_VOY_AVG_SPEED	Dry Cargo Loaded from SG (Voyage Average Speed)	Nautical miles	pch
LIQUID_DICH_VOY_AVG_SPEED	Liquid Cargo Discharged in SG (Voyage Average Speed)	Nautical miles	pch
PORT			
VSL_CALLS	Total Vessel Calls	DWT	pch
VSL_ARVL	Total Vessels Arrivals (>75GT)	Number	pch
BULK_CARGO	Cargo (Bulk)	000'Tonnes	pch
PCI	Port Congestion Index	Index	pch
LOGISTICS AND OTHERS			
BUNKSALES	Bunker Sales	000'Tonnes	pch
MGOBUNKER	MGO Bunker Price	US$/Tonnes	pch
XRATES	Exchange Rates	S$ to US$	pch
LIBOR	Market Interest Rate: US$ LIBOR 6 Months	%	pch
INFLATION_RATE	Inflation Rate	%	pch

The above model specification table 13 specifies the 29 independent variables used in the DFM estimation. It specifies the series ID and series name of all the variables together with its respective unit of measurement and then needed transformation from the available methods of transformation such as changes in difference, year over year (difference), per cent change, year over year per cent change, per cent change (annual), natural log and no transformation. Nevertheless, in this case, per cent change (PCH) is considered for this model to get better results from raw data to transform data. Afterwards, these variables were further subdivided into maritime trade, shipping, port, logistics, and other blocks to determine which impacted more than the dependent variables. Under maritime trade, there are eight (8) series of data; in shipping, the researchers collected twelve (12) variables; in port, there are four (4) measures; and lastly, in logistics and others, there are five (5) independent variables.

Data transformation is crucial at the beginning of the model because not all total indicators release the same pattern, which necessitates regular comparison of these variables to comprehend. For example, for understanding Total Merchandise Import, the data available for merchandise is in whole numbers. Hence, all such data/ time-series are being transformed by applying the per cent change method for a better analysis. Thus, data transformation can increase the efficiency of analytic processes and enable better data-driven decision-making. To convert the raw data to smooth and stationary, the technique of KFS has been used in this model.

Figure 22.

Transformation of raw data for Total Merchandise Export, Total Merchandise Import, Total Vessel Call, Inflation Rate and LIBOR



As presented from the above graphs in figure 22 of total merchandise export and import for Singapore, the raw data reflects balanced growth till 2007 and mirrors the 2008 financial crisis and the pandemic in 2020. While the transformed data of the said variables, the shocks, and the seasonal variations are well absorbed, the graph displays a more consistent pattern for further analysis. While observing the data for vessel calls, a similar pattern is observed in the raw data, but the fall was quite steep in 2020. Similar to the earlier graphs of trade, the transformed data of vessel calls is also relatively stationary. Lastly, the raw inflation and interest rates data portray almost opposite trends. However, transformed data illustrate a steady pace for both variables. Then for the rest 24 variables both raw and transformed data are presented in the appendix-C.

5.1.5 Principal Component Analysis (PCA)

PCA is the core concept of the model, which lessens the large number of variables used into smaller numbers of variables by summarizing the variations among the given set of variables. While finalising the variables, the main aim of this study is to involve indicators that capture the continuous movements of maritime trade activities, including trade, freight, volume, and others. The privilege of this study is the availability of high-frequency data and sufficiently long periods for each time series during the phase of determining the variables. The table reports the time series included with its respective blocks that they load on in the DFM. Block columns indicated are the Maritime Trade, Shipping, Port, Logistics, and others, respectively.

Table 14.

Block Loading Structure

	Maritime Trade	Shipping	Port	Logistics and Others
Total_Merchandise_Imports	1	0	0	0
Total_Merchandise_Exports	1	0	0	0
Exchange_Rates	1	0	0	1
Total_Vessel_Call	1	0	1	0
Total_Re-Exports	1	0	0	0
Total_Re-Imports	1	0	0	0
Total_Bulk_Cargo	1	0	1	0
Port_Congestion_Index	1	0	1	0
BUNKER_SALES	1	0	0	1
MGO_Bunker	1	0	0	1
Market_Interest_Rate:_US$_LIBOR_6_Months	1	0	0	1
DC_load_SG	1	0	0	0
Dry_load_from_SG_(Load_Duration)	1	1	0	0
Dry_load_from_SG_(Disch_Duration)	1	1	0	0
LC_load_SG	1	0	0	0
Liquid_load_from_SG_(Load_Duration)	1	1	0	0
Liquid_load_from_SG_(Disch_Duration)	1	1	0	0
DC_Disch_SG	1	0	0	0
Dry_Disch_in_SG_(Load_Duration)	1	1	0	0
Dry_Disch_in_SG_(Disch_Duration)	1	1	0	0
LC_Disch_SG	1	0	0	0
Liquid_Disch_in_SG(Load_Duration)	1	1	0	0
Liquid_Disch_in_SG_(Disch_Duration)	1	1	0	0
Dry_Load_voy_Avg_speed	1	1	0	0
Liquid_Dich_voy_Avg_speed	1	1	0	0
SCFI_Shanghai-SE_Asia_(Singapore)_Container_Freight_Rate	1	1	0	0
Inflation_Rate	1	0	0	1
Baltic_Exchange_Supramax_Index	1	1	0	0
Total_Number_of_Vessel_Arrival	1	0	1	0
GDP_Singapore	1	0	0	1
Index_of_Industrial_Production	1	0	0	1
Manufacturing	1	0	0	1
Transport_and_Storage	1	0	0	1
Finance_and_Insurance_Services	1	0	0	1

Maritime factors affect all variables. Additionally, other blocks are also involved in order to control for idiosyncrasies in series. Hence, it makes detailed interpretation

possible even if the model is robust to the presence of different correlations. The other defined blocks are as follows: Shipping - variables include duration of loading /discharging and different freight indices giving an overview of the shipping industry, Port - for quantitative data of vessel arrivals, and port congestion index of the country. Logistics and Others include the bunker prices, and some of the financial variables which impact a country's overall economy as shown in the table 14 as block loading structure.

Table 15.

Factor Loadings for Monthly Series

	Maritime Trade	Shipping	Port	Logistics and Others
Total_Merchandise_Imports	0.365	0	0	0
Total_Merchandise_Exports	0.361	0	0	0
Exchange_Rates	-0.014	0	0	-0.019
Total_Vessel_Call	0.468	0	-0.217	0
Total_Re-Exports	0.002	0	0.000	0
Total_Re-Imports	0.020	0	0	0
Total_Bulk_Cargo	0.244	0	0.967	0
Port_Congestion_Index	-0.007	0	0.071	0
BUNKER_SALES	0.293	0	0	0.228
MGO_Bunker	0.089	0	0	-0.064
Market_Interest_Rate:_US$_LIBOR_6_Months	0.034	0	0	0.225
DC_load_SG	0.014	0	0	0
Dry_load_from_SG_(Load_Duration)	0.006	0.200	0	0
Dry_load_from_SG_(Disch_Duration)	0.004	0.193	0	0
LC_load_SG	0.012	0.000	0	0
Liquid_load_from_SG_(Load_Duration)	0.035	0.416	0	0
Liquid_load_from_SG_(Disch_Duration)	0.053	0.389	0	0
DC_Disch_SG	0.056	0	0	0
Dry_Disch_in_SG_(Load_Duration)	0.033	0.304	0	0
Dry_Disch_in_SG_(Disch_Duration)	0.031	0.431	0	0
LC_Disch_SG	0.008	0	0	0
Liquid_Disch_in_SG(Load_Duration)	-0.018	0.311	0	0
Liquid_Disch_in_SG_(Disch_Duration)	0.042	0.419	0	0
Dry_Load_voy_Avg_speed	0.050	0.128	0	0
Liquid_Dich_voy_Avg_speed	0.049	0.133	0	0
SCFI_Shanghai SE_Asia_(Singapore)_Container_Freight_Rate	-0.004	0.109	0	0

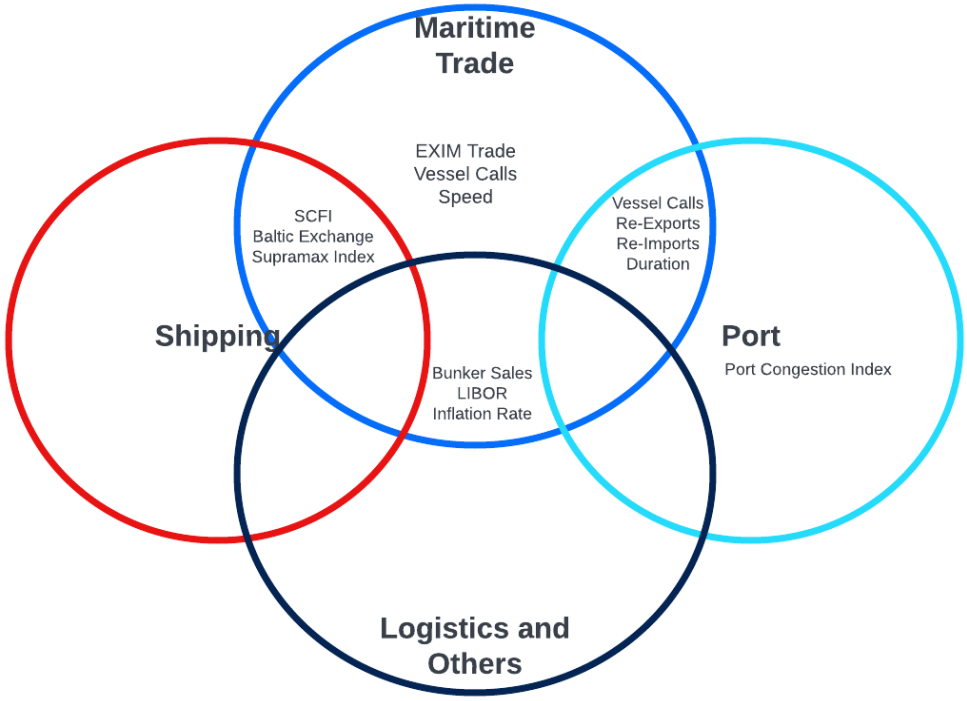
The factor loadings indicate which common trend is related to which time series as shown in table 15. For example, Total Vessel calls are affected by 0.468 amount by

Maritime Trade and negative 0.217 amount by port factor. The total number of vessel calls (y4) in the measurement equation equals 0.468 times f1 and (minus) 0.217 times f3. The DFM results show which factor and how much it impacts each variable. Additionally, it provides details regarding the variable that will exist in a short amount of time.

A visual representation is necessary for improved interpretation and comprehension. The factor loadings can be represented as a Venn diagram to help find groupings in the time series. Both sets of factors influence the variables at the intersection of two sets of factors, but the others are only impacted by one. For instance, marine and port factors record the movements of total import of goods, while port factors impact duration variables.

Figure 23.

Venn Diagram Analysis (Qualitative)



Note: Author's illustration

As per the Venn diagram described above figure 23, four blocks can be identified; namely, the maritime trade block consists of export-import trade, vessel calls, and speed of the vessels. Port block includes vessel arrivals, re-exports, re-imports, and duration to load and discharge at the port. The shipping block mainly includes freight indices such as SCFI and BSI, while the Logistics block includes bunker sales, interest, and inflation rates.

The maritime trade block shows mainly the export-import trade and shipping variables, while the port block is associated with two common trends: maritime trade and port. Using a dynamic factor model can reduce the dimensions of the massive data set for the evaluation of economic conditions.

Table 16.

Quarterly Loadings Sample (Maritime trade flows block)

	f1_lag0	f1_lag1	f1_lag2	f1_lag3	f1_lag4
GDP_Singapore	0.126	0.252	0.378	0.252	0.126
Index_of_Industrial_Production	0.072	0.145	0.217	0.145	0.072
Manufacturing	0.073	0.146	0.219	0.146	0.073
Transport_and_Storage	0.095	0.190	0.285	0.190	0.095
Finance_and_Insurance_Services	0.024	0.047	0.071	0.047	0.024

Similar to Factor Loadings for Monthly Series in Table 16, the quarterly loadings sample is also presented in Table 5. It shows the five lags being considered for the quarterly loadings in this analysis.

5.1.6 Model Estimation

In spite of the fact that the common components give a statistical description of how economic data move together, interpreting them is not simple. The model can incorporate an understandable explanation into the analysis by plotting GDP to the common components. Accordingly, the common factor graph for GDP is presented below.

Figure 24.

The common factor for GDP

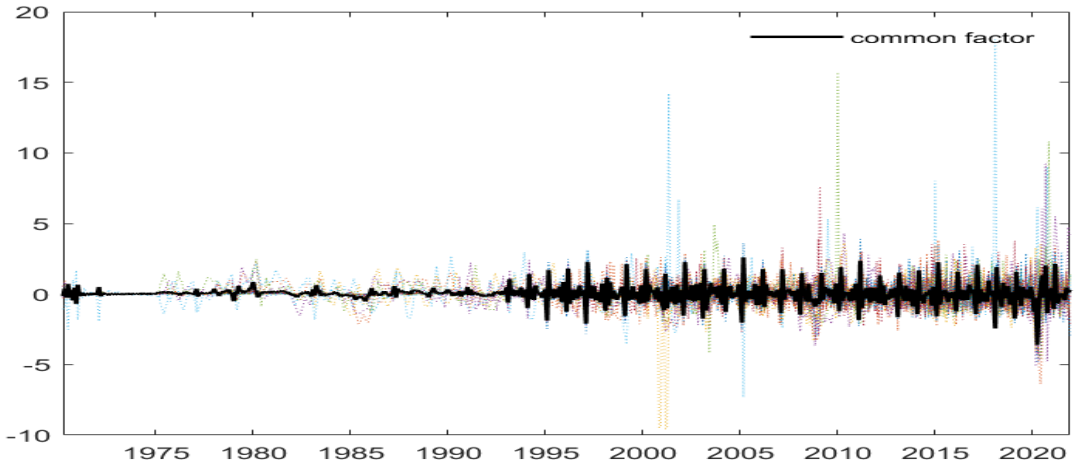


Figure 24 shows that a common component is the time series version of the maritime trade flows factor, which is black and f1. The coloured ones come after the black ones and indicate our factor loadings. It is such a factor that influential maritime trade factors have an effect on all of them. The impact of the 2008 financial crisis, as well as 2020 due to COVID-19, is also viewed in the above graph. So we understand that maritime trade flows indicators affect every variable. According to DFM, these elements shift all the data, which is why black pulls up or down. Therefore, we can gain insight into the changes in other variables by focusing only on the maritime trade flows.

Table 17.

Autoregressive Coefficients on Factors

	AR_Coefficient	Variance_Residual
Maritime Trade	- 0.47	2.07
Shipping	- 0.60	2.32
Port	- 0.45	0.65
Logistics and Others	- 0.14	0.33

Table 17 demonstrates the AR coefficient of the factors - f1, f2, f3, and f4 following maritime trade, shipping, port, logistics & others. The highest coefficient Logistics and others factor represents high sensitivity with the target variables. At the same time, the shipping are the least important factor that impacts the target variables of the model. Lastly, maritime trade and port have almost the same magnitude of impact on the macroeconomic variables of the model.

Table 18.

Autoregressive Coefficients on Idiosyncratic Components

	AR_Coefficient	Variance_Residual
Total_Merchandise_Imports	- 0.32	0.44
Total_Merchandise_Exports	- 0.33	0.43
Exchange_Rates	0.49	0.76
Total_Vessel_Call	- 0.38	0.24
Total_Re-Exports	- 0.01	1.00
Total_Re-Imports	- 0.02	0.99
Total_Bulk_Cargo	- 0.23	0.02
Port_Congestion_Index	- 0.48	0.76
BUNKER_SALES	- 0.41	0.63
MGO_Bunker	0.35	0.85
Market_Interest_Rate:_US$_LIBOR_6_Months	0.50	0.74
DC_load_SG	- 0.40	0.83
Dry_load_from_SG_(Load_Duration)	- 0.30	0.80
Dry_load_from_SG_(Disch_Duration)	- 0.41	0.75
LC_load_SG	- 0.43	0.80
Liquid_load_from_SG_(Load_Duration)	- 0.41	0.27
Liquid_load_from_SG_(Disch_Duration)	- 0.34	0.31
DC_Disch_SG	- 0.32	0.85
Dry_Disch_in_SG_(Load_Duration)	- 0.26	0.62
Dry_Disch_in_SG_(Disch_Duration)	- 0.31	0.25
LC_Disch_SG	- 0.56	0.67
Liquid_Disch_in_SG(Load_Duration)	- 0.45	0.51
Liquid_Disch_in_SG_(Disch_Duration)	- 0.56	0.15
Dry_Load_voy_Avg_speed	- 0.60	0.60
Liquid_Dich_voy_Avg_speed	- 0.59	0.60
SCFI_Shanghai SE_Asia_(Singapore)_Container_Freight_Rate	0.23	0.93
Inflation_Rate	- 0.04	0.74
Baltic_Exchange_Supramax_Index	0.21	0.84
Total_Number_of_Vessel_Arrival	- 0.36	0.16
GDP_Singapore	- 0.17	0.04
Index_of_Industrial_Production	- 0.45	0.09
Manufacturing	- 0.47	0.08
Transport_and_Storage	- 0.73	0.10
Finance_and_Insurance_Services	- 0.54	0.11

As per Table 18, Bunker prices and LIBOR have the highest coefficient, which means that they are very persistent.

Figure 25.

Common Factor Projection for Quarterly Variables

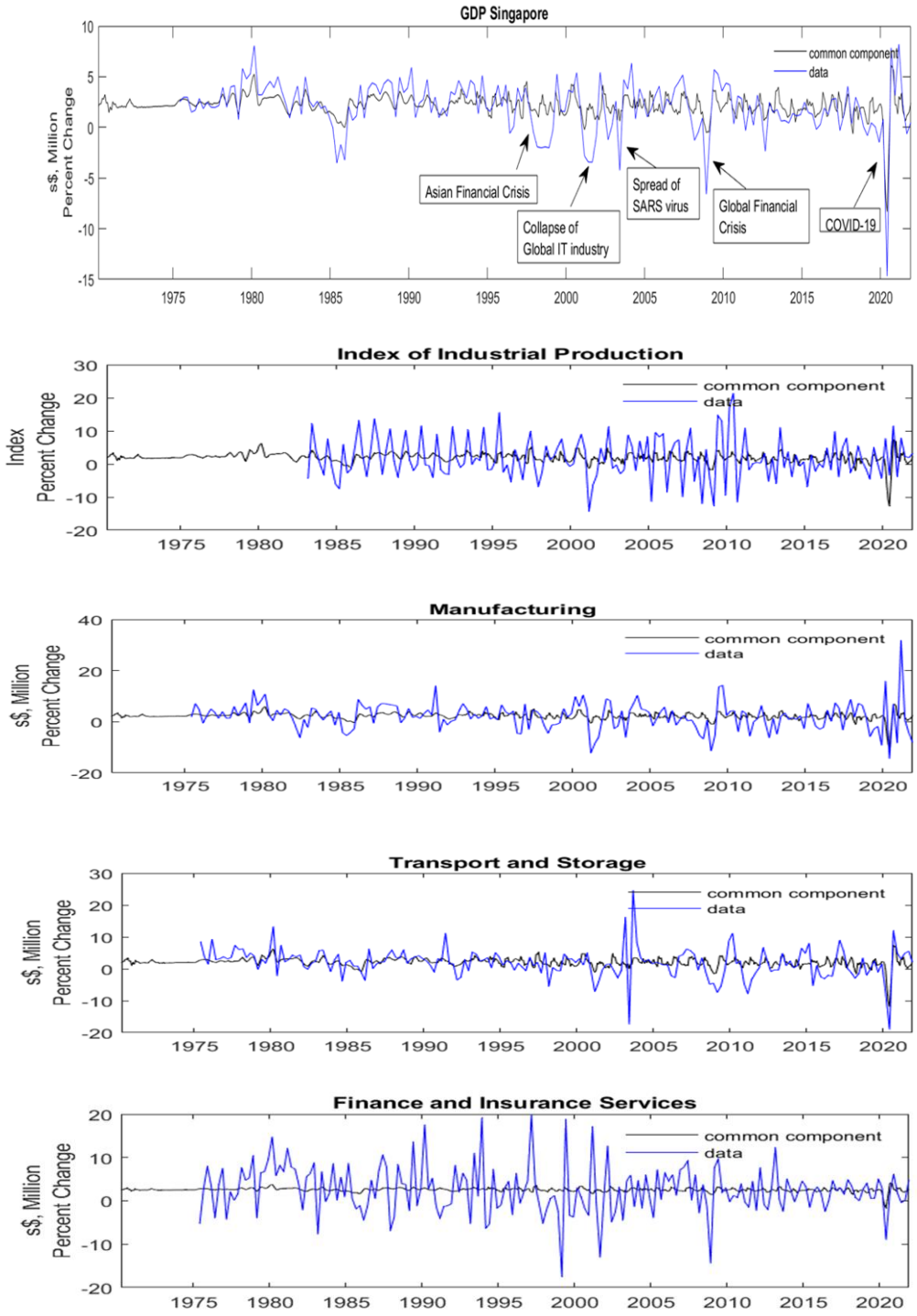


Figure 25 illustrates that our results reciprocate the world trends. These indicate that the component of this model's data we employed is on the same trajectory as the data. The model findings we produced as a consequence accurately reflect the actual data. From the graph of the GDP of Singapore, it clearly shows the fluctuations in the different periods, including the Asian Financial Crisis in 1997, the collapse of the global IT industry in 2001, the spread of the SARS virus in 2003, the GFC in 2008 and finally pandemic in 2020. It was directly affected by maritime trade and shipping activities. Similarly, the rest of the four macroeconomic factors shown in the above figure also depicts more or less similar trends to GDP.

5.2 Empirical Findings

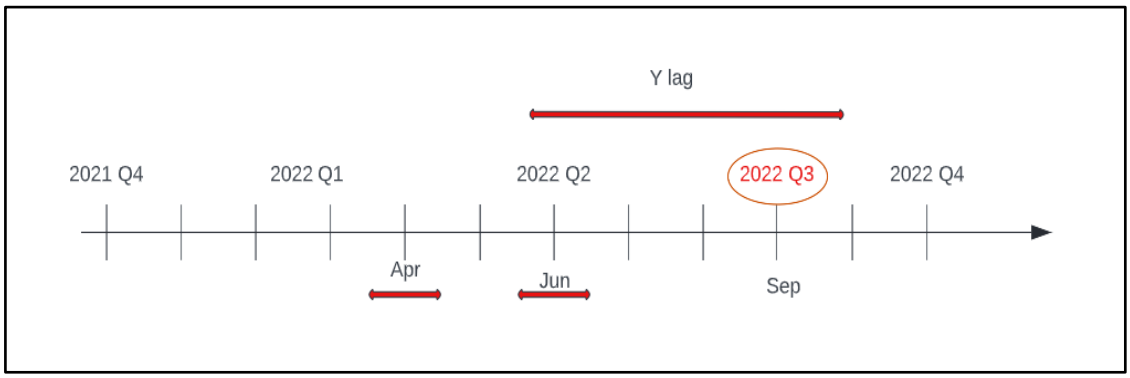
This section presents the empirical findings based on the above-developed DFM to nowcast the quarter-to-quarter GDP, IIP, manufacturing, transportation and storage, financial and insurance Services of Singapore. These findings mainly aim to illustrate how real-time maritime trade, shipping, port, and logistics-related data flow shapes the evolution of consecutive nowcast updates for the third quarter of 2022. More specifically, an examination of how high-frequency data releases of different categories of data revise the forecast and affect the associated uncertainty. This study is interested in incorporating more disaggregated maritime trade and shipping sectoral AIS-based real-time data flows. Such granular real-time high-frequency data are monitored at regular intervals by sectoral experts. They can be significant for improving forecast accuracy and interpreting the forecasts with which variable has a significant impact on these macroeconomic variables. The empirical findings part summarises the performance of five factors for nowcasting and shows the results using dynamic factor models. A comparison has been made between forecasted and actual results with significant impact from a maritime perspective.

5.2.1. Nowcasting Performance of quarterly macroeconomic variables of Singapore

The availability of point-wise data in the process of nowcasting is featured in Figure 26. To summarise, in the first stage, direct forecasts of the missing observations for all leading indicators are computed within blocks of correlated variables. The estimates are produced for the last quarter of 2021 - Q4 where the data from 1970 till 01 December 2021 is taken into account. In the second stage with the available data i.e. the vintage data till 01 April 2022, and 01 June 2022, nowcasting for 2022Q2 and Q3 is carried out.

Figure 26.

Quarterly end of period nowcasting performance



Note: Author's illustration

The model includes 34 (independent and dependent) variables. Financial factors are not included since they tend to be extremely volatile and play a little part in nowcasting GDP. There is no disaggregated data because the advantages in prediction from including them are insignificant. The empirical research of Barhoumi et al. (2010) indicates that disaggregation of the information does not significantly increase the accuracy of short-term GDP estimates. As a result, our model adequately meets the requirements for precise GDP nowcasting. As stated in the introduction section, the goal of using nowcasting is to be able to make comments on today using a few high-frequency data points. Information accessibility is considered when conducting a nowcasting study for a quarter. When we publish the

article, Q2 of 2022 will be the last GDP data point. The current information as of 01 April 2022 is regarded as the vintage data update old and as on 01 June 2022, is regarded as the vintage data update new date as shown in figure 26.

The nowcasting table includes forecasts for June 2022 and Sept 2022, considering the actual data releases for each time series. Since no further actual releases are taken into consideration, no data revisions are considered in the model. Nowcasters are frequently interested in the impact of each new data point. For example, it might be interesting to know the impact of the latest time series figure, which will be available for the five macroeconomic factors.

5.2.2. Nowcasting the GDP of Singapore using a monthly complete sample

This dissertation uses the backcasting concept to assess the model's robustness. With this aim, the GDP of Singapore is estimated with 29 time series data. With the help of DFM, factor loadings, and AR parameters, estimation for December 2021 is done. Moving forward, the nowcasting for each of the macroeconomic variables for 2022-Q2 and 2022-Q3 is presented as follows:

Table 19.

Nowcasting of GDP of Singapore (percentage change) - Q2 and Q3 for 2022

	2022 Q2	2022 Q3
Nowcast Impact Decomposition		
April 01 nowcast:	5.21	2.03
Impact from data revisions:	0.00	0.00
Impact from data releases:	0.32	0.31
Total Impact:	0.32	0.31
Jun 01 nowcast:	6.28	2.72

Model predictions were then obtained on the test set for each test period at two different data vintages. In table 19 for Q2 of 2022, the result of the April nowcast stands at 5.21%, and the impact of June releases is 0.32%, thus adding up to 6.28% as on 01 June 2022. For Q3 of 2022, the result of the April nowcast stands at 2.03 %, and the impact of June releases is 0.31%, thus adding up to 2.72% as on

01 June 2022 and the detailed end-of-period nowcasting results is shown in the appendix D-1.

As compared to traditional techniques of forecasting, the model is based on the use of actual vintage data and provides accurate results by the nowcasting technique. The resulting nowcast measure is less "noisy" and more current than official country GDP measurements. As per the detailed Table 20, Cargo carried and vessel calls are the primary impactors in nowcasting the GDP.

Table 20.

Nowcast Decomposition Table (GDP)

	Forecast	Actual	Weight	Impact
VSL_ARVL	0.679	6.219	0.040	0.221
VSL_CALL	0.602	2.857	0.023	0.052
BULK_CARGO	- 0.075	4.301	0.009	0.038
BUNKSALES	0.352	- 8.781	0.008	- 0.072
TMEREXP	0.289	7.369	0.007	0.052
TMERIMP	0.419	3.626	0.007	0.023
LIBOR	10.463	22.807	0.001	0.016
BSI	2.043	- 10.167	0.000	- 0.004
Liquid_Dich_voy_Avg_speed	2.475	- 21.155	0.000	- 0.006
Dry_Load_voy_Avg_speed	- 0.382	- 17.960	0.000	- 0.004
Liquid_Disch_in_SG(Disch_Duration)	1.202	- 18.922	0.000	- 0.004
Liquid_load_from_SG(Disch_Duration)	5.219	- 19.812	0.000	- 0.004
INFLATION_RATE	14.678	19.023	0.000	0.001
DC_Disch_SG	1.480	- 33.612	0.000	- 0.004
MGOBUNKER	1.456	13.999	0.000	0.001
LC_load_SG	- 0.283	- 4.461	0.000	- 0.000
LC_Disch_SG	6.443	4.842	0.000	- 0.000
Dry_Disch_in_SG(Load_Duration)	6.448	- 15.860	0.000	- 0.001
DC_load_SG	10.934	- 39.567	0.000	- 0.001
Liquid_load_from_SG(Load_Duration)	17.970	- 16.148	0.000	- 0.000
RE_IMP	143.930	1,455.200	0.000	0.001
RE_EXP	104.890	24.317	0.000	- 0.000
Dry_load_from_SG(Load_Duration)	20.174	- 59.873	- 0.000	0.001
Dry_load_from_SG(Disch_Duration)	17.709	- 59.164	- 0.000	0.002
SCFI	3.228	5.838	- 0.000	- 0.000
Dry_Disch_in_SG(Disch_Duration)	12.013	- 4.644	- 0.000	0.001
XRATES	- 1.703	-	- 0.000	- 0.000
Liquid_Disch_in_SG(Load_Duration)	10.520	- 2.617	- 0.000	0.003
PCI	0.191	6.044	- 0.000	- 0.002

As per the table 20 above, the total number of vessel arrivals in Singapore has the highest coefficient (weightage) of 0.040 (4%) and hence, carries the highest sensitivity on the impact as compared to the total value of merchandise imports and exports in SGD with a weightage of 0.007 (0.70%).

5.2.3 Nowcasting the Index of Industrial Production (IIP) of Singapore using a monthly complete sample

The table below shows Singapore's IIP nowcast for Q2 and Q3 of 2022 and the impacts of maritime trade data releases.

Table 21.

Nowcasting of Index of Industrial Production (percentage change) - Q2 and Q3 for 2022

	2022 Q2	2022 Q3
Nowcast Impact Decomposition		
April 01 nowcast:	4.32	1.71
Impact from data revisions:	0.00	0.00
Impact from data releases:	0.43	0.43
Total Impact:	0.43	0.43
Jun 01 nowcast:	5.86	2.70

From the above table 21, to start with Q2 of 2022, the result of the April nowcast stands at 4.32% and the impact of June releases is 0.43%, thus adding up the total to 5.86% as on 01 June 2022. For Q3 of 2022, the result of the April nowcast stands at 1.71% and the impact of June releases is 0.43%, thus adding up to 2.70% as on 01 June 2022 and the detailed end-of-period nowcasting results is shown in the appendix D-2.

Table 22.

Nowcast Decomposition Table (Index of Industrial Production of SG)

	Forecast	Actual	Weight	Impact
VSL_ARVL	0.679	6.219	0.055	0.305
VSL_CALL	0.602	2.857	0.032	0.072
BULK_CARGO	- 0.075	4.301	0.012	0.052
TMEREXP	0.289	7.369	0.010	0.072
TMERIMP	0.419	3.626	0.010	0.032
BUNKSALES	0.352	- 8.781	0.008	- 0.076
MGOBUNKER	1.456	13.999	0.000	0.005
BSI	2.043	- 10.167	0.000	- 0.005
Liquid_Dich_voy_Avg_speed	2.475		0.000	- 0.009
Dry_Load_voy_Avg_speed	- 0.382	- 17.960	0.000	- 0.006
Liquid_Disch_in_SG(Disch_Duration)	1.202	- 18.922	0.000	- 0.006
LIBOR	10.463	22.807	0.000	0.003
Liquid_load_from_SG(Disch_Duration)	5.219	- 19.812	0.000	- 0.006
DC_Disch_SG	1.480	- 33.612	0.000	- 0.006
LC_load_SG	- 0.283	- 4.461	0.000	- 0.000
LC_Disch_SG	6.443	4.842	0.000	- 0.000
Dry_Disch_in_SG(Load_Duration)	6.448	- 15.860	0.000	- 0.001
DC_load_SG	10.934	- 39.567	0.000	- 0.002
Liquid_load_from_SG(Load_Duration)	17.970	- 16.148	0.000	- 0.001
RE_IMP	143.930	1,455.200	0.000	0.002
RE_EXP	104.890	24.317	0.000	- 0.000
Dry_load_from_SG(Load_Duration)	20.174	- 59.873	- 0.000	0.001
Dry_load_from_SG(Disch_Duration)	17.709	- 59.164	- 0.000	0.002
XRATES	- 1.703	-	- 0.000	- 0.000
INFLATION_RATE	14.678	19.023	- 0.000	- 0.000
SCFI	3.228	5.838	- 0.000	- 0.000
Dry_Disch_in_SG(Disch_Duration)	12.013	- 4.644	- 0.000	0.001
Liquid_Disch_in_SG(Load_Duration)	10.520	- 2.617	- 0.000	0.005
PCI	0.191	6.044	- 0.000	- 0.003

As per the IIP nowcast decomposition table 22 above, the total number of vessel arrivals at Singapore has the highest coefficient (weightage) of 0.055 (5.5%) and hence carries the highest sensitivity on the impact as compared to LIBOR (interest rates) with a weightage of 0.008 (0.80%).

5.2.4. Nowcasting the Manufacturing of Singapore using monthly complete sample

From Table 23 for Q2 of 2022, the result of the April nowcast stands at 7.94%, and the impact of June releases is 0.37%, thus adding up the total to 9.27% as on 01 June 2022. For Q3 of 2022, the result of the April nowcast stands at 2.33%, and the impact of June releases is 0.37%, thus adding up to 3.17% as on 01 June 2022 and the detailed end-of-period nowcasting results is shown in the appendix D-3.

Table 23.

Nowcasting of Manufacturing (percentage change) - Q2 and Q3 for 2022

	2022 Q2	2022 Q3
Nowcast Impact Decomposition		
April 01 nowcast:	7.94	2.33
Impact from data revisions:	0.00	0.00
Impact from data releases:	0.37	0.37
Total Impact:	0.37	0.37
Jun 01 nowcast:	9.27	3.17

Table 24.

Nowcast Decomposition Table (Manufacturing)

	Forecast	Actual	Weight	Impact
VSL_ARVL	0.679	6.219	0.049	0.272
VSL_CALL	0.602	2.857	0.029	0.065
BUNKSALES	0.352	- 8.781	0.012	- 0.108
BULK_CARGO	- 0.075	4.301	0.011	0.046
TMEREXP	0.289	7.369	0.009	0.064
TMERIMP	0.419	3.626	0.009	0.029
LIBOR	10.463	22.807	0.003	0.032
BSI	2.043	- 10.167	0.000	- 0.005
Liquid_Dich_voy_Avg_speed	2.475	- 21.155	0.000	- 0.008
INFLATION_RATE	14.678	19.023	0.000	0.001
Dry_Load_voy_Avg_speed	- 0.382	- 17.960	0.000	- 0.005
Liquid_Disch_in_SG(Disch_Duration)	1.202	- 18.922	0.000	- 0.005
Liquid_load_from_SG(Disch_Duration)	5.219	- 19.812	0.000	- 0.005
DC_Disch_SG	1.480	- 33.612	0.000	- 0.005
LC_load_SG	- 0.283	- 4.461	0.000	- 0.000
LC_Disch_SG	6.443	4.842	0.000	- 0.000
Dry_Disch_in_SG(Load_Duration)	6.448	- 15.860	0.000	- 0.001
DC_load_SG	10.934	- 39.567	0.000	- 0.002
Liquid_load_from_SG(Load_Duration)	17.970	- 16.148	0.000	- 0.001
RE_IMP	143.930	1,455.200	0.000	0.002
RE_EXP	104.890	24.317	0.000	- 0.000
Dry_load_from_SG(Load_Duration)	20.174	- 59.873	- 0.000	0.001
Dry_load_from_SG(Disch_Duration)	17.709	- 59.164	- 0.000	0.002
SCFI	3.228	5.838	- 0.000	- 0.000
Dry_Disch_in_SG(Disch_Duration)	12.013	- 4.644	- 0.000	0.001
XRATES	- 1.703	-	- 0.000	- 0.000
MGOBUNKER	1.456	13.999	- 0.000	- 0.002
Liquid_Disch_in_SG(Load_Duration)	10.520	- 2.617	- 0.000	0.004
PCI	0.191	6.044	- 0.000	- 0.002

As per the table 24 above, the total number of vessel arrivals in Singapore has the highest coefficient (weightage) of 0.049 (4.9%) and thus impacts the manufacturing in the country as compared to LIBOR (interest rates) with a weightage of 0.003 (0.30%).

5.2.5 Nowcasting the transportation and storage services of Singapore using a monthly complete sample

Table 25.

Nowcasting of Transportation and Storage (percentage change) - Q2 and Q3 for 2022

	2022 Q2	2022 Q3
Nowcast Impact Decomposition		
April 01 nowcast:	4.77	2.56
Impact from data revisions:	0.00	0.00
Impact from data releases:	0.43	0.41
Total Impact:	0.43	0.41
Jun 01 nowcast:	6.17	3.45

Concerning the transportation and storage factor for Q2 of 2022 in table 25, the result of the April nowcast stands at 4.77%, and the impact of June releases is 0.43%, totalling 6.17% as of 01 June 2022. Whereas for Q3 of 2022, the result of April nowcast stands at 2.56 %, and the impact of June releases is 0.41%, thus adding up to 3.45% as on 01 June 2022 and the detailed end-of-period nowcasting results is shown in the appendix D-4.

Table 26.

Nowcast Decomposition Table (Transportation and Storage)

	Forecast	Actual	Weight	Impact
VSL_ARVL	0.679	6.219	0.055	0.305
VSL_CALL	0.602	2.857	0.032	0.072
BULK_CARGO	- 0.075	4.301	0.012	0.052
TMEREXP	0.289	7.369	0.010	0.072
TMERIMP	0.419	3.626	0.010	0.032
BUNKSALES	0.352	- 8.781	0.008	- 0.076
MGOBUNKER	1.456	13.999	0.000	0.005
BSI	2.043	- 10.167	0.000	- 0.005
Liquid_Dich_voy_Avg_speed	2.475		0.000	- 0.009
Dry_Load_voy_Avg_speed	- 0.382	- 17.960	0.000	- 0.006
Liquid_Disch_in_SG(Disch_Duration)	1.202	- 18.922	0.000	- 0.006
LIBOR	10.463	22.807	0.000	0.003
Liquid_load_from_SG(Disch_Duration)	5.219	- 19.812	0.000	- 0.006
DC_Disch_SG	1.480	- 33.612	0.000	- 0.006
LC_load_SG	- 0.283	- 4.461	0.000	- 0.000
LC_Disch_SG	6.443	4.842	0.000	- 0.000
Dry_Disch_in_SG(Load_Duration)	6.448	- 15.860	0.000	- 0.001
DC_load_SG	10.934	- 39.567	0.000	- 0.002
Liquid_load_from_SG(Load_Duration)	17.970	- 16.148	0.000	- 0.001
RE_IMP	143.930	1,455.200	0.000	0.002
RE_EXP	104.890	24.317	0.000	- 0.000
Dry_load_from_SG(Load_Duration)	20.174	- 59.873	- 0.000	0.001
Dry_load_from_SG(Disch_Duration)	17.709	- 59.164	- 0.000	0.002
XRATES	- 1.703	-	- 0.000	- 0.000
INFLATION_RATE	14.678	19.023	- 0.000	- 0.000
SCFI	3.228	5.838	- 0.000	- 0.000
Dry_Disch_in_SG(Disch_Duration)	12.013	- 4.644	- 0.000	0.001
Liquid_Disch_in_SG(Load_Duration)	10.520	- 2.617	- 0.000	0.005
PCI	0.191	6.044	- 0.000	- 0.003

Similar to other macroeconomic factors explained above, in table 26, the total number of vessel arrivals to the country carries the highest coefficient (weightage) of 0.055 (5.50%) and thus impacts the transportation and storage sector of the country as compared to Bunker sales with the lowest weightage of 0.008 (0.80%).

5.2.6. Nowcasting the Financial and Insurance Services of Singapore using a monthly complete sample

The below figures show Singapore's financial and insurance services nowcast for Q2 and Q3 of 2022 and the impacts from maritime trade data releases.

Table 27.

Nowcasting of Finance and Insurance (percentage change) - Q2 and Q3 for 2022

	2022 Q2	2022 Q3
Nowcast Impact Decomposition		
April 01 nowcast:	3.16	2.47
Impact from data revisions:	0.00	0.00
Impact from data releases:	0.13	0.12
Total Impact:	0.13	0.12
Jun 01 nowcast:	3.58	2.73

Lastly, in table 27 for Finance and Insurance Services in Q2 of 2022, the results of April nowcast were calculated as 3.16 % with an impact of June releases of 0.13%, totalling 3.58% as of 01 June 2022. While Q3 of 2022 indicates the result of April nowcast stands at 2.47%, and the impact of June releases is 0.12%, thus adding up to 2.73 % as on 01 June 2022 and the detailed end-of-period nowcasting results is shown in the appendix D-5.

Table 28.

Nowcast Decomposition Table (Finance and Insurance)

	Forecast	Actual	Weight	Impact
VSL_ARVL	0.679	6.219	0.017	0.092
VSL_CALL	0.602	2.857	0.010	0.022
BULK_CARGO	- 0.075	4.301	0.004	0.016
TMEREXP	0.289	7.369	0.003	0.022
TMERIMP	0.419	3.626	0.003	0.010
BUNKSALES	0.352	- 8.781	0.002	- 0.020
MGOBUNKER	1.456	13.999	0.000	0.002
BSI	2.043	- 10.167	0.000	- 0.002
Liquid_Dich_voy_Avg_speed	2.475	- 21.155	0.000	- 0.003
Dry_Load_voy_Avg_speed	- 0.382	- 17.960	0.000	- 0.002
Liquid_Disch_in_SG(Disch_Duration)	1.202	- 18.922	0.000	- 0.002
LIBOR	10.463	22.807	0.000	0.001
Liquid_load_from_SG(Disch_Duration)	5.219	- 19.812	0.000	- 0.002
DC_Disch_SG	1.480	- 33.612	0.000	- 0.002
LC_load_SG	- 0.283	- 4.461	0.000	- 0.000
LC_Disch_SG	6.443	4.842	0.000	- 0.000
Dry_Disch_in_SG(Load_Duration)	6.448	- 15.860	0.000	- 0.000
DC_load_SG	10.934	- 39.567	0.000	- 0.001
Liquid_load_from_SG(Load_Duration)	17.970	- 16.148	0.000	- 0.000
RE_IMP	143.930	1,455.200	0.000	0.001
RE_EXP	104.890	24.317	0.000	- 0.000
Dry_load_from_SG(Load_Duration)	20.174	- 59.873	- 0.000	0.000
Dry_load_from_SG(Disch_Duration)	17.709	- 59.164	- 0.000	0.001
XRATES	- 1.703	-	- 0.000	- 0.000
SCFI	3.228	5.838	- 0.000	- 0.000
Dry_Disch_in_SG(Disch_Duration)	12.013	- 4.644	- 0.000	0.000
INFLATION_RATE	14.678	19.023	- 0.000	- 0.000
Liquid_Disch_in_SG(Load_Duration)	10.520	- 2.617	- 0.000	0.001
PCI	0.191	6.044	- 0.000	- 0.001

Furthermore, the above table 28 shows that the total number of vessel arrivals to the country carries the highest coefficient (weightage) of 0.017 (1.7%). It thus impacts the transportation and storage sector of the country as compared to bunker sales, with the lowest weightage of 0.002 (0.2%).

This chapter produced GDP nowcasts and backcasts based on the DFM concept that was first put forth by Stock & Watson (1991). First using the KFS technique, this model considers the most recent changes for handling missing data, ragged endpoints, and mixed frequency. In order to nowcast the macroeconomic variables, the approach takes into account the new information received. We also noted that nowcasting and backcasting performances are compatible, despite the information set's restriction to nowcasts from a reference quarter. With the concept of the DFM, the dimensional issues of the large data are overcome, which can pose problems in

real life. Finally, nowcasting for five quarterly variables of Singapore for Q3 is shown with impacts from maritime trade flows, shipping, port, and logistics activities.

Chapter Six: Discussion and Policy Implications

Forecasting the current state of an economy is crucially important for any growing economy for policymakers and industry practitioners, and Singapore is not an exception. This chapter discusses maritime trade-related variables' positive and negative impacts on macroeconomic factors. Besides, this section describes the usage and importance of nowcasting information for economic decision-making. The policy implications section explores how various stakeholders of the Singaporean economy can utilise nowcasting information for informed decision-making.

6.1 Dominance over forecasting technique

Forecasting macroeconomic variables in economics have been crucial and popular among policymakers and economists in recent years. However, reliable short-term forecasting is particularly important in times of economic uncertainties (Hindrayanto et al., 2016). In addition, predictions made now are likely to be more accurate since it is known that the longer the time horizon, the lower the predicted accuracy. This study showcases how to utilise modern econometric techniques for nowcasting macroeconomic variables of Singapore through-the-lens of maritime trade and services based on readily available high-frequency maritime trade data.

With the advancement of technologies, new econometric models are developed that can deal with large datasets containing highly correlated variables with different frequencies and heterogeneous information quality. In macroeconomic policymaking, the ability to nowcast accurately is crucial. The importance of big high-frequency data in making policy decisions is undeniable to understand the economic trends better and track the current condition and immediate alarming indicators of the economy in real-time. Additionally, policymaking institutions such as central banks need to develop a structured nowcasting model based on big data analytics is increasing rapidly (Hajipour et al., 2019).

In contrast to traditional forecasting models, the nowcasting model goes further to help these policy institutions better understand the state of the economy both in the current and in the recent past, even when information on economic indicators has not yet been published. Several economists have already proven this in different economies, including the European GDP (Giannone et al., 2009), German GDP (Marcellino & Schumacher, 2010), US GDP (Aastveit et al., 2014), and so on. Their research indicates that earliest GDP nowcasting can be improved in accuracy and that nowcasting is an exceptionally effective method of predicting GDP growth compared to public data. For example, public data usually lags by several months, leaving crisis-monitoring dashboards and scenario studies reliant on dated data or subjective interpretations, thus compromising decision-making and increasing risk. This has made nowcasting a valuable tool for businesses and authorities to make quick decisions, identify potential outcomes, and precisely predict recovery rates. The model has been particularly effective in cases where traditional models and proxies cannot provide precise projections, and it has given decision-makers and businesses an advantage in crisis situations (Gerhard et al., 2021).

6.2 Importance and uses of end of period nowcasting information

Uncertainty can delay investment choices at the national level, prevent businesses and families from spending as much, and make governments more challenging to govern. Information from nowcasting is crucial for reasons other than simple prediction. Government agencies, central banks, and businesses are more concerned with understanding the current level of economic activity at the earliest opportunity when only insufficient information is available so that data-driven decisions may be taken with ease (Assunço & Fernandes, 2022). The created nowcasting model's objective is to provide a prediction of quarterly macroeconomic indicators and use it as early as feasible to forecast the quarter forecast in real time. This study used DFM to nowcast the macroeconomic factors using maritime data to understand how maritime trade flows, shipping, port, and logistics-related activities

affect Singapore's GDP, industrial production, manufacturing, transportation, and storage, as well as financial and insurance services. Nowcasting is a relatively new technique in the field of maritime economics.

6.3 Impact of maritime trade and services on macroeconomic factors of Singapore

The current study found that maritime trade flows, shipping, port, and logistics activities are closely related to Singapore's economic development. It is also observed that the macroeconomic variables of Singapore are influenced either positively or negatively by these factors. Relatively, it suggests that the patterns of the activities as mentioned earlier, could generate useful insights into the underlying macroeconomic trends.

To start with the most important macroeconomic factor, GDP, we can see that the vessel arrivals and total merchandise imports and exports find a place in the top factors with higher coefficients i.e. weights. Higher weights of the independent variables have a higher impact when considered along with the actuals as per the nowcasting detail table on our macroeconomic targets. Overall, the impact of maritime factors on Singapore's GDP is 2.72% in 2022 Q3, while it was 6.28% in 2022 Q2.

Similar trends followed for all other macroeconomic factors of our model, where in the case of IIP too, the vessel arrivals, as well as the imports and exports, impact the macroeconomic factor with its higher weights positively. The total impact presented by the maritime factors is 2.70 % which includes the data releases impact of 0.43 on account of new vintage data for Q3 -2022.

Moving forward, manufacturing is also impacted mainly by the same independent variables as in the case of GDP and IIP. However, the impact of maritime factors is more than the previous dependent variables as above at 3.17%. This may be because most of the raw materials are being carried by sea to the country. However, the new vintage data impact is only 0.37%. While the major maritime independent factors impact the remaining macroeconomic factors, viz.

transportation and storage, finance, and insurance in the same positive way as in the case of all above described macroeconomic factors, it is impertinent to mention that their impact being 3.45% on transportation and storage, while it is 2.73% on Finance and Insurance, as per the nowcast results for 2022-Q3.

These findings with impacts will doubtless be much scrutinised, but the nowcasting information generates some immediately reliable insights through employing DFM using high-frequency maritime data that can be more insightful to measure the trends of macroeconomic activity and thus helps in making sound policy decisions.

6.4 Policy implications

In recent years, the economy of Singapore has experienced an unprecedented contraction due to COVID-19, the US-China trade war, and its subsequent consequences such as supply chain disruptions, geopolitical instability, etc. Due to these, the downturn was evident across the GDP, IIP, manufacturing, transportation, storage, and financial and insurance service sectors. In particular, the transportation and financial sector have taken the worst hit and recorded sequential contraction due to reduced general business activities and weakened business sentiments, along with the travel ban and Suez Canal blockage. Considering these factors, the developed nowcasting approach can complement and help fill the gaps in the delay of official trade statistics publication in Singapore. Additionally, the end-of-period nowcasting data predicted by this model can offer early warning signals of economic activity turning points, helping investors, central banks, international organisations, and policymakers monitor and respond to shocks and fluctuations in the economy in a timely manner. Although this dissertation focuses on Singapore, the applied DFM model can be extended to various countries and nowcast various economic indicators. Some interesting policy implications of nowcasting GDP and its components in the basis of our study on Singapore are discussed below:

An early warning sign of economic activity: For countries like Singapore that have massive maritime trade, shipping, port, and logistics exposure, this approach could serve as an early warning sign of economic activity by understanding in which direction the economy is heading. Besides, this approach can be combined with

mainstream economic data to get the most accurate forecast (Hu & Yao, 2019). Furthermore, reflecting the monthly releases of high-frequency maritime data, the nowcasts would inform MAS staff and policymakers about the latest status of regional economic development. For example, a negative growth of GDP for two consecutive quarters is technically treated as a recession in any country. Thus, such nowcast data can be produced regularly and used as a reference or an early indicator of potential issues like inflation and combat it by monitoring interest rates and the cash flows in the country.

Monetary policy: For central banks usually change their monetary policy stance during press conferences, but the time interval between the two press conferences can be significantly long and by this time, the market situations and macroeconomic conditions of a country change abruptly. As a result, market participants and policymakers can only rely on nowcasting information to interpret the future path of monetary policies. For instance, European Central Bank (ECB) uses nowcasting information for accurate tracking of its monetary policy stance and decisions of its historical announcements (Marozzi, 2021). So, the nowcast information from the dissertation can be helpful in monetary policy decisions for the Monetary Authority of Singapore (MAS). Besides, central banks need to monitor the economy's inflation rate routinely. In this regard, the nowcasting information regarding GDP and other indicators can help pinpoint the inflation developments and understand the underlying forces that can jeopardise price stability, thereby helping the decision-makers to make timely decisions and avoid such instability (Modugno, 2013). Accordingly, the MAS can use the end-of-period nowcasting information to understand upcoming GDP and inflation trends better.

Fiscal policy and support packages: The government of Singapore and concerned ministries such as the MTI, MOT, etc. can utilise nowcasting information for easy tracking of the current situation of their country and in which direction their economy is heading. Based on the GDP nowcast, the government can make decisions related to economic policy, fiscal policy, revenue planning, cash flow management and so on (Gerhard et al., 2021). Nowcasting information on these factors can provide an assessment of the impacts of previous policies and instruct

the need for adjustment, as well as in the preparation of support packages for industries related to maritime transportation and storage, manufacturing, insurance, and financial services in the event of downturns such as market fluctuations.

Maritime trade policy: This nowcasting approach could be used to assess the impact of export and import policies of Singapore (e.g., trade regionalisation, trade protectionism, trade liberalisation, sanctions, tariff policy modification, quota etc.) to analyse the trade patterns in real-time. Besides, by analysing AIS data the real-time trade activity of this country could be monitored by tracking critical nodes in the shipping and port network by way of illustration if the port traffic or vessels arrivals in Singapore port is declining, then it may be an indication of decreasing trends of trade volume (Verschuur, 2021). Apart from the country-level analysis, this nowcasting approach can be applied to regional port and shipping networks and surveillance analysis that will help to forecast the trade shocks such as transit time between ports.

Investment policy: For the commercial and investment banks and non-bank financial institutions, nowcasting information on macroeconomic factors of Singapore is increasingly important in developing a better investment strategy. However, the economic and financial situation of the country is the key determinant of the asset risks. For banks and FIs, understanding the economic cycles is an important factor for investment success. For these institutions' understanding, the economic cycles are crucially significant. As a result, understanding the current state of the economy is crucial for investors to make informed investment decisions. In that case, nowcasting information regarding key economic indicators may serve as a critical source (Sonntag & Little, 2017). In addition, for investment banks, nowcasting could help to make economic and risk assessments before making investment decisions and identifying investment opportunities in specific sectors or geographies. It also can shape the decisions related to lending and pricing strategies for them. The nowcasting approach for monitoring the financial and insurance services could help Singapore formulate investment policies for economic development.

External engagement with other countries: This nowcast approach could be incorporated in the future based on the framework developed in our study, with regular updates on tracking the real-time economic activity of other or trading countries. Such insights and knowledge of trading partners will also help two-fold: 1) Expand the internal forecasting capacities, and 2) Serve as a basis for future MOUs and bilateral agreements.

Policies towards FDI: Singapore is a country with a diversified economy that attracts a massive foreign investment in manufacturing (e.g., pharmaceuticals, transport machinery and equipment, electronics and petrochemical), industrial production, transportation and storage and financial and insurance services, and this country has remained the leading world maritime and aviation hub including a regional hub for thousands of multinational companies. The end of the period of nowcasting information could help this country attract future foreign investment in digital innovation and cybersecurity, manufacturing, shipping, and logistics.

Besides, the maritime industry practitioners such as port authorities, port users, shipping companies, ship chattering, bunker companies, ship management, classification societies, shipbuilding companies, freight forwarding companies, P&I and H&M insurers can use nowcasted transportation and storage information for developing their business strategies as well as making business decisions.

In addition, based on the nowcasted industrial production and manufacturing information, the industrial businesses and their supporting industries can use this information for forecasting consumer demand, sector evaluation, optimising production as well as allowing them to rethink the production, supply chain, and sales and marketing strategies (Gerhard et al., 2021).

Moreover, in recent years, nowcasting techniques have gained popularity among researchers, economists, and academia. So, the nowcasted information about the five macroeconomic variables of Singapore and the developed model can help them explore new knowledge in maritime economics and finance.

In conclusion, tracking the economic activity for monetary, fiscal, and economic policymaking in a timely and accurate manner is crucial. The maritime trade flows and shipping indicators can help provide an early signal to monitor economies' positions in the business cycles. As a result, the market participants and stakeholders of the economy use nowcasting information for policymaking. The key areas of application of nowcasting information for policymaking are discussed above. This dissertation has led to several interesting findings. The most important aspect regarding the relative contribution of incorporating maritime trade flows, shipping, port, and logistics indicators as they become available in real-time through AIS. However, users of nowcasting information must be aware of the degree of accuracy that can be expected, as this varies across models and time.

Chapter Seven: Recapitulation and Conclusions

7.1 Conclusion

This dissertation sets out to nowcast the GDP and its core components (i.e., manufacturing, transportation and storage, financial and insurance services) as well as IIP of Singapore through-the-lens of maritime trade and services for identifying the key maritime trade flows, shipping, port and logistics factors that directly affect these factors. Besides, this study has discussed the impacts of maritime factors and presented the application of end-of-period nowcasting information of policy decisions. For this intent, this chapter summarises the main findings from the analysis concerning the performance and importance of maritime trade data in nowcasting the macroeconomic factors. It also highlights the importance of using real-time vintage data about the flow of data releases. Finally, some suggestions have been made for the next steps and further research by using any country's real-time maritime trade and services data.

For this purpose, an extensive literature review was carried out to find and resonate the relationship between maritime trade and macroeconomic factors. The most apparent finding from this study is that both merchandise import and export carry the highest weights and thus impact all the macroeconomic factors. Several lines of evidence suggest a close and dynamic relationship exists between the predictors and the target variables. For instance, Lane & Pretes (2020) proved a significant and positive relationship between GDP and merchandise trade ratio. In the same way, this study has also found relationships between macroeconomic factors and maritime trade in Singapore, as economic development is influenced by maritime trade factors and maritime connectivity.

While looking at an individual economy, maritime trade, shipping, port and logistics factors can affect the country-level policies which facilitate global connectivity and promote reduced transportation costs with higher quality services, thereby enhancing trade and economic growth through national competitiveness (Jiang et

al., 2015). Accordingly, this dissertation has considered Singapore as a case country. It may be small in size, but its exposure to maritime trade is huge. Similarly, the strategic and economic importance of Singapore in the region, as well as most of its economic activities, are greatly influenced by maritime trade, shipping, and port activities, hence observing the macroeconomic variables of this country through-the-lens of the maritime perspective has been proven worthy of attention.

This study successfully nowcast the IIP, GDP, and its components for Q3 of 2022. It mainly focused on shipping and port factors, which remained the crux of the study, with some financial indicators like inflation rate, exchange rate, etc. One of the most significant discoveries to emerge from this study is using AIS data to monitor world maritime trade activity. The relevance of nowcasting is supported by the current findings using 29 high-frequency maritime data. The nowcasts are updated each time new data are published, based on data sets with a "jagged edge" that becomes progressively larger as time progresses. The DFM, a well-known technique in the econometrics toolbox of MATLAB codes, is modified to account for data features, including mixed frequencies, missing data, and ragged endpoints. As previously noted, this program makes use of data from numerous monthly variables that were released asynchronously. The ragged and unbalanced data challenge was combated with PCA and KFS techniques. The results demonstrated that this workhorse model could deliver the most precise end-of-period nowcasting results.

The method of this study can be used to produce short-term forecasts, i.e., nowcasts of the target variables based on the most up-to-date information available in a series of underlying indicators, and it is proved that the methodology achieves a good fit with the statistics of our case country. It has been noted that the timing of vintage data releases is a significant factor in determining the magnitude of the release's marginal predictive value (Giannone et al., 2008). When we break down the nowcasts of the dynamic factor model into contributions, the results reported here shed light on the fact that new parameters indeed result in significant modifications.

However, the empirical findings in the earlier chapter indicate that the nowcast GDP and other variables made no significant difference to actual information. The findings of this research also support the notion that real-time data analysis greatly benefits from the exploitation of rich data sets. By way of illustration, the GDP end-of-period nowcasting result of April stands at 5.21%, and the impact of June releases is 0.32%, thus adding up to 6.28 % as on 01 June 2022 (new vintage). While for Q3 of 2022, the result of April nowcast stands at 2.03% and the impact of June releases is 0.31%, thus adding up to 2.72% as on 01 June 2022 (new vintage).

Furthermore, the single most striking aspect to emerge from the results of this study is the fact that the nowcasting concerning percentage change of GDP is almost coinciding with the actual GDP for Q2- 2022, being backcasted in this study with the use of the vintage data. The visual representations illustrated in the earlier chapter also show that nowcasts quickly incorporate the information updates provided by the vintage data of the underlying predictors, correctly identifying the changing trends and turning points in the series. Together these results provide important insights into the relationship between maritime trade factors and the macroeconomic factors being positive for total merchandise trade, vessel calls, and cargo carried.

In summary, for the informants in this study, what are the practical implications of these findings for both industry and literature? By providing early alarming signals of economic activity, the end-of-period nowcasting results provided by this model are highly beneficial for macroeconomic policymakers, central banks, international organisations, and investors to keep track and respond to shocks and fluctuations in the economy in a timely manner. Even academicians can benefit from the similar predictors used in this study being related to maritime activities for their research for different coastal countries, which are quite dependent on maritime trade and shipping connectivity. However, maritime trade factors are a dependable indicator of the economic cycle of any country, and the nowcast results can be treated as early indicators of unknown risks or unforeseen circumstances. Further research could also be conducted to determine the effectiveness of the nowcasting model by incorporating high-frequency maritime data to produce short-term forecasts.

7.2 Suggestions for future research

There is always room for further improvement in any research area, and this study is no exception. The increasing number of literature on nowcasting is promising for future work. For the first time, maritime trade and services data based on AIS activity are used to nowcast Singapore's GDP and other components, which has proved very beneficial in understanding the country's maritime trade flows, shipping, and port activity. In the future, this framework could also be used to estimate other macroeconomic variables, such as inflation and unemployment rates that are influenced by maritime trade and services. More research using other maritime data such as port calls, port stay, port performance, turnaround time in port, etc., may also be beneficial, depending on which country the model is employed.

Another important direction for future research is using explicit and more sophisticated models by using big data in the nowcasting framework. Another avenue of future research is to link the more high-frequency (daily, weekly factors) nowcasting framework with a quarterly structural model and update the nowcasts with the release of new data, thus providing up-to-date results. In their paper, Giannone et al. (2009) suggested that development is in progress. As a result, a by-product of this analysis is that further research can be conducted by obtaining a real-time estimate of variables. One more feature for international trade needs a mention here, where with the help of AIS data, the import data can be extracted in advance based on the loading date elsewhere to Singapore.

It is also pertinent to know that the maritime sector indirectly contributes to employment, construction, and other important sub-economic variables. The comprehensive study on these variables as to how maritime factors would impact such sub-economic variables i.e., positively or negatively, will be quite interesting.
With ports and ships becoming more networked and fully integrated into information technology networks, the maritime industry is increasingly adopting automation. Other trends that are having an impact on the market include a growing move toward digitalization, the development of smart navigation, and advanced analytics

(UNCTAD, 2020). These trends may have further repercussions on macroeconomic variables and should therefore be considered in future studies.

By transitioning to a big data environment, researchers could take advantage of the benefits of machine learning techniques to extract and pick pertinent facts from vast amounts of data and obtain greater nowcasting gains. To examine the most effective method for nowcasting GDP in each nation, it would also be interesting to construct and estimate alternative country-specific machine learning models (Ashwin et al., 2021). As a result, a further study could be conducted by considering the highly data-driven technologies and using newer methodologies such as machine learning and visualisation tools with the ability to interact and connect large databases with big data.

Similarly, ongoing refinements of the algorithms, additional data on the vessel, cargo types (raw materials or finished goods), hinterland statistics, weekly AIS statistics, and country-specific knowledge should help further improve the performance of GDP based on maritime and related industries for several country cases. Additionally, concerning the robustness check and potential source of improvement, the study should be attempted using alternative methodologies like approximation-free models.

Moreover, the co-movement between the variables is constantly changing and evolving. For example, during the pandemic, the trends were ever-changing and unpredictable, which were quite different and surprising, with widespread diffusion from the previous trends in the maritime world. Hence, there is ample room for further progress in determining the variable selections, and such a review of variables should be repeated frequently per the changing environment. However, the study would have been more interesting if it had included key economic indicators from neighbouring economies or major trading partners that may also be considered predictors. This is because they could reflect cross-country spillovers or common regional or global factors (such as financial conditions) affecting different countries simultaneously (Barhoumi et al., 2022). For example, PMIs in China,

Indonesia, Malaysia, and other major regional or global economies could be helpful in further understanding the GDP of the host country.

Over and above that, since this study can nowcast GDP and other macroeconomic variables for other countries or a specific region within a country and at the same time also estimate the GDP growth rates and other variables on an annual basis. Finally, less developed countries that rely heavily on seaborne trade will benefit substantially from the DFM by adding vintage data to understand the maritime trade impact on their economy beforehand. The advanced data on seaborne imports would also support the policymakers and the trade and industry ministries towards early planning of the foreign trade policies by implementing high export subsidies, thereby balancing the foreign exchange reserves and probable currency valuations.
What is now needed is a cross-national study over and above the country-level analysis. This methodology can be applied and extended to regional surveillance such as ASEAN or SAARC countries. Foreseeing the economic shocks resulting from natural disasters, market fluctuations and political crises, or other regional disruptions will undoubtedly be more interesting. Likewise, maritime trade shocks in the regions can be predicted by tracking this economic activity through the nowcasting model (Arslanalp et al., 2021).

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APPENDICES

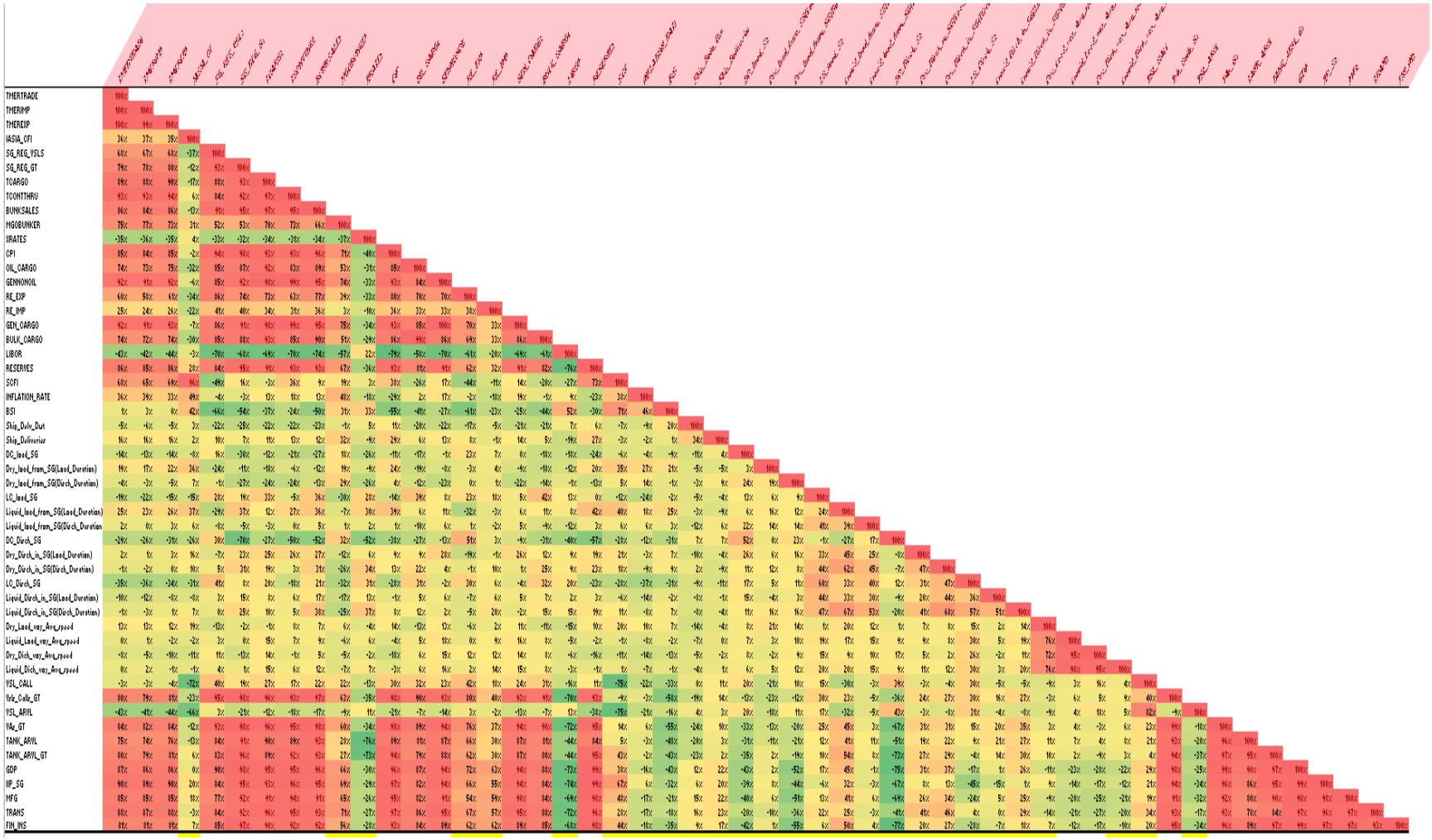
APPENDIX A: INITIAL LIST OF VARIABLES

	Description	Formulation	Frequency	Period Covered	Observations	Source
Dependent Variables						
Macroeconomic Variables						
GDP	Gross Domestic Product at current market prices	Million S$	Q	Jan-1975 to Jun-2022	189	SingStat
IIP_SG	Index of Industrial Production	Index	Q	Jan-1982 to Jun-2022	159	SingStat
MFG	Manufacturing	Million S$	Q	Jan-2002 to Jun-2022	189	SingStat
TRANS	Transportation and Storage	Million S$	Q	Jan-2002 to Jun-2022	189	SingStat
FIN_INS	Financial and Insurance Services	Million S$	Q	Jan-2002 to Jun-2022	189	SingStat
Independent Variables						
Merchandise Trade flows						
TMERTRADE	Total Merchandise Trade, (At 2018 Prices)	000'S$	M	Jan 2002 to Jun 2022	246	SingStat
TMERIMP	Total Merchandise Imports, (At 2018 Prices)	000'S$	M	Jan 2000 to Jun 2022	246	SingStat
TMEREXP	Total Merchandise Exports, (At 2018 Prices)	000'S$	M	Jan 2000 to Jun 2022	246	SingStat
RE_EXP	Total Merchandise Re-Export	US$	M	Jan-2000 to Jun-2022	270	UN Comtrade
RE_IMP	Total Merchandise Re-Import	US$	M	Jan-2000 to Jun-2022	270	UN Comtrade
DC_load_SG	Dry Cargo Loaded from SG Voy intake (MT)	MT	M	Jan-2013 to Aug-2022	114	AXS Marine
LC_load_SG	Liquid Cargo Loaded from SG Voy intake (MT)	MT	M	Jan-2013 to Aug-2022	114	AXS Marine
DC_Disch_SG	Dry Cargo Discharged in SG Voy intake (MT)	MT	M	Jan-2013 to Aug-2022	114	AXS Marine
LC_Disch_SG	Liquid Cargo Discharged in SG Voy intake (MT)	MT	M	Jan-2013 to Aug-2022	114	AXS Marine
Shipping Factors						
Ship_Deliveries	Total Ship Deliveries	$m	M	Jan-1970 to Jun-2022	630	Clarksons
Ship_Delv_Dwt	Total Ship Deliveries	DWT	M	Jan-1970 to Jun-2023	630	Clarksons
Dry_load_from_SG(Load_Duration)	Dry Cargo Loaded from SG Load Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Dry_load_from_SG(Disch_Duration)	Dry Cargo Loaded from SG Disch Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Dry_Load_voy_Avg_speed	Dry Cargo Loaded from SG Voy Avg Speed	Nautical Miles (nm)	M	Jan-2013 to Aug-2022	114	AXS Marine
Dry_Disch_in_SG(Load_Duration)	Dry Cargo Discharged in SG Load Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Dry_Disch_in_SG(Disch_Duration)	Dry Cargo Discharged in SG Disch Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine

Dry_Dich_voy_Avg_speed	Dry Cargo Discharged in SG Voy Avg Speed	Nautical Miles (nm)	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_load_from_SG(Load_Duration)	Liquid Cargo Loaded from SG Load Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_load_from_SG(Disch_Duration)	Liquid Cargo Loaded from SG Disch Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_Load_voy_Avg_speed	Liquid Cargo Loaded from SG Voy Avg Speed	Nautical Miles (nm)	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_Disch_in_SG(Load_Duration)	Liquid Cargo Discharged in SG Load Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_Disch_in_SG(Disch_Duration)	Liquid Cargo Discharged in SG Disch Duration	Days	M	Jan-2013 to Aug-2022	114	AXS Marine
Liquid_Dich_voy_Avg_speed	Liquid Cargo Discharged in SG Voy Avg Speed	Nautical Miles (nm)	M	Jan-2013 to Aug-2022	114	AXS Marine
SCFI	SCFI Shanghai-SE Asia (Singapore) Container Freight Rate	USD ($)/TEU	M	Jan-2010 to Jul-2022	629	Clarksons
IASIA_CFI	Intra-Asia Container Freight Rate Index	Index	M	Jan-2004 to Jul-2022	223	Clarksons
BSI	Baltic Exchange Supramax Index	Index	M	Jan-2013 to Aug-2022	59	Clarksons
SG_REG_VSLS	Singapore Registry Of Ships (End Of Period)	Number	M	Jan-1995 to Jun-2022	330	SingStat
SG_REG_GT	Singapore Registry Of Ships (End Of Period)	000'GT	M	Jan-1995 to Jun-2022	330	SingStat
Port Factors						
TCARGO	Total Cargo	000' Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
GEN_CARGO	Cargo (General)	000' Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
BULK_CARGO	Cargo (Bulk)	000' Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
OIL_CARGO	Cargo (Oil-In-Bulk)	000' Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
GENNONOIL	Cargo (General & Non-Oil In Bulk)	000' Tonnes	M	Jan-1995 to Jun-2022	330	SingStat
VSL_ARVL	Vessels Arrivals (>75GT)	Number	M	Jan-1993 to Jun-2022	354	data.gov.sg
VAs_GT	Vessels Arrivals (>75GT) Shipping Tonnage	GT	M	Jan-1993 to Jun-2022	354	data.gov.sg
VSL_CALL	Total Vessels Calls (>75GT)	Number	M	Jan-1993 to Jun-2022	354	data.gov.sg
Vsls_Calls_GT	Vessels Calls (>75GT) Shipping Tonnage	GT	M	Jan-1993 to Jun-2022	354	data.gov.sg
TANK_ARVL	Tankers Arrivals (>75GT)	Number	M	Jan-1993 to Jun 2022	354	data.gov.sg
TANK_ARVL_GT	Tankers Arrivals (>75GT) Shipping Tonnage	GT	M	Jan-1993 to Jun 2022	354	data.gov.sg
PCI	Port Congestion Index - Containerships At	Thousand TEU	M	Jan-2016 to Jun-2022	78	Clarksons

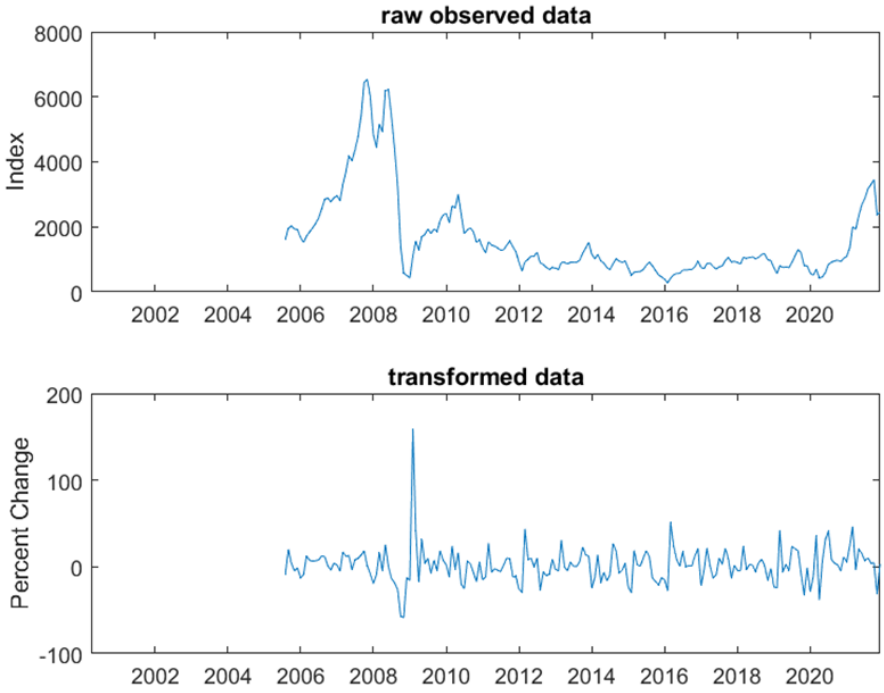
	Singapore, 7dma					
TCONTTHRU	Total Container Throughput	000'TEU	M	Jan-1995 to Jun-2029	330	SingStat
Maritime Logistics Factors						
BUNKSALES	Bunker Sales	000'Tonnes	M	Jan-1995 to Jun-2030	330	Data.gov.sg
VLSFO	VLSFO Bunker Prices (0.5% Sulphur), Singapore	$/Tonne	M	Sep-2019 to Jun-2022	34	Clarksons
MGOBUNKER	MGO bunker Price, Singapore	USD/Tonnes	M	Jan-1990 to Jul-2022	1700	Clarksons
Other Factors (Economic & Financial)						
XRATES	Exchange Rate	SGD to USD	M	Apr-1991 to Jul-2022	377	Clarksons
LIBOR	Interest rate	Rate	M	Apr-1989 to Jul-2022	1634	IMFdata
INFLATION_RATE	Inflation Rate	%	M	Jan-1970 to Jun-2022	630	rate.inflation.com
RESERVES	Total Foreign Reserve	S$ in Million	M	Jan-1972 to Jul-2022	607	eservices.mas.gov.sg
CPI	Consumer Price Index	Index	M	Jan-1970 to Jun-2022	630	SingStat

APPENDIX B: INITIAL CORRELATION TABLE

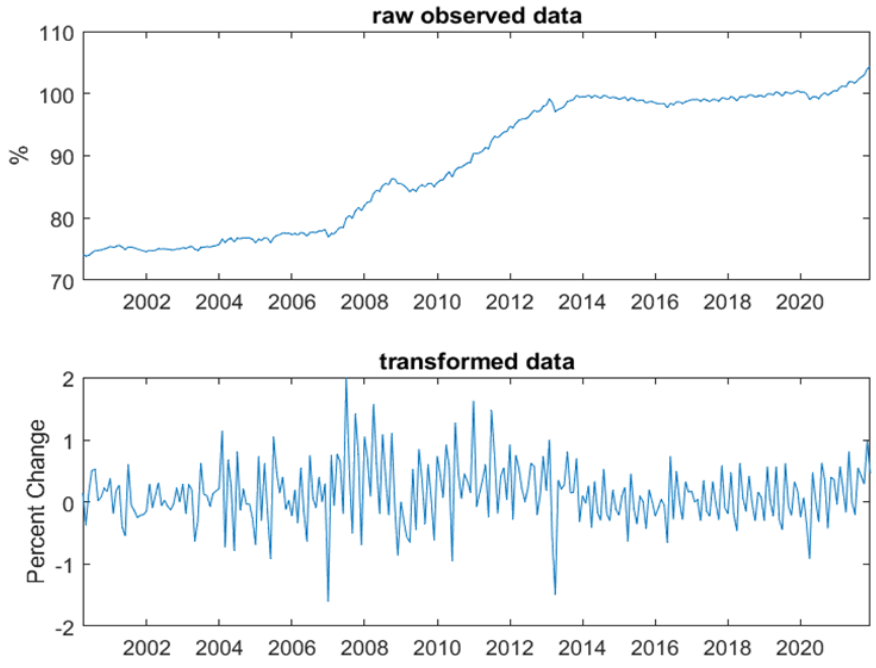


APPENDIX C: RAW AND TRANSFORMED DATA FOR ALL SIGNIFICANT VARIABLES

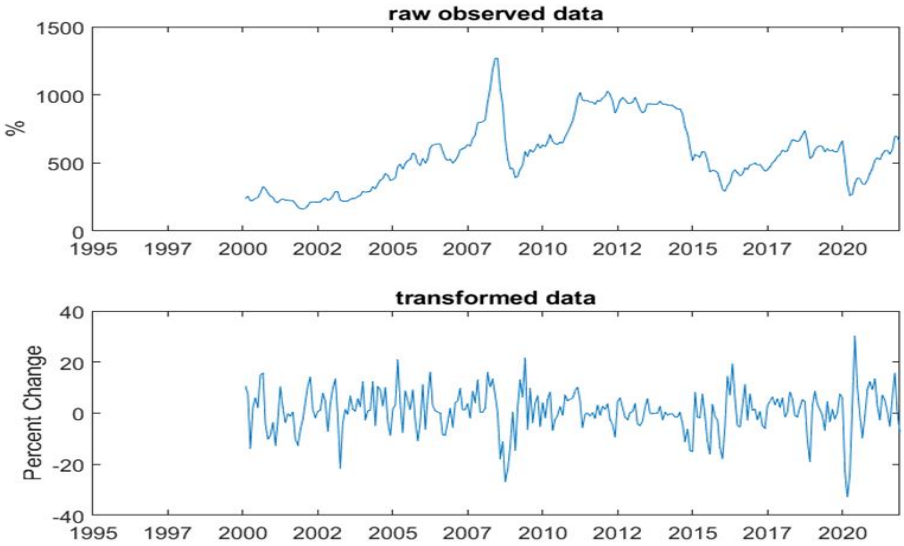
BALTIC EXCHANGE SUPRAMAX INDEX (BSI)



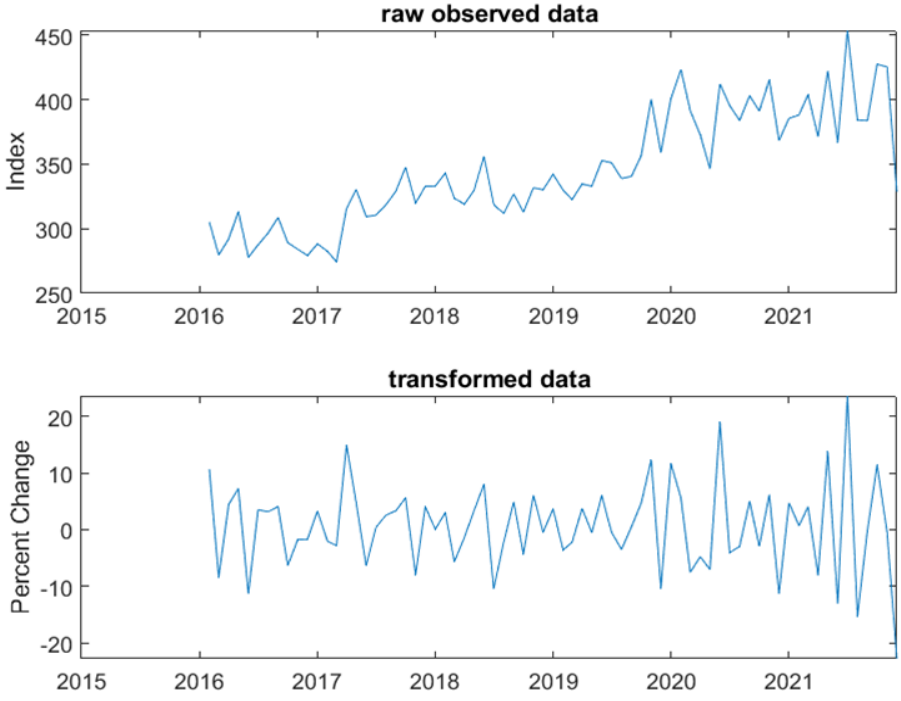
CONSUMER PRICE INDEX (CPI)



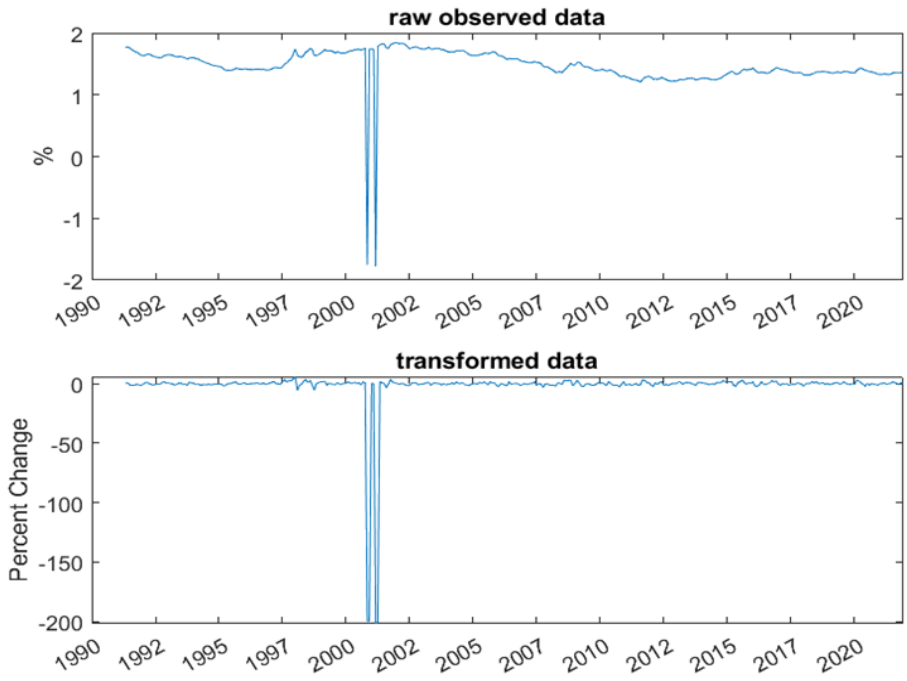
MGO BUNKER PRICE



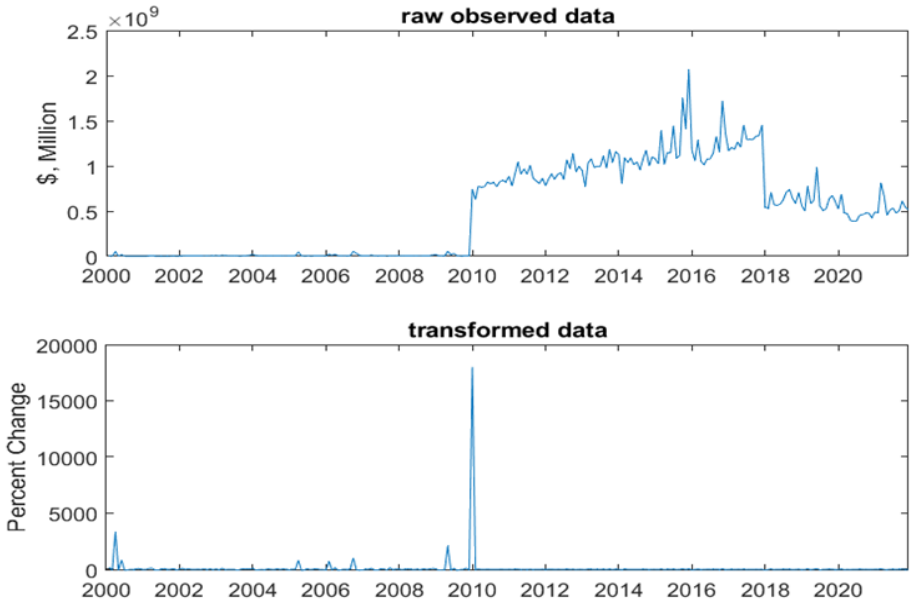
PORT CONGESTION INDEX



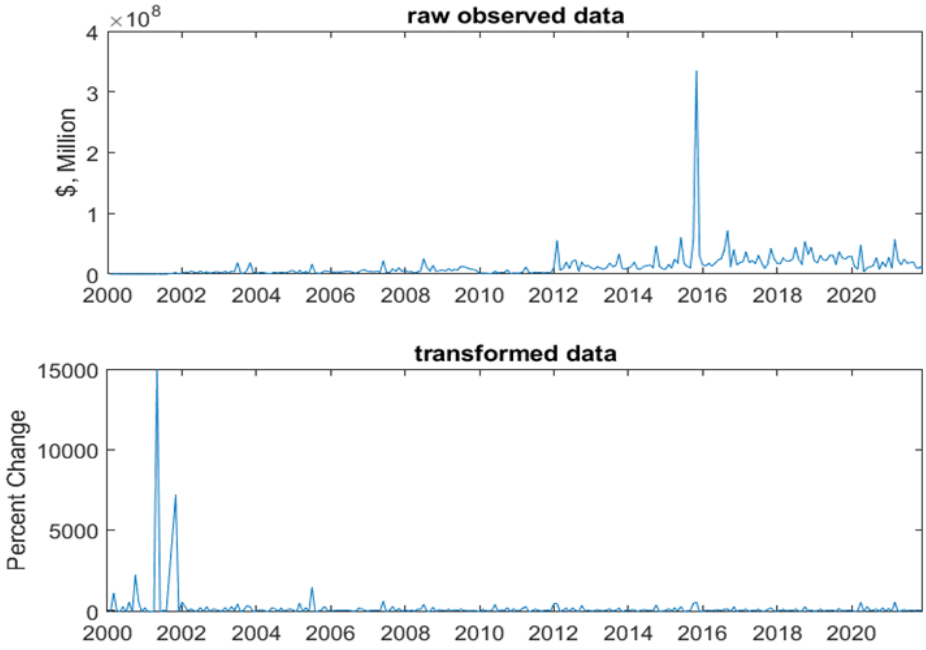
EXCHANGE RATES



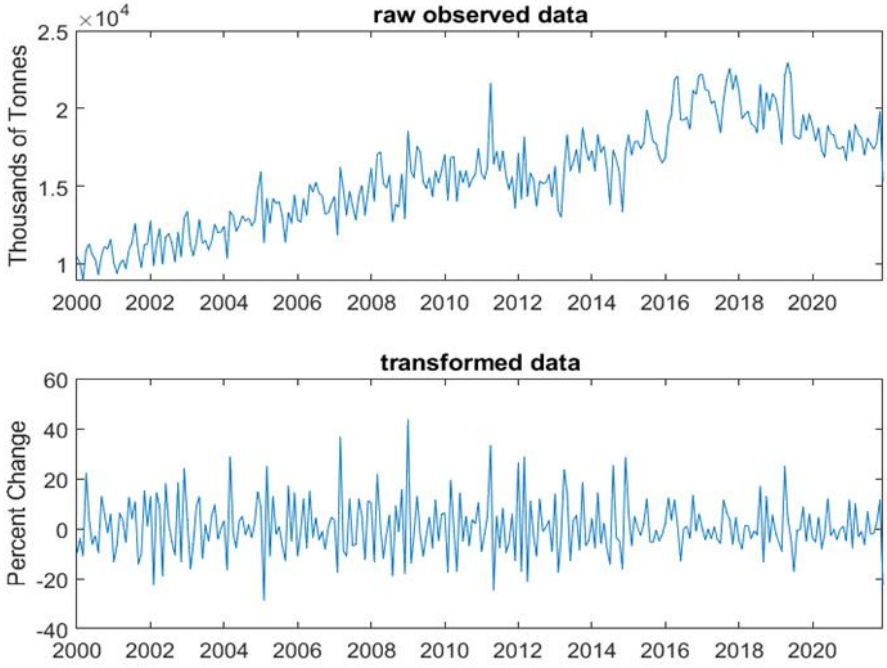
RE-EXPORT



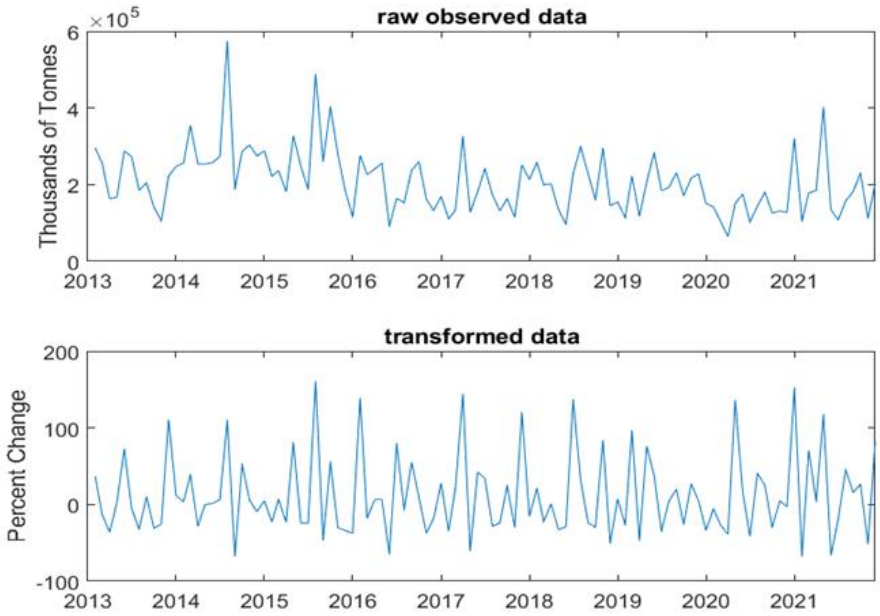
RE-IMPORT



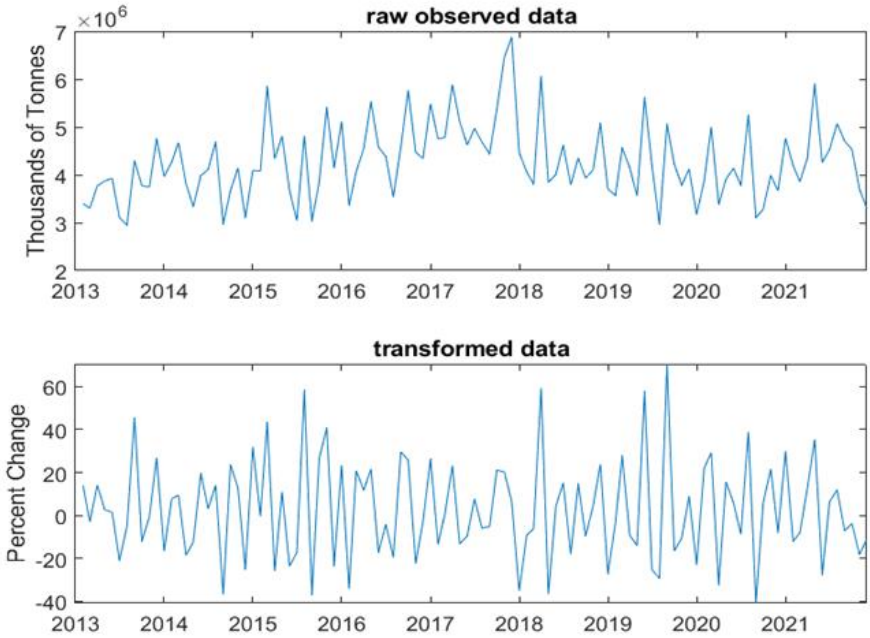
BULK CARGO



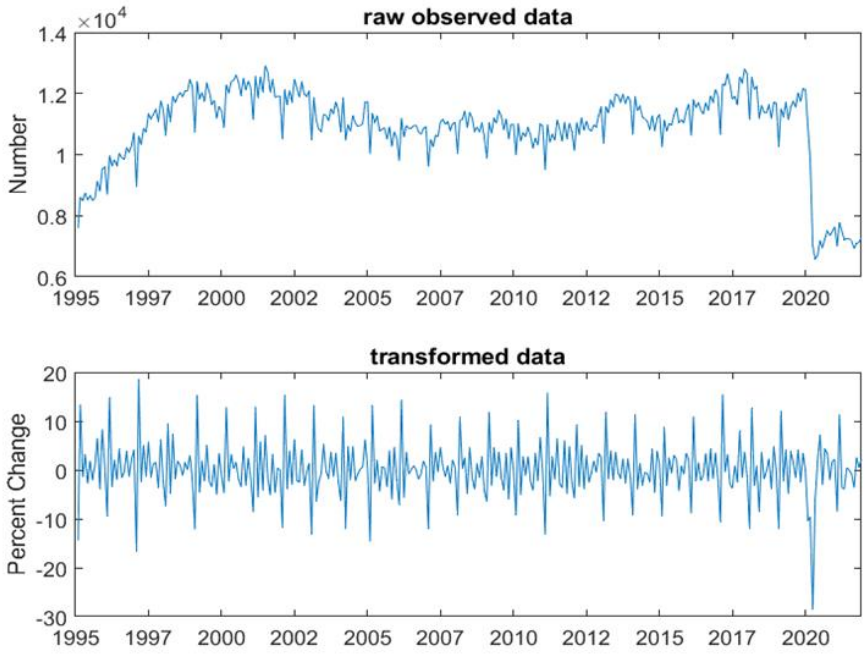
DRY CARGO LOADED FROM SINGAPORE (AVERAGE VOYAGE INTAKE)



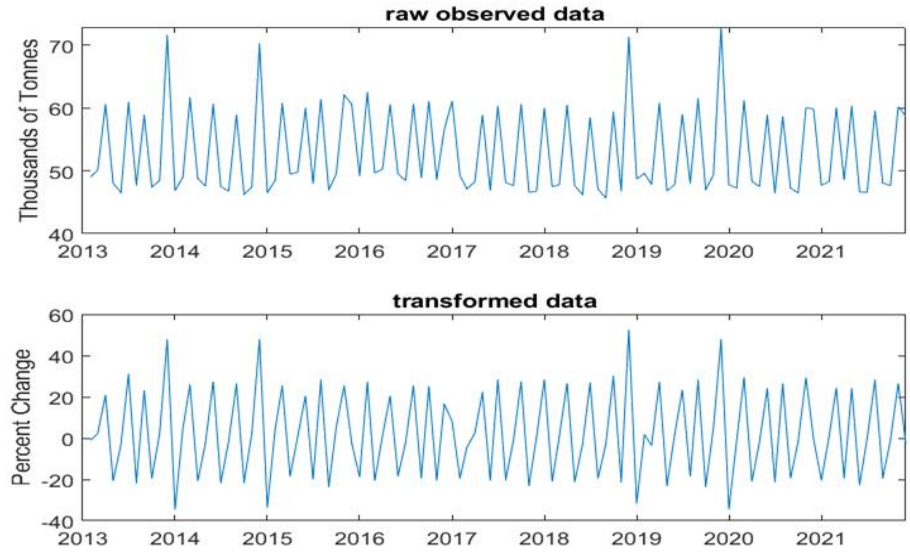
LIQUID CARGO LOADED FROM SINGAPORE (AVERAGE VOYAGE INTAKE)



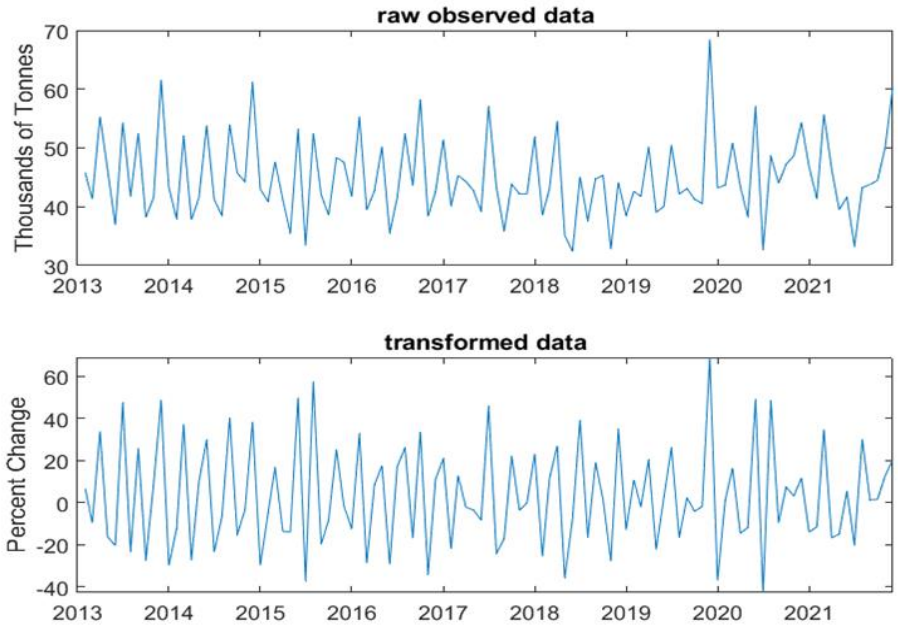
VESSEL ARRIVAL



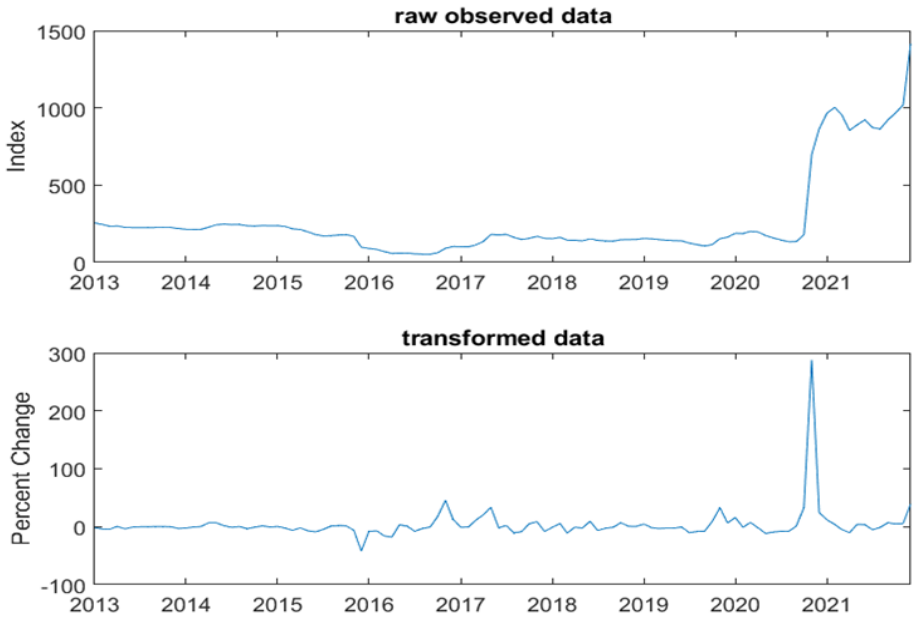
LIQUID_DICH_VOY_AVG_SPEED



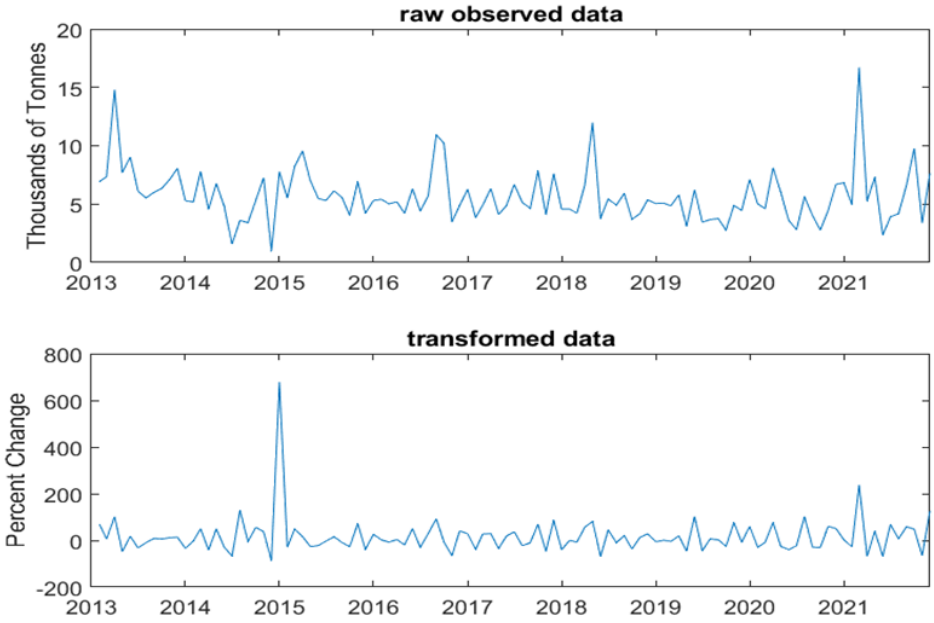
DRY_LOAD_VOY_AVG_SPEED



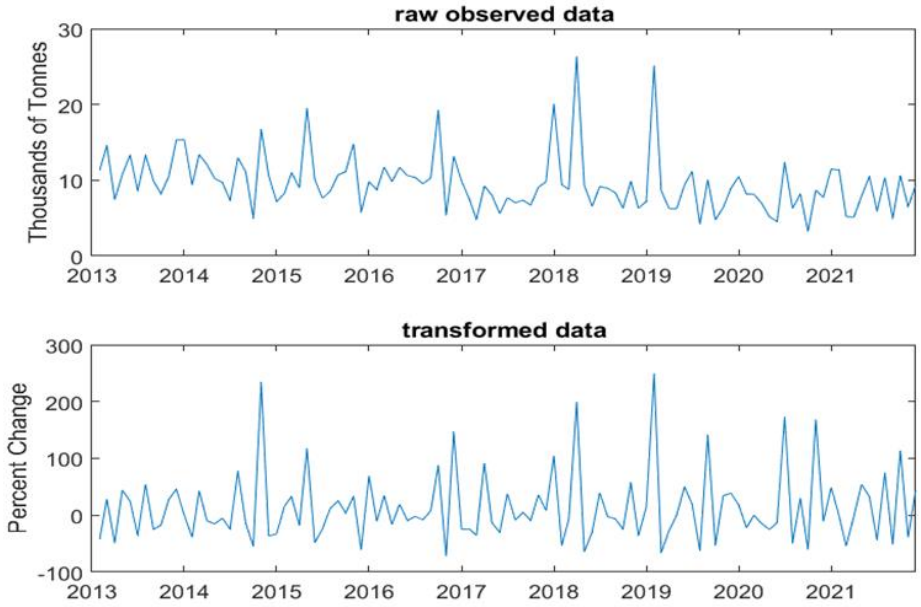
SHANGHAI CONTAINER FREIGHT RATE



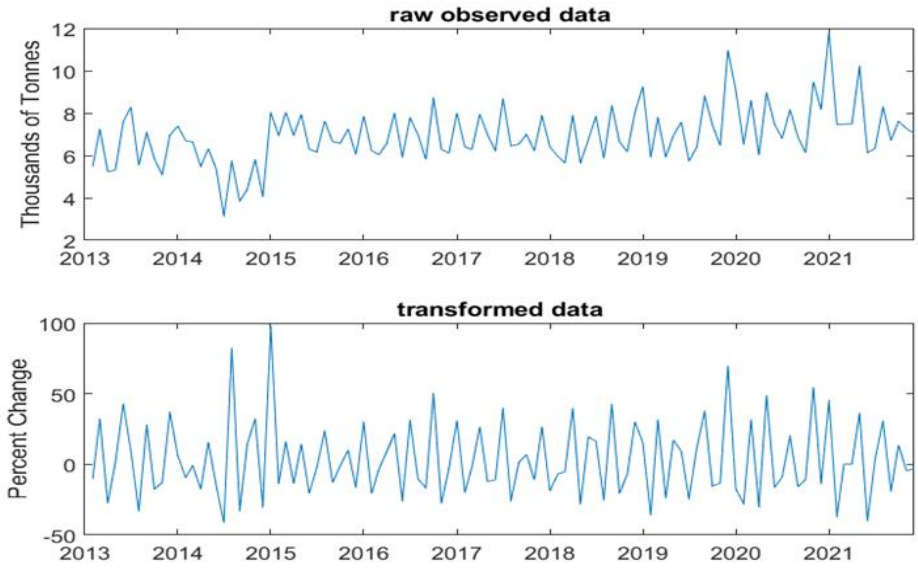
DRY_LOAD_FROM_SG(LOAD_DURATION)



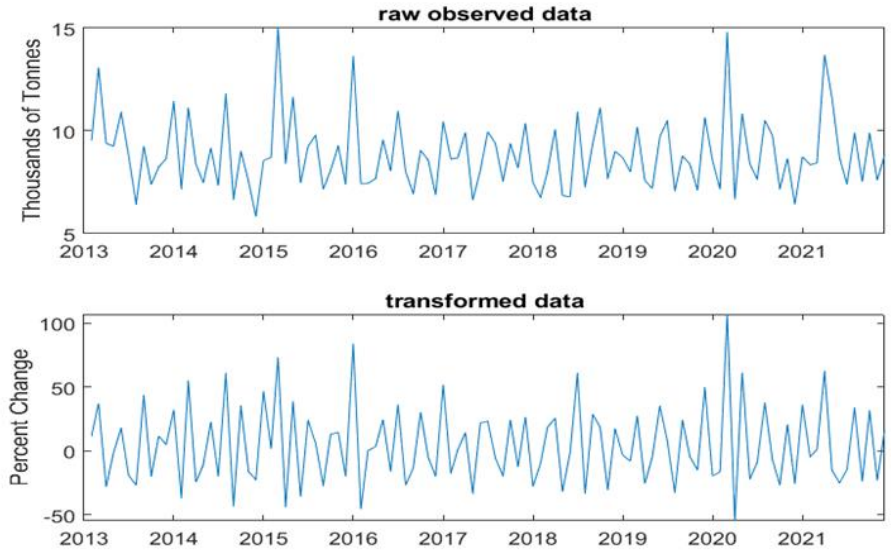
DRY_LOAD_FROM_SG(DISCH_DURATION)



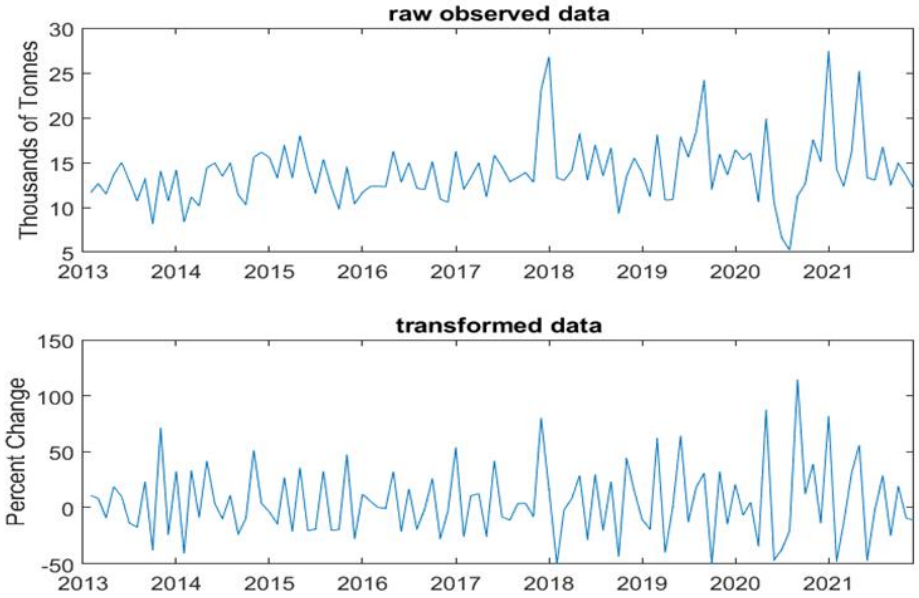
LIQUID_LOAD_FROM_SG(LOAD_DURATION)



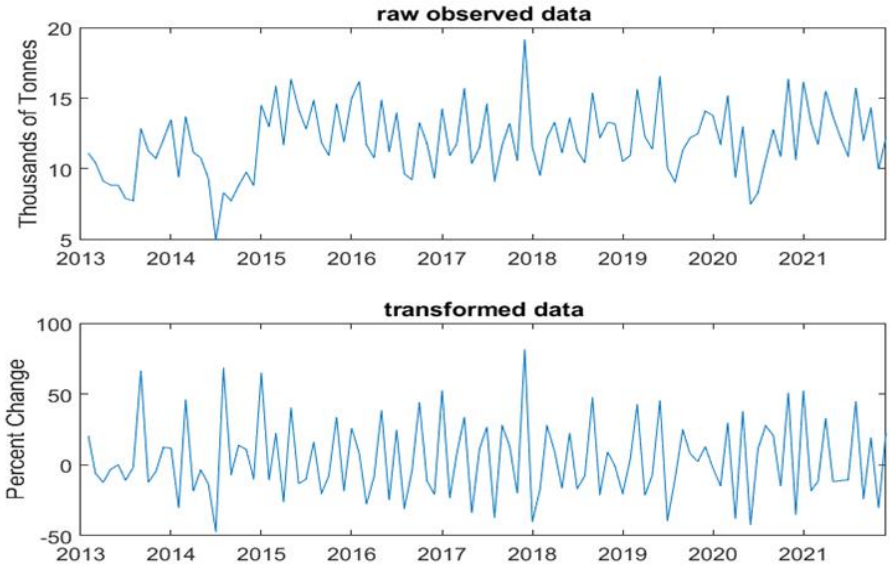
LIQUID_LOAD_FROM_SG(DISCH_DURATION)



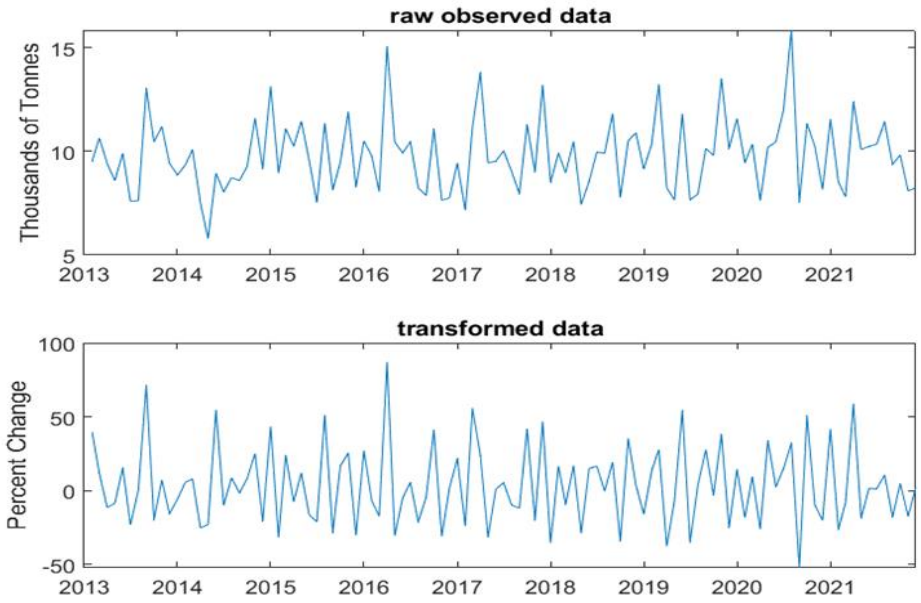
DRY_DISCH_IN_SG(LOAD_DURATION)



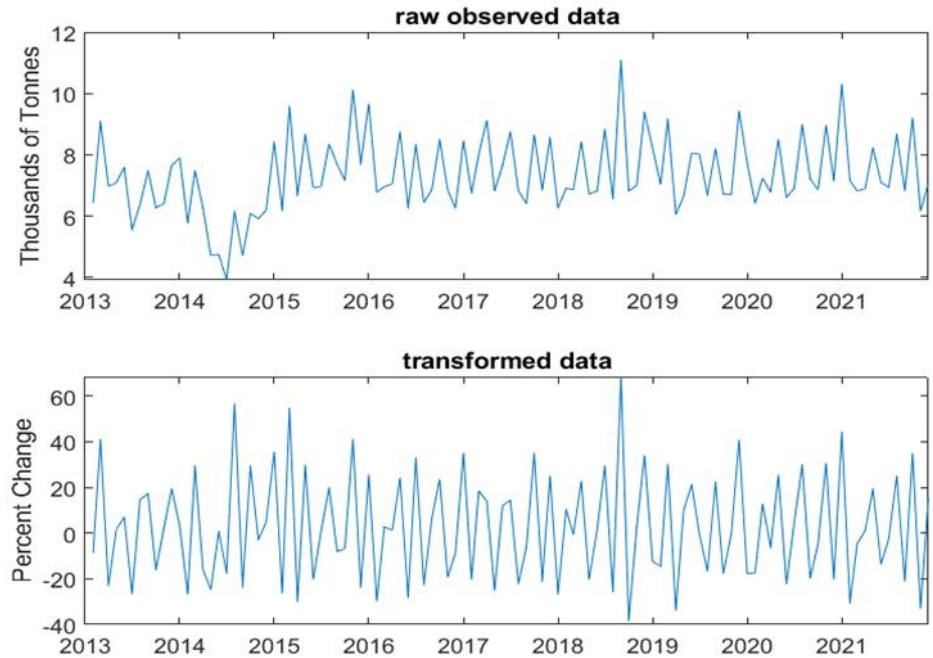
DRY_DISCH_IN_SG(DISCH_DURATION)



LIQUID_DISCH_IN_SG(LOAD_DURATION)



LIQUID_DISCH_IN_SG(DISCH_DURATION)



APPENDIX D: END-OF-PERIOD NOWCASTING RESULTS

D-1. GROSS DOMESTIC PRODUCT (GDP)

Nowcast Update: June 01, 2022
Nowcast for GDP Singapore (Percent Change), 2022:Q2

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		5.21
Impact from data revisions:	0.00	
Impact from data releases:	0.32	
Total impact:	0.32	
Jun 01 nowcast:		6.28

Nowcast Update: June 01, 2022
Nowcast for GDP Singapore (Percent Change), 2022:Q3

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		2.03
Impact from data revisions:	0.00	
Impact from data releases:	0.31	
Total impact:	0.31	
Jun 01 nowcast:		2.72

D-2. INDEX OF INDUSTRIAL PRODUCTION (IIP)

Nowcast Update: June 01, 2022
Nowcast for Index of Industrial Production (Percent Change), 2022:Q2

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		4.32
Impact from data revisions:	0.00	
Impact from data releases:	0.43	
	+_____	
Total impact:	0.43	
Jun 01 nowcast:		5.86

Nowcast Update: June 01, 2022
Nowcast for Index of Industrial Production (Percent Change), 2022:Q3

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		1.71
Impact from data revisions:	0.00	
Impact from data releases:	0.43	
	+_____	
Total impact:	0.43	
Jun 01 nowcast:		2.70

D-3. MANUFACTURING (MFG)

Nowcast Update: June 01, 2022
Nowcast for Manufacturing (Percent Change), 2022:Q2

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		7.94
Impact from data revisions:	0.00	
Impact from data releases:	0.37	
	+	
Total impact:	0.37	
Jun 01 nowcast:		9.27

Nowcast Update: June 01, 2022
Nowcast for Manufacturing (Percent Change), 2022:Q3

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		2.33
Impact from data revisions:	0.00	
Impact from data releases:	0.37	
	+	
Total impact:	0.37	
Jun 01 nowcast:		3.17

D-4. TRANSPORTATION AND STORAGE (TRANS)

Nowcast Update: June 01, 2022
Nowcast for Transport and Storage (Percent Change), 2022:Q2

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		4.77
Impact from data revisions:	0.00	
Impact from data releases:	0.43	
	+_____	
Total impact:	0.43	
Jun 01 nowcast:		6.17

Nowcast Update: June 01, 2022
Nowcast for Transport and Storage (Percent Change), 2022:Q3

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		2.56
Impact from data revisions:	0.00	
Impact from data releases:	0.41	
	+_____	
Total impact:	0.41	
Jun 01 nowcast:		3.45

D-5. FINANCE AND INSURANCE (FIN_INS)

Nowcast Update: June 01, 2022
Nowcast for Finance and Insurance Services (Percent Change), 2022:Q2

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		3.16
Impact from data revisions:	0.00	
Impact from data releases:	0.13	
Total impact:	0.13	
Jun 01 nowcast:		3.58

Nowcast Update: June 01, 2022
Nowcast for Finance and Insurance Services (Percent Change), 2022:Q3

Nowcast Impact Decomposition
Note: The displayed output is subject to rounding error

Apr 01 nowcast:		2.47
Impact from data revisions:	0.00	
Impact from data releases:	0.12	
Total impact:	0.12	
Jun 01 nowcast:		2.73